Formal and informal quota enforcement

Linda Nøstbakken[*]

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Abstract

I study renewable resource use and compliance in a dynamic model with both informal and formal modes of enforcement. Agents obtain utility from both resource use and from behaving according to a norm of quota compliance. The users can exceed their quota at the risk of being detected and formally punished, but they also risk informal sanctions in the form of social disapproval and guilt. I find that when accounting for informal enforcement, there is an indirect effect of regulatory change in addition to the intended direct effect. When policy change, such as tougher enforcement, makes individuals more compliant, the norm of compliance is gradually strengthened, which in turn induces more compliant behavior. I study the implications of policy change on compliance level, quota prices, and the norm of compliance, and show how the properties of the punishment function have important implications for the outcome.

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[*]Alberta School of Business, University of Alberta, Edmonton, AB, T6G 2R6, Canada. Tel: +1 (780) 248-1266. Email: Linda.Nostbakken@ualberta.ca

1 Introduction

Common property resources (CPRs) are characterized by an externality in resource use or extraction. Without regulations, the result can be a gradual destruction of the resource, known as the tragedy of the commons. To avoid such a tragedy, regulations are commonly used. However, regulations do not necessarily remove the agents' incentives to excessively use the resource. Indeed, regulatory non-compliance is a serious problem in many CPRs. There is a large literature on how norms and social interaction may alleviate the tragedy of the commons problem. The purpose of this paper is to analyze the implications of dynamic compliance norms on CPR use. In particular, I focus on the interplay between formal regulations and enforcement, and on the role of informal enforcement, which is driven by people's own desire to obey a norm of compliance.

If norms cause agents to behave closer to what is socially desirable and thereby alleviating free-riding problems, they can be of significant value and should be considered as a form of social capital. In the CPR setting, this is the case if norms and social interaction restrain the individual agents from excessive resource use. Dynamic norms are affected by the collective actions of the agents. A change of formal regulation that affects the agents' behavior can therefore affect the evolution of the norm. This, in turn, affects the level of informal enforcement and the value of the norm. Consequently, there is a close relationship between formal and informal enforcement. A complete understanding of the implications of a (formal) policy change requires, then, the analysis of both enforcement mechanisms.

There are many examples of regulated CPRs where non-compliance is widespread. Pargal & Wheeler (1996) study pollution in developing countries and describe how informal enforcement is an important factor in limiting emissions. Another well-known example are the fisheries. Unreported catches and landings are a serious problem worldwide. In a recent study, Agnew et al. (2009) estimate that illegal and unreported catches amount to about 20% of reported catches in world fisheries, but there is variation both across regions and fish species, as well as over time. Empirical studies of determinants of compliance in fisheries indicate that social norms and moral obligations play an important role in the compliance decision of fishermen (Hatcher et al., 2000; Hatcher & Gordon, 2005). Another example is in forestry, where illegal logging in many areas is of a significant concern. Much work has been done on Indonesian forestry, where illegal logging is a main reason for the deforestation that has occurred over past decades (Palmer, 2000). Ostrom (1990) presents other examples including irrigation, where informal enforcement has prevented the tragedy of the commons.

I introduce a dynamic norm of quota compliance into the standard model of a

renewable resource managed by tradable quotas. The utility effect of violating the compliance norm is introduced through a non-pecuniary (intrinsic) cost that depends on the agent's propensity to obey the compliance norm as well as the norm itself. The model is used to analyze the conditions under which agents violate quotas, the optimal resource use and the quota purchases, and particularly, how norm-based behavior affects these decisions. The dynamic nature of the model is important, as the extent of non-compliance affects the future availability of the resource. In addition, the current actions of agents affect the evolution of the norm, and consequently, the future actions of agents. Hence, there are two externalities in the model: agents do not take into account the effect of their own use of the resource on others, and they do not consider the impact of their actions on the evolution of the compliance norm.

The main effect of introducing a dynamic norm of compliance into the model arises from the fact that the norm changes depending on the actions of the individual agents. Any policy change that is intended to change the behavior of at least some agents may indirectly and over time change the norm, which in turn affects the behavior of these and other agents. Consequently, regulatory change has two main effects: a direct effect arising immediately as the agents respond to the new regulatory regime and an indirect effect arising gradually as the norm adjusts to a new equilibrium induced by the policy change (a social multiplier effect). Another result is that in a quota regulated industry with heterogeneous agents, the agents with the highest propensity to violate regulations, that is, those who have the lowest intrinsic cost of doing so, have a competitive advantage and obtain higher extraction revenues. Finally, I analyze the implications of introducing a non-linear formal punishment function, rather than the standard linear function that I use in the base model. I show that with non-compliance and an expected punishment function that is non-linear in quota and extraction level, the market can drive the quota price above the output price. In this case, agents with low intrinsic costs of violating the norm of compliance have a cost advantage in the quota market and can drive the more law abiding agents out of the industry altogether.

Introducing a norm of compliance into the CPR model is in line with the growing literature that incorporates norms and non-pecuniary incentives in the study of economic behavior (see the survey by Fehr & Falk, 2002, for an overview). The literature on self-governance also deals with similar issues (e.g. Ostrom et al., 1992; Bowles & Gintis, 2002). Furthermore, several economic studies account for the dynamic nature of norms (Sethi & Somanathan, 1996; Noailly et al., 2007; Lindbeck et al., 1999; Nyborg & Rege, 2003; Rege, 2004; Nyborg et al., 2006; Azar, 2008, to name some). However, these studies do not explicitly analyze the role of formal enforcement nor do they analyze the interplay between formal enforcement, informal enforcement and dynamic

norms.[1]

The interplay between norms and CPR use has been previously studied. Sethi & Somanathan (1996) developed an evolutionary game model of CPR use, which was later exteded by Osés-Eraso & Viladrich-Grau (2007) and Bulte & Horan (2010). In all these models, myopic agents choose between compliance or non-compliance by replicating the behavior of more successful individuals. While Sethi & Somanathan (1996) allow individuals to punish agents who do not comply, agents are motivated to comply as compliance yields social approval in the model of Osés-Eraso & Viladrich-Grau (2007). Finally, Bulte & Horan (2010) introduce the concept of identity, allowing different agents to have different identities or personal values that affect their payoffs. This work is closely related to the current study, but there are several important differences. First, contrary to the evolutionary game approach, I model the interplay between norms and CPR use within a standard economic model where rational individuals with constant preferences maximize expected utility. Second, I focus on a quota regulated CPR rather than an unregulated resource. I analyze how individual differences in the importance of social and moral norms affect individual behavior, CPR dynamics, the equilibrium quota price, and the distribution of resource extraction across agents. Finally, I analyze the effect of changing formal enforcement and the interplay between policy and dynamic norms.

The paper is organized as follows. In the next section, the basic model is presented and analyzed. I start out by analyzing individual agents' optimal behavior, before introducing a resource manager and characterizing the dynamic model. In section 4, I illustrate the results by providing a numerical example of resource and compliance dynamics. In section 5, I consider two model extensions. In the first extension I study CPR dynamics under welfare maximizing policies, and in the second extension I introduce a non-linear punishment function and show that this has important implications for the quota price. The final section concludes.

2   The Model

I develop a model that is based on the standard fisher model of quota enforcement (Nøstbakken, 2008). I extend this model by incorporating norm-based drivers of be-

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[1] Informal enforcement in environmental and natural resource management has been studied by, among others, Pargal & Wheeler (1996). However, these studies consider a different form of informal enforcement as they focus on enforcement in the form of "*social pressure on workers and managers, adverse publicity, the threat (or use) of violence, recourse to civil law, and pressure through politicians, local administrators, or religious leaders.*"

havior. More specifically, I assume that the compliance behavior of individual agents is influenced by both social and moral drivers. This is a reasonable assumption of many types of resource users, including fishermen operating in regulated fisheries. In his study of compliance behavior in a Norwegian fishery, Gezelius (2002) found that fishermen choose regulatory compliance partly because they do not want a bad reputation, and that this may result in compliance even in situations where the fishermen consider the risk of formal detection and punishment to be close to zero. The work of Gezelius (2002) also shows that these fishermen follow a norm of compliance. One fisherman was asked about the main reason why he complies with regulations and responded: *"Well, it's because it's the law. One would rather keep to the law"* (Gezelius, 2002, p. 309). With this motivation for the basic structure of my model, I will introduce the model.

Consider a quota regulated CPR, such as a fishery. There are two types of decision makers: the resource manager and individual resource extractors. The resource manager sets the total quota at the beginning of every period. If extraction from the stock is viable, the total quota in period t is given by Q_t. There is also a rental market for quotas that determines the quota price r. The quota of agent i is denoted q_{it}.

The dynamics of the resource stock are given by:

$$X_{t+1} - X_t = G(X_t) - Y_t, \tag{1}$$

where X_t is the resource stock at the beginning of period t and $Y_t = \sum_{i=1}^{n} y_{it}$ is total extraction in period t. $G(X)$ is the natural growth function, which is given by $G(X_t) = hX_t\left(1 - \frac{X_t}{K}\right)$, where h is a growth rate and K defines the upper limit on the resource stock. This type of growth function is commonly used to describe stock growth in fisheries, but also other renewable resources (Clark, 1990).

The focus of this study is not on the optimal regulation of the CPR, but on the effects of dynamic norms on regulatory compliance. Hence, for ease of exposition, I assume that the resource manager's objective is to maintain the resource stock at a certain predetermined level $\bar{X}$. This implies that the resource manager is not a social planner, but has been delegated the task of implementing an agreed-upon extraction policy.[2] Although this assumption may seem simplistic, it gives a reasonable representation of the quota setting process for many resources. In fisheries a stock management plan is typically determined at the national or international level, implemented by a regulatory agency who determines quotas and other regulatory measures (season lengths,

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[2]In section 5.1, I use numerical methods to characterize the welfare maximizing policy, and discuss the implications of using welfare maximizing policies rather than the simpler stock-target policy.

mesh sizes, minimum sizes, etc), and enforced by an enforcement agency. I take the management plan and the enforcement level as given and model the resource manager who must determine the total quota Q_t to achieve the stock target.

