

## Compliance, environmental regulation, and quota markets

Florian Diekert, Yuanhao Li, Linda Nøstbakken, Andries Richter

### Angaben zur Veröffentlichung / Publication details:

Diekert, Florian, Yuanhao Li, Linda Nøstbakken, and Andries Richter. 2026. "Compliance, environmental regulation, and quota markets." *Journal of Environmental Economics and Management* 138: 103345. <https://doi.org/10.1016/j.jeem.2026.103345>.



## Compliance, environmental regulation, and quota markets<sup>☆</sup>

Florian Diekert<sup>a, b</sup>, Yuanhao Li<sup>c</sup>, Linda Nøstbakken<sup>c, d, e, \*</sup> , Andries Richter<sup>b, f</sup>

<sup>a</sup> Centre for Climate Resilience & Faculty of Business and Economics, University of Augsburg, Augsburg, Bavaria, Germany

<sup>b</sup> Department of Biosciences, University of Oslo, Oslo, Norway

<sup>c</sup> SNF – Centre for Applied Research at NHH, Bergen, Vestland, Norway

<sup>d</sup> Statistics Norway, Pb. 2633 St. Hanshaugen, 0131 Oslo, Norway

<sup>e</sup> NHH Norwegian School of Economics, Bergen, Norway

<sup>f</sup> Environmental Economics and Natural Resources group, Wageningen University, Wageningen, Gelderland, Netherlands (the)

### ARTICLE INFO

#### JEL classification:

K42

Q2

Q5

#### Keywords:

Environmental regulation

Compliance behavior

Quota markets

Market-based instruments

Enforcement

### ABSTRACT

Market-based instruments are widely promoted for their efficiency in achieving environmental goals, but their effectiveness depends on enforcement and compliance, which are often imperfect. We develop a theoretical model in which agents face both technological standards and quota regulations, with the possibility of non-compliance with both at the risk of fines. Within this model, we investigate how intrinsic motivation to comply with different regulations affects investment behavior in quota markets. We find that a greater willingness to invest in quotas can result from either a strong intrinsic motivation to comply with quota regulations or a weak motivation to comply with technological standards. To test these predictions, we use survey data and incentivized economic experiments with Norwegian fishers. The empirical results confirm the theory predictions: Fishers who find technological violations less acceptable tend to invest less in quotas, while those who disapprove of quota violations tend to buy more quotas. These findings highlight the critical role of compliance attitudes for quota market behavior and offer insights for designing more efficient environmental regulations.

### 1. Introduction

Market-based instruments are widely used to regulate environmental problems, often in combination with technological standards. In particular, tradable quota systems have been implemented to regulate emissions affecting environmental quality, as well as extraction of natural resources such as water, timber, fish, and wildlife. These systems incentivize firms to optimize their combination of production inputs and can enhance allocative efficiency. However, their success critically depends on strong enforcement of the underlying regulations (Nøstbakken, 2008; Shimshack, 2014; Stranlund, 2017). Weak enforcement and non-compliance can undermine the economic efficiency of market-based mechanisms, both in terms of individual firms' production decisions and the allocative efficiency of the industry as a whole. Understanding the relationship between firms' non-compliance behavior, production choices, and environmental quota markets is therefore important for effective policy design.

Under imperfect enforcement, rational agents may decide to violate regulations if the expected benefits exceed the expected costs (Becker, 1968; Harrington, 2012, 2023). While expected fines and detection probabilities are standard determinants of compliance behavior, non-pecuniary factors could also play a significant role (see e.g., Burby and Paterson, 1993; Frey, 1997; Kuperan and

<sup>☆</sup> We thank the editor, anonymous reviewers, and seminar and conference participants for helpful comments and suggestions. The usual disclaimer applies. Financial support from the Research Council of Norway (grant no. 280541) is gratefully acknowledged.

\* Corresponding author at: Statistics Norway, Pb. 2633 St. Hanshaugen, 0131 Oslo, Norway.

Email address: [ldn@ssb.no](mailto:ldn@ssb.no) (L. Nøstbakken).

Sutinen, 1998; Viteri and Chàvez, 2007). First, reputational concerns affect firms' compliance decisions, as consumers and (potential) employees consider the reputation of a company when making purchasing and employment choices. Second, regulatory inspections are often non-random, meaning that detected violations may increase the chance of future inspections, which are time-consuming and distracting. Third, intrinsic motivations, such as managers' and employees' satisfaction from working for a 'good' firm, can affect compliance behavior. These factors vary across firms, leading to heterogeneous intrinsic motivations to comply with regulations.

The objective of this paper is to investigate the interaction between compliance with environmental regulations and environmental quota markets, both theoretically and empirically. We build a stylized model in which firms face environmental regulation in the form of (i) technological standards and (ii) tradable quotas. Firms may choose to violate regulations in either or both dimensions. Compliance decisions depend on two components: First, standard economic incentives based on the expected benefits against the costs, which depend on both the probability of detection and the severity of penalties (see, for example, the survey by Shimshack, 2014); and second, intrinsic motivations to comply, which may also play a crucial role in imperfectly enforced regulatory systems. Because firms have to comply with several regulations that may affect different parts of the production process, partial compliance is possible; for example, firms may violate technological requirements, but respect the quota regulations. While our model is general and applicable to tradable quota systems, it is also relevant for contexts where quotas regulate extraction, such as fish or water. From our model, we derive two testable predictions, validated using data on Norwegian fishers, with direct implications for the joint enforcement of technological and quota-based regulations: because violations of these two types affect quota demand in opposite directions, regulators cannot infer agents' compliance types from their behavior in the quota market alone.

Empirical studies of non-compliance face several challenges (Boonstra et al., 2017). First, researchers typically cannot observe violations unless they are detected. Second, attempts to observe or measure violations can alter the tendency to violate, complicating measurement. Third, researchers usually cannot observe individuals' intrinsic motivations to comply. Fourth, individuals' risk preferences, which affect compliance behavior, are usually unobservable. To overcome these challenges, we construct a novel dataset combining a series of incentivized web-based economic experiments and survey data from Norwegian fishers. The experiments measure risk preferences using monetary incentives, while the survey captures moral motivations to comply with regulations related to fishing technologies and quotas, self-reported violation frequencies, and past investments in quota and production capital.

Our theoretical analysis yields two propositions: Firms are more likely to invest in quotas when they (i) have a stronger intrinsic motivation to comply with quota regulations, or (ii) have a weaker intrinsic motivation to comply with technological standards. Our empirical results support these hypotheses. To approximate the intrinsic costs of violating quota and technological regulations, we construct proxies derived from agents' responses to survey questions about the perceived justifiability of violating different types of regulations. Our empirical results are robust to different model specifications.

Our study contributes to the literature on non-compliance in environmental markets (Stranlund, 2017; Shimshack, 2014; Nøstbakken, 2008). A long tradition of research examines how imperfect enforcement of quota regulations affects firms' compliance decisions and equilibrium quota prices (e.g., Malik, 1990; Keeler, 1991). Typically, imperfect enforcement opens the possibility of violating quota regulations, which reduces quota demand among non-compliant firms and leads to lower equilibrium quota prices (Arguedas et al., 2010; Villegas-Palacio and Coria, 2010). These theoretical predictions are supported by laboratory experiments (Vidal-Meliá et al., 2022; Murphy and Stranlund, 2007), also pointing to behavioral factors shaping compliance decisions. These mechanisms have also been applied to the field of fisheries, where a key finding is that the possibility of violating quota lowers equilibrium quota prices (Hatcher, 2005; Chavez and Salgado, 2005). A potential policy implication from this literature is that linking penalties or monitoring probabilities to quota prices may help stabilize markets and improve compliance (Stranlund et al., 2019). These insights rely to a great extent on the realistic, yet limiting assumption that investing in abatement technology and quotas are close substitutes in the firm's compliance decision. In many industries, fisheries being a prime example, investments in technology and quotas are much weaker substitutes or even complements. For example, investments in vessel capacity or gear may increase the marginal value of holding more quota or violating quota regulations. This has been formalized in Lazkano and Nøstbakken (2016), who show that stricter enforcement can reduce quota violations but simultaneously lower incentives to invest in vessel capacity.