The resource manager knows the agents' extraction costs and the *distribution* of their intrinsic motivation to comply with quotas. However, the resource manager cannot observe individual agents' behavior and does not know their intrinsic motivation to comply with quotas. Hence, the total quota depends on the resource manager's expectation of the industry's response to quota, $E_t[Y_t|Q_t]$. Therefore, the manager sets the total quota Q_t at the beginning of period t so that next period's expected initial stock size equals $\bar{X}$. Formally, the quota is determined as follows:

$$E_t[X_{t+1}] = X_t + G(X_t) - E_t[Y_t|Q_t] = \bar{X}, \tag{2}$$

where E_t indicates the expectation at the beginning of period t. Over time, as the resource manager observes how the industry responds to Q_t, the accuracy of the expectation term in (2) increases.[3]

The resource can be extracted by a large but finite number of agents $n < \infty$, all of whom take all input and output prices as given. The assumption of a large number of agents reduces the problem to a static one, since agents cannot individually influence the future resource stock or norm.[4]

The market price of the extracted resource is p, and the agents maximize utility, which is measured in monetary terms:

$$U_{it} = py_{it} - C(X_t, y_{it}) - r_t q_{it} - \mathcal{P}(y_{it}, q_{it}, \phi) - M(y_{it}, q_{it}, m_i, S_{it}), \tag{3}$$

where y_{it} is the extraction of agent i so that the first term represents revenues, $C(\cdot)$ is agent i's extraction cost, the term rq_i is the acquisition cost of quota, with r representing the (rental) price of quota, $\mathcal{P}(\cdot)$ is a punishment function that gives the expected fine for quota violations, and finally, $M(\cdot)$ denotes the intrinsic (social and moral) cost of non-compliance. The properties of the elements of the utility function are presented in what follows.

The extraction cost of agent i is given by the following quadratic variable cost

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[3]Although the resource manager cannot directly observe individual extraction levels, aggregate extraction can be inferred from the evolution of the resource stock and the norm.

[4]We can think of n as the number of extraction licenses issued or the number of agents living within reach of a CPR. The assumption of a finite number of potential resource users rather than a continuum, does not affect the conclusions of the paper and is made for ease of exposition.

function (Smith, 1969):

$$C\left(X_t, y_{it}\right) = \frac{cy_{it}^2}{X_t},$$ (4)

where $c > 0$ is a constant cost parameter. The cost function is convex and increasing in extraction, while it is decreasing in stock size. This quadratic cost specification is commonly used to describe costs in renewable resource models, where extraction becomes increasingly costly the lower the availability of the resource.

The quota market enables agents to adjust their legal production levels. In addition, they have the possibility to violate quotas at the risk of detection and punishment. Agents are risk neutral, and hence, concerned only about the expected punishment. This is represented by the punishment function $\mathcal{P}(\cdot)$, which is the product of the probability of detection and the fine, where the latter depends on the agents' extraction level and the quota.[5] The punishment function is linear in the absolute violation and specified as follows:

$$\mathcal{P}\left(y_{it}, q_{it}, \phi\right) = \phi\left(y_{it} - q_{it}\right), \quad y_{it} \geq q_{it}, Q_t > 0.$$ (5)

If an agent does not violate the quota $(y_{it} \leq q_{it})$, the expected punishment is zero, and if $Q_t = 0$ the expected punishment approaches infinity. The latter assumption implies that there is no extraction if there is no quota.[6] For $y_{it} \geq q_{it}$, the punishment function is increasing linearly in the absolute violation $y_{it} - q_{it}$ and the enforcement intensity ϕ.[7] While the specification of the punishment function does not drive any of my main results, I analyze the implications of relaxing the assumption of a linear punishment function below (section 5.2).

Let us now introduce informal enforcement, which occurs as a consequence of individuals' incentives to follow the norm of compliance, regardless of formal enforcement. Agents have incentives to behave according to the norm because they experience both guilt and social disapproval if they act otherwise. Hence, the norm is not a purely moral or social norm, but a combination of the two, or what Elster (2009) refers to as quasi-moral norms. Norms have been suggested by many as important drivers of

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[5]Sanctioning behavior is not discussed in the paper, but can easily be accounted for in the model, e.g. by modifying the penalty function to account for sanctioning by other agents in addition to formal punishment enforced by laws and regulations.

[6]This assumption can be motivated by the fact that it is far easier to detect violators in a situation when everyone knows no extraction should take place. In what follows, I do not explicitly discuss the case of $Q_t = 0$ as I assume the resource is well-managed and there is no need to ban extraction.

[7]Enforcement intensity ϕ is exogenous to the model. The higher the inspection probability and the higher the fines, the higher the value of ϕ will be. These factors are assumed exogenous since the focus of the current work is on the relationship between formal and informal enforcement, not on the optimal formal enforcement. Furthermore, for most CPRs, fines and inspection budgets are beyond the control of the resource manager.

compliance and behavior in general (Elster, 1989; Fehr & Falk, 2002). Defying a norm yields a sense of dissatisfaction or disutility. Agents differ in how guilty they feel when violating norms and in how much they care about social disapproval. In the model, this is captured by the agent's propensity to obey the norm, m_i, which is private information. The disutility from violating the norm of compliance can be thought of as a moral or social intrinsic cost. This cost is not a pecuniary cost, but the pecuniary value of the agent's disutility from violating the norm. As such, the intrinsic cost is taken into account by agents when deciding on how much to extract legally and illegally. This introduction of non-pecuniary costs is in line with Levitt & List (2007).

Formally, I introduce the norm into the model as follows. Each agent has an individual propensity to obey the norm represented by the variable m_i, where $0 \leq m_i \leq \infty$ for all i.[8] However, all agents face the same norm of compliance S, but they differ in how much importance they place on the norm when making decisions. The evolution of the norm depends on how agents behave and can therefore change over time. Hence, the norm of quota compliance S_t is a second state variable in the model. Following Azar (2008), the dynamics of the social norm are given as follows:[9]

$$S_{t+1} - S_t = \omega \left(\max \left[\frac{Y_t}{Q_t}, 1 \right] - S_t \right), \tag{6}$$

where $\omega \in [0, 1]$ is an adjustment parameter. All agents have the same subjective impression of the size of S_t. Using this specification, S is a measure of how the industry as a whole complies with the total quota. Obtaining an accurate measure of S is perhaps difficult for most agents, but equation (6) can be thought of as a proxy describing the underlying realities.[10]

The reference value of the norm variable is $S = 1$, the level at which the industry on average fully complies. $S > 1$ implies that illegal extraction is socially acceptable

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[8]Differences in m_i across agents are due to differences in how both moral and social norms affect them. If a person is little affected by the norm of compliance, it means that this person does little self-sanctioning (e.g. guilt) and is relatively unaffected by other people's approval or disapproval. Individual differences in the propensity to obey the norm is in line with the empirical findings of Allcott (2011), who study how social norms affect energy conservation.

[9]Note that this implies that the social norm evolves on the same time-scale as the resource stock. This is reasonable if the agents only learn the extent of non-compliance in period t once they observe the stock size in period $t + 1$. We can also think of S_t as the value of the norm at the time within period t when agents make their decisions about the period's quota purchases and extraction.

[10]While the analysis is done using only one value of the norm that applies to all agents, S can alternatively be defined as a vector of interdependent norms applying to different subgroups of agents. Furthermore, assuming more complex norm dynamics, either by assuming that some individuals are more influential than others or that the number of violators plays a role, would not change the results quantitatively. As long as the norm adjusts toward the aggregate compliance behavior of the agents, my results hold.

to a certain degree, and the higher S is, the more the quota violations are tolerated. As long as resource extraction is profitable, the norm variable never takes on values below one ("1"), since the model ensures that agents always fully utilize their quotas. The max operator in equation (6) ensures that over-compliance if full quota utilization is not profitable, does not push the value of the norm below 1.

Agent i's intrinsic cost of violating the quota in period t is given by the following intrinsic cost function:[11]

$$M\left(y_{it}, q_{it}, m_i, S_t\right) = \frac{\alpha m_{it}}{S_t}\left(y_{it} - q_{it}\right),\qquad(7)$$

where α is a positive constant. The intrinsic cost of violating regulations increases in the absolute quota violation. Furthermore, a higher propensity to follow the norm increases the value of $M(\cdot)$, whereas a higher social acceptance for violating quotas, as reflected by a higher value of S, reduces the intrinsic cost.[12] By definition, the cost function is always zero if the propensity to follow the norm is zero; $m_i = 0$. As m_i increases, the marginal intrinsic cost of violating quotas will at some point outweigh the marginal revenue and the agent will always comply, regardless of other factors. Each agent's propensity to follow the norm, m_i, is private knowledge and cannot be used strategically by the resource manager, the enforcement agency, or by any other resource user.[13] I assume that m_i is uniformly distributed over the interval $a \leq m_i \leq b$: $m_i \sim u(a,b)$, where $a \geq 0$.

Having fully specified the objective function of the resource users, their maximization problem can be stated as follows:[14]

$$\max_{y_i,q_i} U_i = py_i - \frac{cy_i^2}{X} - rq_i - \max\left[\left(\phi + \frac{\alpha m_i}{S}\right)\left(y_i - q_i\right), 0\right],\qquad(8)$$

where the max operator is included because the last term is zero if the agent complies $(y_i \leq q_i)$. Agents must choose how much to extract and the number of quota units to acquire in order to maximize their utility (8). The agents' problem is static because the number of agents, n, is large and each agent only has a negligible effect on the

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[11]The specification is chosen to keep the analysis tractable while ensuring that the model complies with some basic properties of social approval identified by Gächter & Fehr (1999).

[12]This formulation is similar to that of Osés-Eraso & Viladrich-Grau (2007), who introduce social approval as a driver of cooperation in their evolutionary game framework of CPR use.

[13]An alternative interpretation of the intrinsic cost function $M(y_i, q_i, m_i, S)$ is in terms of identity. Within the identity framework of Akerlof & Kranton (2000), the actions of individual i are given by y_i, m_i represents i's characteristics, q_i represents the individual's ideal, while S captures the actions of others. One important difference is that while individual's in Akerlof & Kranton (2000) can change their identity, m_i is fixed in my model. See also Bulte & Horan (2010) for an application to CPR use.

[14]For ease of notation, the time dependency of all variables is mostly suppressed throughout the paper.

development of the resource stock and the dynamic norm. Furthermore, quotas are purchased (rented) on a period-to-period basis.

2.1 Individual extraction and compliance

Having specified the model, the next step is to analyze optimal individual behavior. Later, I will use this to study industry dynamics.

The problem of the individual agent is to maximize equation (8), subject to $y_i \geq q_i \geq 0$. This implies that the agent can choose inactivity, quota compliance, or quota violation, where the latter incurs expected formal punishment and the non-pecuniary cost $M(\cdot)$ of violating the norm. An agent complies if the shadow price of the quota constraint does not exceed the marginal expected punishment ($\mathcal{P}'(\cdot)$) and the marginal intrinsic cost ($M'(\cdot)$) of violating. With tradable quotas, the shadow price of the quota constraint is the quota price r. The formal and informal marginal punishment of exceeding the quota is $\phi + \alpha m_i/S$ for an agent currently complying. Hence, agent i complies if and only if $\phi + \alpha m_i/S \geq r$. Solving for the individual norm sensitivity parameter m yields the following compliance condition:

$$m_i \geq \frac{S}{\alpha}(r - \phi) \equiv \bar{m}. \tag{9}$$

This implies that the more an agent cares about following norms (the higher the m_i), the more likely (s)he is to comply with regulations.

Compared to the traditional model without informal punishment, the main difference is that the agent now takes into account the marginal intrinsic costs of increased extraction and decreased quota holdings. This yields a higher level of compliance, which is evident from the compliance condition (9) by comparing the cases of $m = 0$ (no intrinsic costs) to $m > 0$ (positive intrinsic costs).

The necessary and sufficient first-order conditions of the utility maximization problem are:[15]

$$U'_y = p - \frac{2cy_i}{X} - \lambda_i = 0 \tag{10}$$
$$U'_q = -r + \lambda_i = 0. \tag{11}$$

where $\lambda_i = \min(\phi + \alpha m_i/S, r)$. If $r \leq \phi + \alpha m_i/S$, the agent complies by purchasing quotas so that $y = q$. It is never optimal to purchase more quotas than what are used.

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[15]The utility function is concave and the first order conditions are therefore necessary and sufficient for a maximum.

If, on the contrary, $r > \phi + \alpha m_i / S$, the agent buys no quotas at all, since the marginal expected formal and informal punishment is less than the quota price.[16]

According to the optimality conditions, optimal behavior requires that marginal benefit equals marginal cost. The marginal benefit of increasing production y_i is the output price per unit, regardless of whether the agent chooses to comply or to violate. While the marginal cost for a compliant agent is the sum of the marginal production cost and the rental cost per unit of quota, for a non-compliant agent, it is given by the marginal production cost and the marginal formal and informal punishment.

We can solve for individual optimal extraction y_i from the optimality conditions (10 and 11):

$$ y_i^* = \begin{cases} \frac{X}{2c}(p - r) & \text{if } m_i \geq \bar{m} \\ \frac{X}{2c}\left(p - \phi - \frac{\alpha m}{S}\right) & \text{if } m_i < \bar{m} \end{cases}, \tag{12} $$

where the first and second lines are the optimal extraction levels of a compliant and non-compliant agent, respectively. Similarly, an agent's optimal quota purchase q_i is given by:

$$ q_i^* = \begin{cases} \frac{X}{2c}(p - r) & \text{if } m_i \geq \bar{m} \\ 0 & \text{if } m_i < \bar{m} \end{cases}. \tag{13} $$

It is easily confirmed that per-period extraction by agent i is increasing in stock size due to the lower costs of extraction from a larger stock, decreasing in the extraction cost parameter c and increasing in the output price p. For a compliant agent, extraction decreases in the rental price of quota r. The quota price has no impact on the extraction of a non-compliant agent unless it causes the agent to become compliant. The non-compliant agent's extraction level is decreasing in the enforcement level ϕ and the propensity to abide by norms m_i, while it is increasing in the norm value S. The latter is the result of the informal punishment of violating quotas decreases as quota violations become more socially acceptable (shown by a higher S).

The linear punishment function (5) yields a corner solution for agents' quota purchases. Hence, just by observing quota purchases we know who is compliant and who is not. Any agent who purchases at least one quota is compliant. If the regulator could use this information strategically, inspection resources would focus on those who do not purchase quota, thereby increasing the inspection rate for this group while reducing the inspection rate for the agents who purchase quota. This would change the analysis completely. However, the result that only compliant agents purchase quotas is an artifact of the stylized nature of the model and would not follow from a slightly

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[16]This is driven by the linearity of the punishment function. I return to this in section 5.2, where I assume a non-linear punishment function.

more complex setup, as I give an example of in section 5.2. I therefore assume that the regulator cannot strategically use agents' quota purchases to infer compliance behavior. This is a reasonable assumption since in the more complex world there are many additional sources of private information and uncertainty that preclude the resource manager from using information on individual quota purchases to infer compliance behavior.[17] In section 5.2, I show the implications of assuming a non-linear punishment function that ensures an interior solution for quotas.

2.2 Market clearing in the quota market

The quota price is determined by the market clearing condition. The supply is the total quota set by the regulator $\bar{Q}$, while the demand is given by the aggregate quota demand of the n agents. I have established that only compliant agents demand quotas. Hence, the aggregate quota demand is given by the sum of compliant agents' extraction levels.

$$Q_d = \frac{n_c X}{2c} (p - r), \tag{14}$$

where n_c is the number of compliant agents, which can be calculated from the compliance condition (9) using the fact that m is uniformly distributed over the interval (a, b).[18] This, in turn, yields:

$$n_c = \frac{n(b - \bar{m})}{b - a} = \frac{n}{b - a} \left(b - \frac{S}{\alpha} (r - \phi) \right), \tag{15}$$

where n is the total number of agents. Note that the number of compliant agents is a function of the quota price r. The higher the quota price, the less compliant agents there are, all else equal.

As violators do not buy quotas, a situation where all agents violate is not possible since this would imply an aggregate demand for quotas of zero, which would, consequently, drive the quota price to zero. However, as the price approaches zero, the expected formal and informal punishment of violating the quota will exceed the quota price for at least some agents, who would then become compliant and demand quotas. Hence, the following must hold: $0 \leq n_c < n$.

Next, by setting quota demand (14) equal to quota supply $\bar{Q}$ and substituting in

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[17]For example, agents may differ in how they perceive the marginal expected punishment they face if exceeding quotas, in extraction costs, and risk preferences.

[18]Note that this is an approximation since I assume a finite number of agents, not a continuum of agents. However, when the number of agents is large, as assumed here, such approximation is quite accurate.

for n_c from (15), I can solve for the market clearing quota price:

$$r = \frac{A_1 - \sqrt{A_1^2 - 4A_2}}{2}, \tag{16}$$

where A_1 and A_2 are defined as follows:

$$A_1 \equiv \frac{\alpha b}{S} + \phi + p, \tag{17}$$

$$A_2 \equiv p \left(\frac{\alpha b}{S} + \phi \right) - \frac{2\alpha c(b-a)\bar{Q}}{nSX}. \tag{18}$$

Taking the partial derivative of (16) with respect to the quota $\bar{Q}$ confirms that the equilibrium quota price is declining with the size of the quota, as expected. Furthermore, it is easily verified that the equilibrium quota price is increasing in the output price p, decreasing in the extraction cost c, and increasing in the total number of agents n. Finally, by taking the partial derivative of the quota price with respect to the enforcement effort ϕ, I find that the quota price is increasing in the level of enforcement ϕ. This is because higher enforcement causes more agents to comply, which increases quota demand and, therefore, the quota price. I use this result when I analyze the implications of tougher enforcement on individual behavior below.

Notice also from equation (16) that the quota price is affected by norm-based incentives to comply. The market-clearing quota price is a function of the norm S and the parameters of the distribution of m values in the population, a and b. This has important consequences for the information value of the quota price. Price is often used as an indicator of extraction costs in resource industries (see e.g. Arnason, 1990). However, when there are norm-based drivers of behavior, the market price does not give an accurate representation of production costs, since it is also affected by norm-based variables. Hence, a declining price can be due to norm-based factors such as a weakening of the compliance norm, or, that agents with relatively high m values are replaced by agents with lower m values. It can also be due to more lenient formal enforcement, in addition to increased efficiency in extraction.

2.3   The resource manager's problem

The problem of the resource manager is to maintain the resource at a predetermined level. Let us assume that the desired level of the resource stock $\bar{X}$ is the level that maximizes sustainable yield from the resource stock (cf. equation 1). The quota setting problem of the resource manager is given by equation (2).

The resource manager determines the quota based on the initial stock size in every

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period. The actual aggregate extraction as a response to the total quota, $E(Y|Q)$ (cf. equation 2), is unknown to the resource manager since the intrinsic costs of agents are private information. However, the extraction costs and revenues of the agents, as well as stock dynamics, are known. If the resource manager believes agents are driven only by traditional (pecuniary) economic incentives, (s)he over-estimates illegal extraction, as the norm-based incentives to comply are ignored. Let us refer to this case as the *naive* regulator. Over time, the resource manager learns more about aggregate extraction as a response to the total quota. Eventually, the quota decision can be made based on an unbiased expectation of aggregate extraction as a function of the total quota (19). Let us refer to this case as the *insightful* regulator.

Let us first consider the *naive* regulator case. In this case, the regulator believes that all agents are identical and that there are no norm-based incentives ($m_i = 0 \ \forall i$). According to the reaction functions derived above, the naive resource manager assumes all agents violate if the expected punishment is lower than the unit cost of quota $\phi < r$. Without informal punishment, no agent would be willing to pay more for a unit of quota than ϕ. However, if the quota price falls below ϕ, all agents would prefer purchasing quota instead of extracting illegally, and the price would be driven back up to $r = \phi$. Hence, the naive regulator would expect all agents to extract the same quantity $y = \frac{X}{2c}(p - \phi)$ and that the market clearing price would be $r = \phi$, so that agents would be indifferent between compliance and non-compliance. As a consequence, the quota instrument, in this case, would be ineffective.