Building on these insights, our paper advances the literature by analyzing a setting with two regulatory constraints – a catch quota and a technology standard – and allowing for violations of both. Whereas most existing work focuses on quota non-compliance alone, we show that technological and quota violations are driven by different incentives and have distinct effects on quota demand and compliance behavior. This multi-dimensional structure implies that enforcement targeted at one constraint can unintentionally shift violations to the other, underscoring the importance of treating the two margins jointly.

Further, we link these theoretical insights to the broader literature on firms' internal motivations for regulatory compliance and their consequences for environmental markets (e.g., Nøstbakken, 2013; Leibbrandt and Lynham, 2018). Our study builds on work that uses surveys to document compliance attitudes across small firms (Hatcher and Gordon, 2005; Graafland and Gerlagh, 2019; Oyanedel et al., 2020), showing that firms differ systematically in their intrinsic willingness to comply. We extend this line of research by demonstrating that intrinsic compliance incentives shape behavior in environmental quota markets in distinct ways depending on the type of regulation involved, implying that intrinsic motivations interact with regulatory design rather than affecting compliance uniformly.

These findings provide insights for policymakers by highlighting how enforcement of technological regulations can help mitigate distortions in environmental markets. The interaction between compliance attitudes and quota markets affects both the effectiveness and efficiency of environmental regulation. A high demand for quota could signal a high propensity to comply with quota regulations, but it could also indicate a low propensity to comply with technological regulations. This ambiguity implies an adverse selection problem in the quota market. Furthermore, our research suggests that non-compliance behavior can propagate not only due to gradual erosion of social norms (Kuperan and Sutinen, 1998), but also because of changes in the distribution of agents participating

in environmental markets. Consequently, our study points out additional benefits of enforcing compliance with environmental rules and regulations.

## 2. A stylized model of environmental regulation, quota markets, and compliance

In this section, we develop a stylized static model of firms whose operations affect the natural environment. Each firm chooses a technology specification ( $t$ ) and emission level ( $e$ ). Environmental regulation takes two forms: (i) a technological standard, which prescribes a specific technological setup, and (ii) a quota system, which sets firm-level limits on allowable emissions. Firms may comply with or violate these regulations—either adopting or bypassing the prescribed technology, and emitting within or beyond their quota.

The model is sufficiently general to apply to both traditional pollution contexts, where  $e$  directly reflects harmful emissions, and resource extraction cases, where  $e$  represents harvesting activity (e.g., fishing) that depletes a natural resource stock. In both cases, the collective actions of all firms influence the overall quality of the environment.

To keep the model tractable, we abstract from internal firm dynamics such as organizational culture, firm-specific policies, or incentive structures that shape how employees and managers perceive and respond to compliance obligations.<sup>1</sup> Hence, we do not model how compliance behavior is formed or enforced within firms, but assume that an individual owner makes decisions on behalf of the firm. This simplification aligns with our empirical context, where we have data on owner-operated firms. In what follows, we use the terms *firm* and *agent* interchangeably.

A price-taking agent earns operating profit,  $\pi = \pi(e, t)$ , which depends on the emission level  $e$  and technology  $t$ , and includes all relevant costs and returns related to these choices. Throughout, we treat the market quota price as exogenous from the perspective of the individual agent. Given this structure, we analyze how firms trade off profit gains from non-compliance against expected penalties and intrinsic motivations to comply.

The agent can violate both the technology ( $t$ ) and the quota ( $e$ ) regulations. We first introduce the technology violation. Assume the regulator requires a certain technology standard, potentially based on 'best practices,' which is normalized to  $t = 0$ . Compliant agents set  $t = 0$ , but they can also decide to violate the technology regulation by setting  $t > 0$ . In such case, agents use more efficient but illegal technologies that allow for higher profits. We assume that  $\pi(e, t)$  is continuous and twice differentiable, monotonically increasing and concave in both arguments.