Next, I analyze the more interesting quota setting problem of the *insightful* regulator. Total extraction as a function of the total quota can then be expressed as follows:

$$
Y_t(Q_t) = \frac{n - n_c\left(r_t(Q_t)\right)}{\bar{m}\left(r_t(Q_t)\right) - a} \int\limits_{a}^{\bar{m}(r_t(Q_t))} \frac{X_t}{2c}\left(p - \phi - \frac{\alpha m}{S_t}\right) dm
$$
$$
+ n_c\left(r_t(Q_t)\right) \frac{X_t}{2c}\left(p - r_t(Q_t)\right). \tag{19}
$$

The first term of (19) is the total extraction of non-compliant agents, while the second term is the total extraction of compliant agents. Each non-compliant agent's extraction level depends on the agents propensity to obey the norm m_i, which is uniformly distributed over the interval $(a, \bar{m})$. Hence, the aggregate extraction of non-compliant agents is calculated by taking the integral over m values over this interval. Since all compliant agents extract the same quantity, aggregate compliant extraction is found by multiplying this quantity by the number of compliant agents n_c.

Note that both the threshold value $\bar{m}$, the number of compliant agents n_c, and the quota price r in (19) depend on the quota size Q. Hence, to derive the quota setting rule, it is necessary to substitute in for $\bar{m}$, n_c and r from equations (9), (15) and (16), respectively.

By solving the integral and then simplifying, (19) can be stated as:

$$Y_t(Q_t) = \frac{X_t}{2c} \Bigg\{ [n - n_c(r_t(Q_t))] \left[p - \phi - \frac{\alpha [\bar{m}(r_t(Q_t)) + a]}{2S_t} \right]$$
$$+ n_c(r_t(Q_t))(p - r(Q_t)) \Bigg\}. \tag{20}$$

If $X_t + G(X_t) \leq \bar{X}$, the quota is zero (cf. 2). A closed form solution for Q_t does not exist, but the quota rule can easily be found using numerical methods. In what follows, I assume the regulator is insightful and applies the quota rule (20).

3 The effects of tougher formal enforcement

The main objective of this paper is to analyze the effects of changes in formal enforcement on resource extraction, compliance, and informal enforcement. It is therefore interesting to analyze how compliant and non-compliant agents' extraction and compliance levels, as well as the norm and the quota price, are affected by an increase in the enforcement parameter ϕ. I start out by analyzing the direct (static) effects, before turning to the indirect (dynamic) effects. I assume that there are at least some non-compliant agents prior to the increase in the enforcement effort; otherwise such an increase would have no effect.

3.1 Direct effect

Tougher formal enforcement $\Delta\phi > 0$ has several direct implications for resource use and compliance. It increases the overall compliance level by causing non-compliant agents to reduce their extraction levels, and, by strengthening agents' incentives to comply. The resource manager anticipates higher compliance and therefore increases the total quota to maintain the stock at its target level. These changes, in turn, have implications for the quota price and the extraction level of compliant agents. I start out by looking at the effect of increased enforcement on the quota price, which is summarized in proposition 1.

Proposition 1. *In a situation where both compliance and non-compliance occur, tougher enforcement causes an immediate drop in the equilibrium quota price.*

Proof. Due to the stock target, the regulator will adjust the quota to ensure that $\frac{\partial Y}{\partial \phi} = 0$. Hence, the total derivative of (20) with respect to ϕ must be zero:

$$\frac{d}{d\phi}\left\{\frac{X}{2c}\left[n_c(p-r)+(n-n_c)\left(p-\phi-\frac{\alpha}{2S}[\bar{m}+a]\right)\right]\right\} = 0 \tag{21}$$

Taking the derivative of (21) yields:

$$\frac{\partial n_c}{\partial \phi}(p-r) - n_c\frac{\partial r}{\partial \phi} - \frac{\partial n_c}{\partial \phi}\left(p-\phi-\frac{\alpha}{2S}[\bar{m}+a]\right) - (n-n_c)\left(1+\frac{\alpha}{2S}\frac{\partial \bar{m}}{\partial \phi}\right) \tag{22}$$

Note the following relationships and partial derivatives:

$$\bar{m} = \frac{S}{\alpha}(r-\phi)$$

$$n_c = \frac{n}{b-a}\left(b-\frac{S}{\alpha}(r-\phi)\right)$$

$$\frac{\partial \bar{m}}{\partial \phi} = \frac{S}{\alpha}\left(\frac{\partial r}{\partial \phi}-1\right)$$

$$\frac{\partial n_c}{\partial \phi} = -\frac{nS}{\alpha(b-a)}\left(\frac{\partial r}{\partial \phi}-1\right)$$

By substituting in for $\bar{m}$, n_c, $\frac{\partial \bar{m}}{\partial \phi}$, and $\frac{\partial n_c}{\partial \phi}$ in (22), solving for $\frac{\partial r}{\partial \phi}$, and simplifying, I obtain the following:

$$\frac{\partial r}{\partial \phi} = \frac{\frac{\alpha a}{S}+\phi-r}{\frac{\alpha b}{S}+\phi-r}. \tag{23}$$

For compliance to occur, the compliance condition must hold for at least one agent. The agent that is most likely to comply is the agent with the highest m value. Hence, the compliance decision must be satisfied for $\max m_i = b$. Similarly, for non-compliance to occur, the compliance condition must be violated for at least one agent. The agent that is most likely to violate is the one who cares the least about norm compliance, that is, the agent with $\min m_i = a$. Substituting in for these two values of m in the compliance condition yields the following:

$$r > \phi + \frac{\alpha a}{S}$$

$$r \leq \phi + \frac{\alpha b}{S}.$$

By applying these two inequalities to equation (23), we see that $\frac{\partial r}{\partial \phi} \leq 0$. $\qquad\square$

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The change in the quota price comes from two main sources. First, tougher enforcement increases the overall compliance level, and hence, the resource manager must increase the total quota for the aggregate extraction to remain unchanged. A larger quota means a positive shift in quota supply, which has a negative effect on the quota price. However, tougher enforcement also causes more agents to choose compliance over non-compliance. This represents a positive shift in demand and has a positive effect on the quota price. Proposition 1 implies that the supply effect is stronger than the demand effect.

Note that this result is driven by the resource manger's objective of maintaining the stock at a certain predetermined level. This causes him to reduce the quota to ensure the stock target is met also after the policy change. If the quota had been held constant, thereby eliminating the supply effect described above, the partial effect of tougher enforcement on the quota price would be positive. However, in section 5.1 I show numerically that the results presented above hold also if we assume a social planner who sets the quota to maximize welfare from the resource.

Having established the direct effect of tougher enforcement on the quota price, I summarize the remaining direct effects in proposition 2.

Proposition 2. *In a situation where both compliance and non-compliance occur, the direct effects of tougher enforcement are reduced violations by non-compliant agents, a reduction in the share of non-compliant agents, and increased extraction by compliant agents.*

Proof. First, non-compliant agents respond to tougher enforcement by reducing their extraction levels. Formally, it is easily shown that the partial derivative of the extraction level of a non-compliant agent with respect to ϕ is negative (cf. equation 12):

$$\frac{\partial y_i^{nc}}{\partial \phi} = -\frac{X}{2c} < 0,$$

where superscript nc denotes non-compliant.

Second, tougher enforcement increases the number of compliant agents by lowering the threshold value $\bar{m}$. Taking the derivative with respect to ϕ of $\bar{m}$, as defined by the compliance condition (9), yields:

$$\frac{\partial \bar{m}}{\partial \phi} = \frac{S}{\alpha}\left(\frac{\partial r}{\partial \phi} - 1\right) < 0.$$

Following proposition 1, which establishes that $\frac{\partial r}{\partial \phi} \leq 0$, this expression must be negative.

Third, the extraction level of compliant agents is affected through the change in the quota price. The partial derivative of the compliant agents' extraction level with respect to the quota price is:

$$\frac{\partial y_i^c}{\partial \phi} = -\frac{X}{2c}\frac{\partial r}{\partial \phi} \geq 0,$$

where superscript c denotes compliant. The expression must be positive, since we know from proposition 1 that $\frac{\partial r}{\partial \phi} \leq 0$. □

The insightful regulator adjusts the quota to maintain the stock at the desired equilibrium level $\bar{X}$. This implies that the aggregate extraction level is the same before and after the change of the policy. Since the extraction levels of non-compliant agents decline when enforcement is toughened, compliant agents must extract a larger share of the total in this case. This effect is evident in the proof of proposition 2.

Note also that although compliant agents are not directly affected by increased enforcement, they are indirectly affected through the change in the equilibrium of the quota price r. Hence, tougher enforcement reduces the extraction levels of non-compliant agents, while increasing individual extraction levels for compliant agents.

3.2   Indirect effect

The dynamics of the system are straightforward once the system reaches its steady state. In its steady state, there is no change in the resource stock or the norm from period to period, and hence, the total quota, the quota price, and individual extraction levels are constant over time. It is therefore more interesting to analyze the dynamics following a policy shock. Such shock brings the system out of its steady state and we can analyze how the system gradually approaches a new steady state.

Above, I established the direct (static) effects of tougher enforcement. I will now analyze the indirect effect of a permanent increase in the level of enforcement. These direct effects cause an indirect effect that works through the dynamic norm of compliance. I present the main results on the indirect effects in proposition 3.

Proposition 3. *There is an indirect effect of tougher compliance that occurs through the evolution of the norm, which gradually adjusts downward toward the new aggregate compliance level. Agents, who take the norm into account when making decisions, respond by reducing illegal extraction.*

Proof. Consider a permanent policy shock in the form of tougher enforcement, $\Delta\phi > 0$, that occurs at time $t = \tau$. I assume the system is in steady state prior to the shock,

with $S_\tau = \tilde{S} = \tilde{Y}/\tilde{Q} > 1$ and $X_\tau = \tilde{X}$, where tilde indicates the initial steady-state value of a variable. There is a certain level of non-compliance prior to the policy shock, and hence, $\tilde{S} > 1$ and $n_c < n$. From proposition 2, we know that tougher enforcement causes an immediate increase in the aggregate level of compliance. With $\Delta_\tau (Y/Q) < 0$, we know from (6) that $S_{\tau+1} < S_\tau$. Therefore, in period $(\tau + 1)$ agents make their extraction and quota rental decisions based on a norm that is less tolerant to violations. By taking the derivative of $\bar{m}$ (from equation 9) with respect to S:

$$\frac{\partial \bar{m}}{\partial S} = \frac{1}{\alpha}(r - \phi) > 0,$$

it is clear that a lower tolerance for non-compliance ($\Delta S < 0$) increases the number of compliant agents n_c. In addition, a lower S induces non-compliant agents to extract less (cf. equation 12):

$$\frac{\partial y_i^{nc}}{\partial S} = \frac{X}{2c}\frac{\alpha m_i}{S^2} > 0.$$

Hence, a reduction in the norm variable S, from period τ to $(\tau + 1)$, will lead to a subsequent reduction in illegal extraction, all else equal. The insightful regulator anticipates this and increases the quota to maintain aggregate extraction at the target level. Reduced illegal extractions, combined with an increase in the quota, yield an increase in the aggregate compliance level, which in turn, affects the evolution of the norm. The norm variable again adjusts downward, $\Delta S_{\tau+1} < 0$, which means that even less non-compliance is tolerated. This gradual downward adjustment in the norm variable and extraction levels continue until the system reaches a new steady state. The new equilibrium is characterized by less non-compliance and a lower value of the norm variable S. $\qquad\square$

The indirect effect strengthens the direct effect of policy change. Hence, the adjustment in the dynamic norm following policy change yields a multiplier effect or motivational crowding-in. Note that I have not considered possible motivational crowding-out effects in this analysis. The presence of such effects could counteract both the direct and indirect effects discussed herein. This would be the result if the tougher enforcement crowds out intrinsic motivation to obey the compliance norm (see e.g. Gneezy & Rustichini, 2000, on the well-known daycare example). This may occur if tougher enforcement is perceived by the agents as controlling rather than supporting (Frey, 1997). For the quota regulated CPR case, this implies that the results presented above hold as long as agents share the view that there is need for tougher quota enforcement to maintain a healthy resource stock (see Acheson & Gardner, 2010; Gezelius, 2002).

4 Numerical example

In this section, I will illustrate the main results of the paper by providing a numerical example. The focus is on CPR dynamics, and particularly, on the impact of the dynamic norm on the behavior of the agents and the development of the CPR, quota prices, and the norm itself. The parameters used in the numerical analysis are given in table 1.

Table 1: Parameter specification

Parameter	Value	Description
K	100	Carrying capacity of resource stock
h	0.5	Intrinsic growth rate of resource stock
X_0	50	Initial resource stock level
p	2	Output price
c	75	Parameter, cost function
n	200	Number of agents
α	1	Parameter, intrinsic cost function
$[a, b]$	$[0, 3]$	Distribution of m_i values
ω	0.25	Adjustment parameter, norm (S_t)
S_0	1	Initial value of norm
ϕ_0	1.5	Initial enforcement intensity
ϕ_1	1.6	Enforcement intensity after policy change

I assume that the regulator's quota decision is made based on unbiased expectations of the total extraction as a response to the total quota, that is, the *insightful* regulator case analyzed above. Recall that the manager's objective is to maintain the stock at the level that maximizes sustainable extractions. For parameter values as given in table 1, this implies a target stock level of $\bar{X} = 50$.

The numerical results presented in what follows are obtained by the use of simulations. Initially, the stock size is $X_0 = 50$ and the norm variable is set to $S_0 = 1$.[19] I calculate the market clearing rental price of quotas from equation (16). The agents' propensity to abide by norms m_i $(i = 1, ..., n)$ are uniformly distributed over the interval $[0, 3]$.

I start out by analyzing how the system evolves from its initial state (cf. table 1) until it reaches its initial equilibrium. Next, I analyze the dynamics of increased

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[19]Neither the choice of initial values for X and S, nor other parameter values, qualitatively affect the results. The only requirement is that resource extraction is viable and that at least some agents find it optimal to violate their quotas initially.

enforcement, by increasing the value of ϕ from 1.5 to 1.6 (from time period 51 onward).

4.1   Dynamics and initial equilibrium

Figure 1 shows the dynamics of the norm S and the threshold value of the norm sensitivity parameter $\bar{m}$. For now, I focus on the period up until the policy change, which is indicated by vertical blue lines in the figures. The norm variable S increases over time from its initial level $S_0 = 1$ until it levels out at the initial steady state level of 1.378. This implies that total extraction exceeds the total quota by 37.8%. The total quota and the market clearing quota price are shown in figure 2. As the value of the norm increases, which reflects a higher tolerance for quota violations (or lower informal enforcement), the total quota declines. This is necessary to maintain the stock at the target level $\bar{X} = 50$, as discussed above.

**Figure 1:** Compliance dynamics: Norm and threshold value $\bar{m}$.
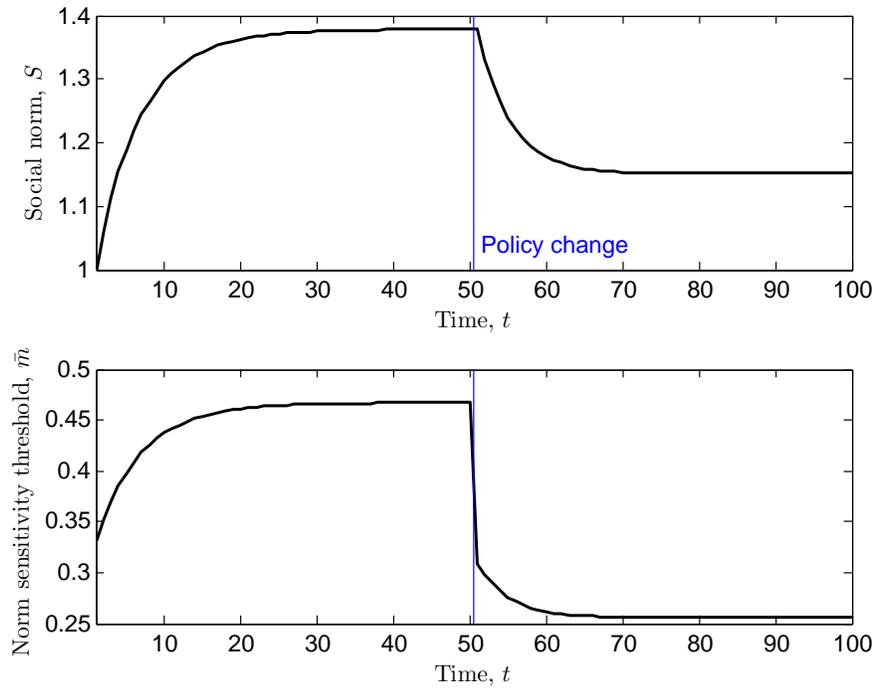
As the norm value increases, the agents' intrinsic costs of violating the quota fall, and the share of compliant agents declines. This is evident in figure 3. In the first period, when the norm variable is $S_0 = 1$, 89.0% of agents comply. As the norm variable adjusts upward, the share gradually declines to an equilibrium level of 84.4%. This development can also be seen in the bottom panel of figure 1, which shows how

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the threshold level $\bar{m}$ increases and levels out at an equilibrium level of $\bar{m} = 0.467$.

Furthermore, as the norm and the level of non-compliance increase, the regulator gradually reduces the total quota. However, more non-compliant agents means more agents that do not buy any quotas, and hence, the aggregate quota demand declines. The overall effect is a fall in the quota price, in line with proposition 1.

Figure 2: Compliance dynamics: Total quota.
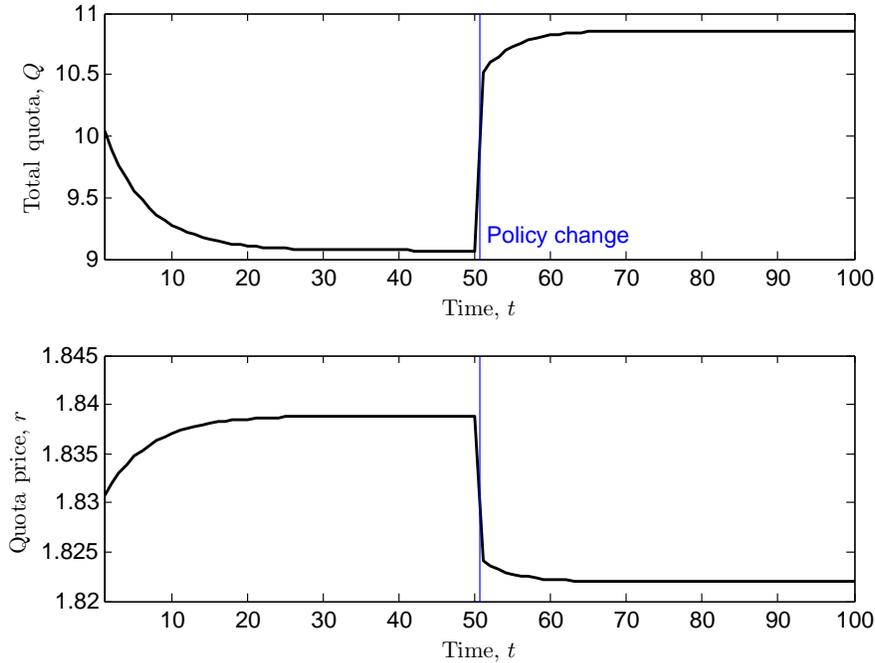
Note that agents who care relatively little about obeying the norm (low m), become dominating in the resource industry. In equilibrium, each compliant agent extracts 0.0537 units, while each non-compliant agent extracts between 0.0573 and 0.1667 units, depending on their individual m values (with an average of 0.1102 units). Hence, the agents who care the least about obeying norms obtain significantly higher monetary payoffs than agents who put more weight on norms. Consequently, in an industry with extraction licenses or similar instruments to limit entry, the agents who care the least about the compliance norm would have a clear competitive advantage in the market for licenses.

If, however, formal expected punishment is non-linear as opposed to the linear punishment function I have assumed here, non-compliant agents may have a higher willingness to pay for quotas than compliant agents. Hence, with an alternative specification of the punishment function, agents with low m values may have a competitive

advantage over agents with higher m values also in the quota market. I analyze this in section 5.2 below.