Let  $q = e - v$  denote the individual quota held by the agent. The variable  $v \geq 0$  is thus the degree to which the agent violates the quota. An agent who complies with the quota regulation sets  $v = 0$  ( $e = q$ ), while quota violation implies  $v > 0$  ( $e > q$ ). We assume that quotas are perfectly divisible and traded in a perfectly competitive quota market without transaction costs. The agent's opportunity cost of using quota is equal to the market price of quota, which we denote by  $z$ .<sup>2</sup> Since quota is costly, no agent will purchase quota in excess of their emission level.

We also assume that quota and technology are complementary factors of production ( $\pi_{e,t} > 0$ ), i.e., the marginal benefit of more efficient technology ( $t$ ) is greater at higher emission levels,  $e$ .

A control agency may detect the technology and quota violations. For simplicity, we assume the probabilities of detection are the same for the two types of violations. We let  $p$  denote the probability that violating behaviors are detected, which measures the inspection intensity. Penalties increase linearly with the size of the violation for both types when detected by the control agency. Specifically, the penalty for violating technology regulations is  $F_t t$ , while the penalty for violating quota regulations is  $F_q v$ . We assume that the control agency will detect and punish both types of violations (or no violations) when inspecting a non-compliant agent.

In addition to formal regulatory enforcement, we consider the agent's intrinsic motivations to comply. For a given level of violations, we assume the agent incurs an intrinsic cost  $\mu M(t)$  from violating the technology regulation, and a intrinsic cost  $\nu N(v)$  from violating the quota. The parameters  $\mu$  and  $\nu$  are the agent's weights on the intrinsic costs of technology and quota violations, respectively, in the objective function. We assume the intrinsic cost functions  $M(\cdot)$  and  $N(\cdot)$  are continuous, twice differentiable, monotonically increasing and convex with respect to their arguments, with  $M(0) = N(0) = 0$ . Since each intrinsic cost function depends only on its own argument, the cross-partial derivative with respect to  $t$  and  $v$  is zero. In addition, we assume the two types of intrinsic costs are additively separable in the agent's objective function. We discuss the implications of additive separability for our results in later sections.

Given that the agent chooses emission rate  $e$ , technology  $t$ , and quota violation  $v$ , to maximize expected profits net of intrinsic costs, we can define the following optimization problem<sup>3</sup>:

$$\begin{aligned} \max_{e,t,v} \quad & V = \pi(e, t) - z(e - v) - pF_t t - pF_q v - \mu M(t) - \nu N(v) \\ \text{s.t.} \quad & t \geq 0, v \geq 0 \end{aligned} \tag{1}$$

<sup>1</sup> Although beyond the scope of our study, the literature on corporate crime shows how compliance varies across industries, companies, and individual characteristics (Rorie, 2015; Peeters et al., 2020).

<sup>2</sup> We can think of the quota price  $z$  as a rental price in a competitive market. Under Coase-type conditions (low transaction costs), the initial allocation does not affect equilibrium outcomes.

<sup>3</sup> Note that this formulation, in which the agent's objective function is linear in profit, penalties, and intrinsic costs, implicitly assumes risk neutrality. In the empirical analysis, we control for risk aversion at the individual level.

The corresponding Lagrangian is:

$$\mathcal{L} = \pi(e, t) - z(e - v) - pF_t t - pF_q v - \mu M(t) - \nu N(v) + \lambda^t t + \lambda^v v, \tag{2}$$

where  $\lambda^t$  and  $\lambda^v$  are the shadow prices associated with the constraints  $t \geq 0$  and  $v \geq 0$ , respectively. The necessary conditions for optimality are:

$$\frac{\partial \mathcal{L}}{\partial e} = \pi_e(e, t) - z = 0 \tag{3}$$

$$\frac{\partial \mathcal{L}}{\partial t} = \pi_t(e, t) - pF_t - \mu M'(t) + \lambda^t = 0 \tag{4}$$

$$\frac{\partial \mathcal{L}}{\partial v} = z - pF_q - \nu N'(v) + \lambda^v = 0 \tag{5}$$

$$\text{and: } t \geq 0, \lambda^t \geq 0, t\lambda^t = 0; \quad v \geq 0, \lambda^v \geq 0, v\lambda^v = 0 \tag{6}$$