In reality, agents are likely to differ in variables other than just in their propensity to obey norms. With differences also in extraction costs, the most competitive agents will be those with the lowest combined intrinsic cost and extraction cost. Nonetheless, the agents with relatively low m values still have an advantage over other agents, all else equal. The results are therefore applicable to more general situations than the stylized case considered herein.

Figure 3: Compliance dynamics: Share of agents who comply.
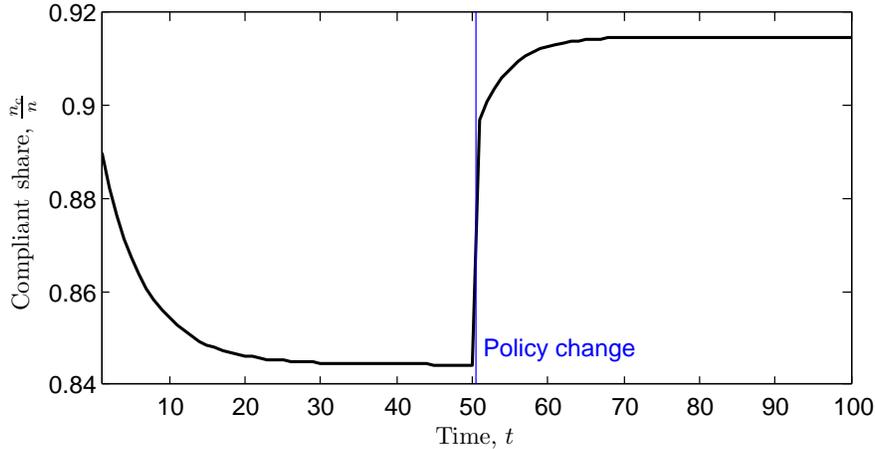
4.2 The effect of policy change

Let us now turn to the dynamic effects of policy change. I investigate the implications of increasing the enforcement intensity from $\phi_0 = 1.5$ to $\phi_1 = 1.6$. The results are summarized in figures 1, 2, and 3, where the policy change is introduced from period 51 onwards, as indicated by the vertical blue lines in the figures.

Tougher enforcement immediately shifts the quota up and the threshold level of the norm sensitivity variable $\bar{m}$ down, in line with my theoretical results presented above. This is also evident in figure 3, which shows a significant upward shift in the share of compliant agents. Since overall compliance improves when enforcement intensity increases, the regulator reduces the quota to reach the extraction target (maintain stock at $\bar{X}$).

More compliant agents increase the quota demand, while a larger total quota increases quota supply. The latter effect dominates and the quota price declines from

1.839 to 1.824 in the first period after the policy change: a 0.8% reduction. The quota price then gradually approaches its new equilibrium level $r = 1.822$. A lower quota price implies higher extraction levels for compliant agents. Compliant agents now extract 0.0593 units each, a 10.4% increase relative to the situation prior to the policy change. Non-compliant agents now extract between 0.0619 and 0.1667 units, with an average of 0.0963, which represents a 12.6% reduction relative to the average prior to the policy change. Hence, tougher enforcement improves the conditions for compliant agents (those who care the most about obeying the compliance norm) at the cost of non-compliant agents (those who care the least about obeying the compliance norm).

Turning to the norm, the top panel of figure 1 shows how S exhibits a gradual downward adjustment towards its new equilibrium level $S = 1.1511$, in line with proposition 3. A change in the norm affects the agents' behavior, since the norm enters their utility functions. Hence, the norm adjusts gradually until it fully reflects the new compliance level of the agents. This gradual adjustment can be thought of as a social multiplier effect, since it strengthens the direct effect of tougher enforcement by causing higher informal enforcement of quota violations.

Tougher enforcement reduces the level of non-compliance (Y/Q) from 37.8% to 15.1%. Of this, the direct effect reduces non-compliance from 37.8% to 18.8%, while the indirect effect, driven by the changing norm, accounts for the remaining reduction from 18.8% to 15.1%. Note that while the relative size of the indirect effect depends on the specification of the numerical model, the existence of an indirect effect is a general result that only requires a dynamic norm that depends on aggregate behavior, and policy change that affects at least some agents' behavior.

To summarize, tougher formal enforcement increases the expected formal punishment of quota violations, which strengthens the agents' formal incentives to comply. This has several implications. First, there is an immediate direct effect due to reduced marginal benefits of violating quotas, and hence, illegal extraction goes down. As a consequence, the regulator must reduce the total quota in order to achieve the extraction target. Second, the market clearing quota price immediately falls, which increases the extraction level of every compliant agent. When the agents change their compliance behavior, this gradually shifts the norm, increasing the informal punishment of violating quotas. Since agents care about the norm, this feeds back into their utility maximization problem and affects their quota purchase and extraction decisions. Thus, there is a gradual change in all variables reflecting this adjustment until a new equilibrium level is reached.

5 Model extensions

In this section, I extend the base model presented above. I start out by investigating the implications of assuming a social planner who maximizes welfare rather a resource manager who implements the target stock policy. Next, I investigate how a non-linear punishment function affects the results from the base model.

5.1 Welfare maximization

The purpose of this section is to numerically investigate the welfare optimizing policy for the model presented above. I start out by characterizing the optimal policy and investigating how it is affected by changes in the cost of enforcement. Next, I show that the analytical results on direct and indirect effects of policy change also hold when quotas are set optimally in order to maximize welfare.

Let us introduce a social planner who seeks to maximize the net present value of aggregate welfare obtained from resource use. The social planner knows the extraction costs and the distribution of m values, which represent the agents' propensities to comply with the norm. The problem of the social planner is to solve the following welfare maximization problem:

$$\max_{\{Q,\phi\}} \sum_{t=0}^{\infty} \beta^t W_t, \tag{24}$$

subject to norm and resource stock dynamics given by equations (6) and (1), the distribution of m values, and the market clearing quota price (16), which determines the compliance behavior of agents.

The welfare function representing welfare in period t can be stated as follows:

$$W_t = R_t - VC_t^c - VC_t^n - mC_t - c_e\phi^2 \tag{25}$$

where the term R_t represents total extraction revenues, VC_t^c and VC_t^n denote the aggregate variable extraction costs for all compliant and non-compliant agents, respectively, mC_t denotes the non-pecuniary costs (of non-compliant agents), and the term $c_e\phi^2$ is the enforcement cost, which I assume is increasing and convex in the level of enforcement ϕ. Fine payments are transfers from quota violators to the government and are therefore not included in the welfare function. I will consider two alternative measures of welfare, differing in whether non-pecuniary costs mC_t are included. Let $\hat{W}_t$ denote welfare when non-pecuniary costs are disregarded, that is, $\hat{W}_t = W_t + mC_t$.

Every term in (25) can be calculated from the reaction functions of the agents presented earlier. Total extraction revenues are given by the product of aggregate

extraction from equation (20) and the output price, p. Note that this implies that I assume illegal extractions have the same value as legal extractions.

$$R_t = \frac{pX_t}{2c} \left\{ (n - n_{c,t}) \left[p - \phi - \frac{\alpha (\bar{m}_t + a)}{2S_t} \right] + n_{c,t} (p - r_t) \right\}. \tag{26}$$

It is straightforward to calculate the variable cost of compliant firms as they all extract the same quantity, and hence, have the same extraction cost. Multiplying this extraction cost by the number of compliant agents and simplifying yield:

$$VC_t^c = \frac{n_{c,t} X_t}{4c} (p - r_t)^2. \tag{27}$$

It is slightly more tedious to calculate the costs of non-compliant agents, since their extraction levels depend on their m_i parameters. We can calculate the aggregate costs as the integral over the uniform distribution of m from a to $\bar{m}_t$, which represents the population of non-compliant agents at time t. This yields the following aggregate extraction cost for non-compliant agents:

$$VC_t^n = (n - n_{c,t}) \int_a^{\bar{m}_t} \frac{c}{X_t} \left[\frac{X_t}{c} \left(p - \phi - \frac{\alpha}{S_t} m \right) \right]^2 \frac{1}{\bar{m}_t - a} dm$$

$$= (n - n_{c,t}) \frac{X_t}{4c} \left[(p - \phi)^2 - \frac{\alpha}{S_t} (p - \phi) (\bar{m}_t - a) + \frac{\alpha^2}{3S_t^2} \left(\bar{m}_t^2 + a\bar{m}_t + a^2 \right) \right] \tag{28}$$

Similarly, the aggregate non-pecuniary cost of violating the norm of compliance is given by:

$$mC_t = (n - n_{c,t}) \int_a^{\bar{m}_t} \frac{\alpha m}{S_t} \frac{c}{X_t} \left(p - \phi - \frac{\alpha m}{S_t} \right) \frac{1}{\bar{m}_t - a} dm$$

$$= (n - n_{c,t}) \frac{\alpha X_t}{4cS_t} \left[(p - \phi) (\bar{m}_t - a) - \frac{2\alpha}{3S_t} \left(\bar{m}_t^2 + a\bar{m}_t + a^2 \right) \right] \tag{29}$$

The welfare maximization problem (24) does not have a closed form solution. The problem is actually more complicated than what it may seem based on the above set of equations. This is because r_t, $n_{c,t}$, and $\bar{m}_t$ in equations (26)-(29) are functions of the optimization problem's state and control variables. When substituting in for these variables the problem becomes very complex and highly non-linear. I therefore use numerical approximation to identify the optimal policy.

To solve the problem numerically, I assume a functional form for the quota feedback policy and use a numerical algorithm to identify the parameter values of this feedback

function, along with the enforcement level that maximize welfare (24).[20] Once I have characterized the optimal policy, I can use the policy functions to run simulations and analyze different scenarios. To solve the welfare optimization problem, I use the parameter values presented in table 1, assume the enforcement cost parameter $c_e = 1$, discount factor $\beta = 1$, and initial values of the state variables $X_0 = 50$ and $S_0 = 1$.

I start out by identifying the optimal policy for each of the two welfare measures presented above: W_t and $\hat{W}_t$. The optimal steady-state policy and norm for different values of the enforcement cost parameter c_e are presented in figure 4. The higher the cost of enforcement, the lower the enforcement level and the quota. This causes an increase in illegal extraction, while legal extraction falls. However, the steady-state total extraction level is basically constant at approximately 12.4 for the range of enforcement costs considered in figure 4, independently of welfare measure considered. Hence, as enforcement becomes more costly it is optimal to shift extraction from legal to illegal, keeping the aggregate extraction level, and hence, the stock size constant. Consequently, the optimal policy yields similar steady-state results as the far simpler target-stock policy I assumed in the base model.

Figure 4: Steady-state optimum by enforcement cost for welfare measure W_t (solid line) and $\hat{W}_t$ (dashed line): (a) Optimal enforcement level (black lines) and social norm (gray lines). (b) Optimal quota.


(a)   (b)
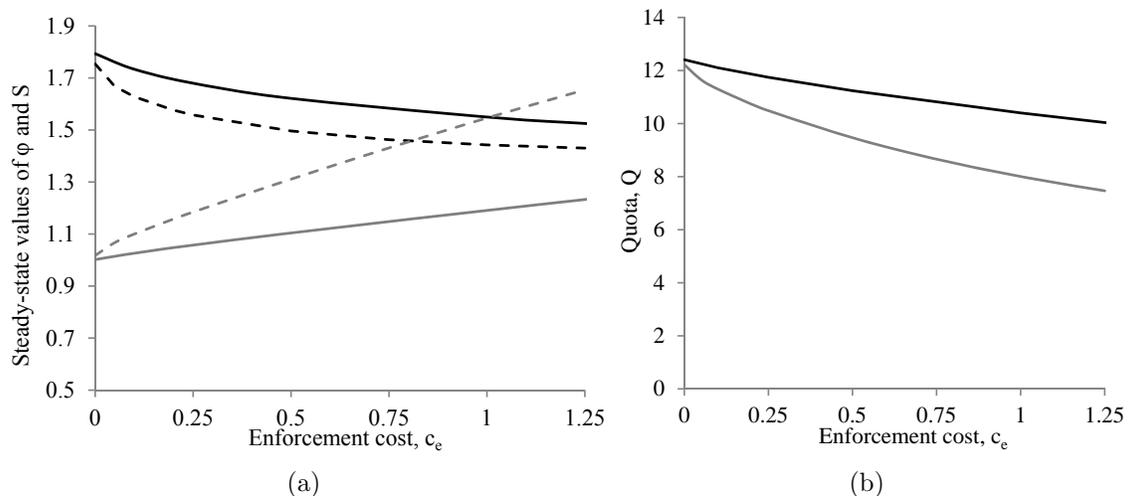
Let us now investigate how a change of enforcement affects the CPR under the welfare maximizing policies. To analyze this, I impose the enforcement levels used

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[20]Due to the complexity of the problem, I approximate the solution by assuming a feedback policy for the quota, where the quota is a function of the two state variables X_t and S_t, while I restrict the enforcement level to be constant over time.

in the numerical analysis described in section 4, and solve the maximization problem (24) with the quota as the only control variable. The results are shown in figure 5. Note that the main results from the theoretical analysis in section 3 still hold when we impose a welfare maximizing policy. As is shown in figure 5, tougher enforcement causes an immediate direct effect, which increases the compliance level. Due to increased compliance, the quota is immediately increased and the quota price responds by dropping below the initial level.

Figure 5: Compliance dynamics: Welfare measures W_t (solid line) and $\hat{W}_t$ (dotted line).
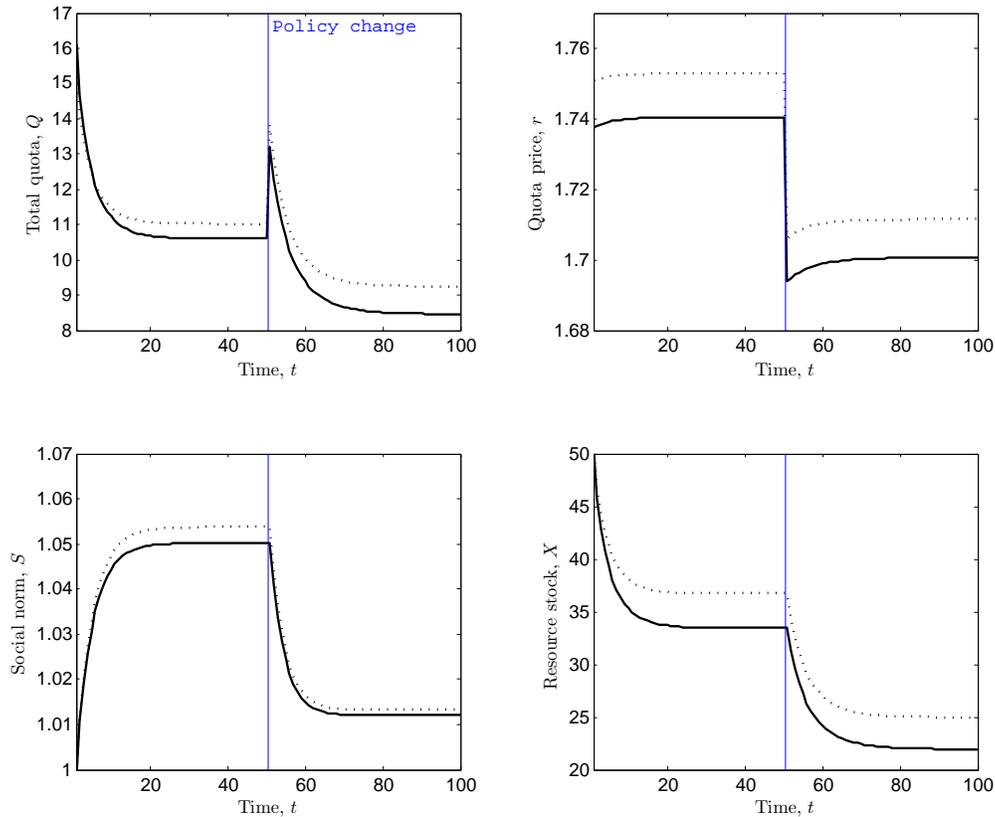
The main difference compared to the target-stock policy applied in the base model is that the resource stock no longer is held constant regardless of enforcement. With tougher enforcement it becomes optimal to reduce the stock level. The steady-state stock level falls from 47.4 to 47.0 under the optimal policy for welfare measure W_t, and from 48.0 to 47.8 for welfare measure $\hat{W}_t$. This downward adjustment in stock level is achieved by a one-period increase in the quota, which causes a temporary drop in the quota price. This one period spike in the quota to adjust the stock level is the only qualitative difference in terms of the dynamic effects of policy change compared to the

base model.

The results also show that the quota and the social norm are basically unaffected by the choice of welfare measure. The optimal stock level and the quota price are, however, affected. If we account for all costs in our welfare measure (W_t), both the resource stock and the equilibrium quota price are below the corresponding values if we ignore non-pecuniary costs $(\hat{W}_t)$. This has a simple explanation: a lower quota price increases the share of compliant agents, which in turn reduces the non-pecuniary cost of violating the norm of compliance.

5.2 Non-linear punishment function

The base model presented above assumes a linear punishment function that yields a corner solution for agents' quota purchases; you either cover your entire extraction with quotas or do not obtain quotas at all. In this section, I show that this assumption does not drive the main results of the paper. However, the choice of punishment function has important implications for the equilibrium quota price. If non-compliant agents do not buy quotas at all, as in the base model, the quota price can never exceed the output price. This is because only compliant agents operate in the quota market and they are never willing to pay more per unit of quota than the output price p (cf. equation 12). If, however, the punishment function is non-linear and the quota purchase decision is an interior solution, non-compliant agents will choose to cover some of their extractions by quotas. As a result, their willingness to pay for quotas depends on both the legal and illegal extractions that each unit of quota warrants, and they may have a willingness to pay for quotas that exceeds the output price. As a consequence, the quota price may be driven above the output price.

Let us now modify the base model by assuming the following non-linear punishment function:

$$\mathcal{P}\left(y_{it}, q_{it}, \eta\right) = \frac{\eta\left(y_i - q_i\right)^2}{q_i}. \tag{30}$$

If an agent does not violate the quota, the punishment is zero. For $y_{it} > q_{it}$, the punishment function is convex and increasing in y_{it}, convex and decreasing in q_{it}, and increasing in enforcement intensity η.[21] This specification implies that it is never optimal to extract without a positive quota holding, since the expected punishment approaches infinity as $q \to 0$ for $y > 0$.[22] This may be an appropriate representation when it is easy to identify resource users without quotas.

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[21]η is equivalent to ϕ in the base model, but is now given per unit of relative quota violation.

[22]This implies that if the resource manager sets the total quota to $Q_t = 0$, no extraction would occur.

Agent i complies if and only if $\alpha m_i / S \geq r$, which yields the following compliance condition:

$$m_i \geq \frac{rS}{\alpha}. \tag{31}$$

Optimal extraction and quota purchase for a compliant agent is the same as in the base model (equation 12) and is given by:

$$y_i^c = q_i^c = \frac{X}{2c}(p - r). \tag{32}$$

The highest price a compliant agent is willing to pay per unit quota is $\bar{r}_i^c = p$. At quota prices above this level, the agent prefers inactivity.

The optimal extraction and quota purchase of a non-compliance agent are:

$$y_i^{nc} = \frac{X}{2c}\left[p - 2\eta(\gamma_i - 1) - \frac{\alpha m_i}{S}\right] \tag{33}$$

$$q_i^{nc} = \frac{y_i^{nc}}{\gamma_i}, \tag{34}$$

where $\gamma_i > \sqrt{\frac{1}{\eta}(r + \eta - \alpha m_i / S)} \geq 1$. Notice that γ is the ratio of total extraction to quota, y/q. It is easily confirmed that both y and q (equations 33 and 34) are increasing in the size of the resource stock X and the output price p, and decreasing in the cost parameter c. An increase in the quota rental price reduces both q and y, whereas γ, the y/q ratio, increases. Turning to the informal punishment, the lower the agent's value of m, the higher the total extraction (and γ). An increase in S implies that the norm tolerates higher levels of non-compliance. This reduces the intrinsic cost of violating quotas for all agents and therefore leads to higher aggregate extraction relative to the total quota.