Analyzing the Kuhn-Tucker conditions (6) yields four cases: a fully compliant case ( $t = v = 0$ ), two partially compliant cases ( $t > 0, v = 0$  and  $t = 0, v > 0$ ), and a fully non-compliant case ( $t > 0$  and  $v > 0$ ). In the following, we discuss each of the four cases. Although we are mostly interested in the non-compliant case, it is useful to start by analyzing the fully compliant case as a baseline. We then look at the two partially compliant cases, which allow us to examine how  $t$  and  $v$  individually affect emissions and quota purchase, before we analyze the (fully) non-compliant case. Throughout the analysis, we assume that the second-order sufficient conditions for a maximum are satisfied. Appendix A.1 provides a formal analysis of these conditions, which require sufficient concavity of the profit function and convexity of the intrinsic cost functions.

### 2.1. Characterizing different compliance cases

#### The fully compliant case

If the agent's expected cost of violating regulations is sufficiently high relative to the benefits, agents will choose full compliance ( $t = v = 0$ ). Then  $\lambda^t > 0$  and  $\lambda^v > 0$ , and the agent's optimal emission rate,  $e^o$ , is given by the following equation:

$$\pi_e(e^o, 0) - z = 0. \tag{7}$$

The agent will choose the required technology ( $t^o = 0$ ) and purchase the necessary quota to match the emission level ( $v^o = 0$  and  $q^o = e^o$ ). The optimal emission level  $e^o$  is given by Eq. (7), which equates the marginal return of emissions,  $\pi_e(e^o, 0)$ , with quota price  $z$ . The price of quota,  $z$ , also reflects the opportunity cost of holding quotas, because the agent has the option to sell a unit of quota in the quota market at price  $z$  (or buy less) by emitting one less unit.

#### A partially compliant case with technology violation

In the first partial compliance case, the agent violates the technology regulation ( $t > 0$ ) and complies with the quota ( $v = 0$ ). In this case, the expected cost of quota violation is sufficiently large to fully deter such violations given the potential gains ( $\lambda^v > 0$ ), but this is not true for technology violations. The agent chooses  $t > 0$ , and we know  $\lambda^t = 0$ .

We denote the optimal values of the control variables in this case with superscript  $*t$ . Optimal emissions,  $e^{*t}$ , and optimal technology violation,  $t^{*t}$ , are then given by:

$$\pi_e(e^{*t}, t^{*t}) - z = 0 \tag{8}$$

$$\pi_t(e^{*t}, t^{*t}) - pF_t - \mu M'(t^{*t}) = 0 \tag{9}$$

Comparing Eqs. (7) and (8) yields  $\pi_e(e^o, 0) = \pi_e(e^{*t}, t^{*t}) = z$ . Combining this and the assumption that  $\pi_{et} > 0$ , the following must hold:  $\pi_e(e^{*t}, t^{*t}) > \pi_e(e^{*t}, 0)$ . Hence, we know  $\pi_e(e^o, 0) > \pi_e(e^{*t}, 0)$ , and because  $\pi(\cdot)$  is concave in  $e$ , we can conclude that  $e^o < e^{*t}$ . This implies that the emission rate with technology violations is higher than the emission rate in the fully compliant case. Hence, a partially compliant agent (with  $t^{*t} > 0$ ), who operates in the same industry and faces the same quota price  $z$  as a fully compliant agent (with  $t^o = 0$ ), will emit more. This result follows from the assumption that technology violations enhance the marginal return of emissions ( $\pi_{et} > 0$ ). Since agents in this case comply with quota regulations, agents who violate technology regulations will demand more quota.