The highest price a non-compliant agent is willing to pay per unit of quota is:[23]

$$\bar{r}_i^{nc} = p + \frac{1}{4\eta}\left(p - \frac{\alpha m_i}{S}\right)^2. \tag{35}$$

The bracketed term is positive since $p > \frac{\alpha m_i}{S}$ for non-compliance agents. It follows that agents are willing to pay more per quota unit if they violate quotas than if they comply ($\bar{r}^{nc} > \bar{r}^c = p$).[24] The reason is that non-compliant agents have a higher willingness to pay for quotas because they also pay for the right to extract illegally. This is driven by the specification of the penalty function (5), which approaches infinity as the agent's

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[23]$\bar{r}^{nc}$ is the highest price that yields a positive extraction level (cf. 33) and a positive quota level (cf. 34).
[24]See Hatcher (2005) for a discussion of how non-compliance affects the quota price in his study of non-compliance in fisheries.

quota approaches zero, and, is increasing and convex in the absolute violation.

Figure 6: The quota demand of a non-compliant agent (nc) and a compliant agent (n).
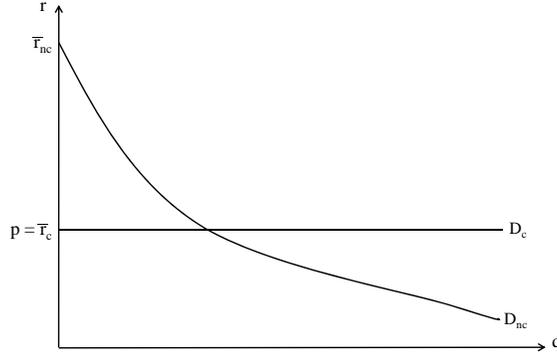
The difference in compliant and non-compliant agents' demand is illustrated in figure 6. The non-compliant agent's quota demand is high at low quota levels and declines with the quota. This is because the value of reduced expected punishment is very high as the quota level approaches zero, but declines as the agent obtains more quotas. A compliant agent would never pay more than the output price p for a quota, which is why the demand function of compliant agents is flat.

With this in place, I analyze resource and compliance dynamics numerically. I use the same parameter values as reported in table 1, but with enforcement intensities $\eta_0 = 0.9375$ and $\eta_1 = 1$ before and after the change of policy, respectively.[25] The policy change occurs at the beginning of period 51. The dynamics of the norm S and the quota price r are shown in figure 7.

Let us first consider the period prior to the policy change. The norm variable increases over time until it levels out at its initial equilibrium level with $S = 1.6163$. In equilibrium, no agent operates in compliance with quotas. Either agents are inactive or they exceed their quota. This is the result of a high quota price, which reaches 2.04 in equilibrium - a level that exceeds the output price ($p = 2$). Since compliant agents only purchase quotas if the output price exceeds the quota price, they are inactive from period seven onward (the first period when the quota price exceeds the output price). In equilibrium, agents with m values below $\bar{m} = 2.5779$ are active. With m uniformly distributed over $[0, 3]$, this implies that 85.93% of agents are active and non-compliant, while the remaining 14.07% are inactive. The quota price declines as the norm value shifts upward, indicating reduced informal punishment of quota violations,

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[25]With these numbers, the relative increase in enforcement intensity is the same as the increase considered for the base model in section 4.

which increases the non-compliant agents' willingness to pay for quotas.

Figure 7: Compliance dynamics: Norm and quota price.
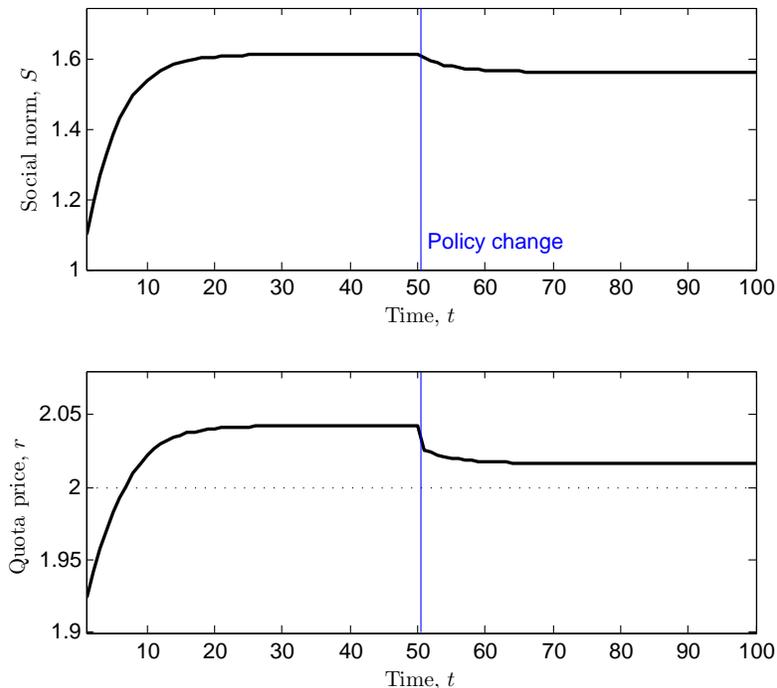
Let us next consider the dynamic effect of tougher enforcement. The effects are very similar to the results for the base model presented in section 4. Tougher enforcement increases the expected punishment of quota violations, which strengthens the agents' formal incentives to comply. This has two implications. First, it increases the expected punishment of active agents, since we know that all active agents violate quotas. Hence, their willingness to pay for quotas declines and the market clearing quota price falls. This, in turn, affects the compliance condition (31) and causes formerly inactive agents to become active. Second, tougher formal enforcement reduces aggregate extraction relative to the total quota (Y/Q). This shifts the norm downward. Therefore, in line with the results of the base model, tougher enforcement has a direct effect and an indirect effect, which both contribute to reduced illegal extraction. Furthermore, tougher enforcement enables more agents to be active and therefore reduces the differences in extraction revenues between agents with high and low m values.

The main implication of introducing the non-linear punishment function is, however, that the market price of quotas can exceed the output price. With a non-linear punishment function, quota demand is also motivated by reduced (formal) punishment

for exceeding the quota. Hence, the agents' willingness to pay accounts for a certain level of extraction in excess of the quota (cf. γ in equation 33), which can drive the quota price above the output price. This result is independent of the presence of informal enforcement and happens as long as the enforcement level η is not high enough to deter violations to this extent.[26]

6   Concluding Remarks

In this paper, I develop a dynamic model of a quota regulated CPR where resource users have the option to violate their quotas. The resource users seek to maximize their utility from using the CPR. In addition to the traditional pecuniary incentives, they care about obeying a norm of quota compliance. This can be thought of as the individual's preference to violate quotas independently of formal enforcement. Formally, this is done by introducing an intrinsic cost, which represents the agent's disutility from violating the norm of compliance. The norm is dynamic and depends on the aggregate behavior of the resource users. The higher the value of the norm, the lower the utility loss of exceeding ones quota as perceived by the individual agent. I use the model to analyze optimal behavior by individual agents, as well as the dynamics of the CPR following a change of enforcement. I present a numerical example to illustrate the results.

This analysis yields several new results. Agents with low intrinsic costs of violating the norm are more likely to violate quotas. Hence, these agents have a competitive advantage in the industry. The results confirm that agents with a lower sensitivity to obeying the norm extract far more than their law-obedient colleagues. Furthermore, I show that the quota price is affected by the distribution of individual agents' propensity to obey the norm, as well as by the norm itself. As a result, a change in the quota price can be a sign of a change in the norm of compliance or a change in attitude toward the norm by the agents currently using the resource - and not necessarily a change in pecuniary extraction costs. Consequently, the quota price is affected by other variables than just the traditional economic factors. This, in turn, has consequences for resource managers that use quota prices as indicators for their industry's cost structures.

An important result of introducing dynamic norms to the CPR model is the increased effect of policy change, such as tougher enforcement, which is a multiplier effect. As in the traditional models of regulatory compliance, there is a direct effect of increasing the enforcement level through an increase in expected punishment, which reduces non-compliant behavior. However, we now have an additional indirect effect

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[26]The result requires some source of heterogeneity across agents.

of increasing regulatory enforcement. When tougher enforcement causes agents today to reduce their illegal resource extraction, this affects the norm, which in turn has a deterrent effect on illegal extraction in subsequent periods.

It should be noted that when analyzing specific CPRs, the importance of social and moral norms likely depends on the characteristics of the CPR. Gezelius (2002) finds that an "*informally enforced moral obligation to obey the law was the single most important factor explaining compliance*" in a study of regulatory compliance in a small fishing community in Norway. The fishery studied by Gezelius (2002) is characterized by relatively small, owner-operated boats. It is unlikely that he would reach the same conclusions if he had studied larger and more mobile vessels that travel long distances to participate in various fisheries. One reason is that the group that creates the social pressure to obey the norm of compliance might not be as well-defined in such cases (Sethi & Somanathan, 1996). This is supported by the results of Katz (2000) who studies CPR use in two regions of Guatemala, and finds that in the region where people move around a lot, excessive resource use is a bigger concern than in the region where a fairly homogenous and stable group operates.

Little work has been done on the implications of social and moral norms on economic behavior, particularly the implications for CPR regulation, enforcement and compliance. There are therefore many possibilities for extending the current work. I have illustrated how a change of formal enforcement affects informal enforcement. However, I made the assumption that the resource manager's only objective is to set the total quota so as to maintain the resource stock at a predetermined level. The size of the quota affects the quota price, compliance level, and hence, the development of the norm and informal enforcement. While formal enforcement is costly, informal enforcement is not. Hence, a possibility is to investigate what the optimal quota policy is given an objective to maximize the value of the resource, net of enforcement costs. That is, the way in which the management system could be designed to take advantage of valuable norms (social capital).

Another possibility for future work is to empirically analyze quota prices in CPR industries, and particularly, if and how they respond to permanent shocks to enforcement variables, such as punishment levels or control efforts. While standard enforcement theory predicts an immediate response in the quota price (direct effect), the presence of a dynamic norm suggests a gradual approach as the norm adjusts (indirect effect). One approach is to estimate a structural model derived from the theoretical model developed above, using data on fisheries or other CPRs for which quota prices are available, with the objective of identifying the relative importance of formal and informal enforcement.

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