The intuition is that technology violations raise the marginal productivity of emissions because technology violations and emissions are complements in the profit function ( $\pi_{et} > 0$ ). This induces the agent to emit more than a fully compliant agent would at the same quota price. Since the agent in this case complies with quota regulations, the higher emission level must be matched by a correspondingly larger quota position.

#### A partially compliant case with quota violation

In the second partial compliance case, the agent complies with the technology regulation ( $t = 0$ ) and violates the quota ( $v > 0$ ). This could for example occur if the expected penalty for technological violations,  $pF_t$ , is sufficiently large to deter violations ( $\lambda^t > 0$  and the agent chooses  $t = 0$ ), while the expected penalty and intrinsic cost of quota regulations are not large enough to fully deter violations. Hence,  $v > 0$ , and we know that  $\lambda^v = 0$ .

We denote the optimal levels of the control variables in this case with superscript  $*$ . Optimal emissions,  $e^{*v}$ , and optimal quota violation,  $v^{*v}$ , are then given by:

$$\pi_e(e^{*v}, 0) - z = 0 \tag{10}$$

$$z - pF_q - vN'(v^{*v}) = 0 \tag{11}$$

Comparing Eqs. (7) to (10) tells us that the emission rate is the same as in the full compliance case, although we now consider quota violations. This means that a non-compliant agent, who emits the same quantity as a compliant agent, would purchase less quota. Agents' motivation for purchasing quota is to reduce the expected penalty and intrinsic cost from quota violations, and they purchase quota until the marginal benefit of doing so,  $pF_q + vN'(v^{*v})$ , equals the marginal cost, which is given by the quota price  $z$ .

*The non-compliant case*

In the non-compliant case, the agent violates both types of regulations. We consider an interior solution where  $t > 0$  and  $v > 0$ , so that  $\lambda' = \lambda^v = 0$  (cf. Eq. (6)). We can then characterize the agent's optimal choices by the following three equations:

$$W_1 \equiv \pi_e(e^*, t^*) - z = 0 \tag{12}$$

$$W_2 \equiv \pi_t(e^*, t^*) - pF_t - \mu M'(t^*) = 0 \tag{13}$$

$$W_3 \equiv z - pF_q - vN'(v^*) = 0 \tag{14}$$

Comparing  $W_1$  and  $W_2$  with Eqs. (8) and (9), we see that  $e^* = e^{*t}$  and  $t^* = t^{*t}$ . The agent's technology violation and emission rate depend on the profit function and the expected penalty and intrinsic cost of technology regulations. Technology violations give the agent an incentive to emit more, as the marginal return per unit emitted increases.

Comparing  $W_3$  with Eq. (11), we can see that  $v^* = v^{*v}$ . Again, the agent purchases quota up until the marginal benefit,  $pF_q + vN'(v^{*v})$ , equals the marginal cost,  $z$ .

From the analysis of the compliance cases above, we can derive the following two propositions which we will test empirically.

**Proposition 1.** *Agents with higher costs of violating technological regulations are less likely to violate technological regulations and less willing to buy quotas.*

**Proof.** Mathematically, Proposition 1 can be expressed as  $\frac{dt^*}{d\mu} < 0$  and  $\frac{dq^*}{d\mu} < 0$ . See Eqs. (A4) and (A6) in Appendix A.1, where we undertake a comparative static analysis, for proofs. □

**Proposition 2.** *Agents with higher costs of violating quota regulations are less likely to violate quota regulations and more willing to buy quotas.*

**Proof.** Mathematically, Proposition 2 can be expressed as  $\frac{dv^*}{dv} < 0$  and  $\frac{dq^*}{dv} > 0$ . See Eqs. (A9) and (A10) in Appendix A.1, where we undertake a comparative static analysis, for proofs. □

In other words, agents with a high willingness to pay for quota could have a high propensity to comply with quota regulations, but their high demand for quota could also be due to a low propensity to comply with technological regulations. There is thus an adverse selection problem in the quota market.

We now turn to the empirical analysis to test these model predictions.

**3. Empirical application: compliance and quota markets in fisheries**

To empirically test the predictions from our model, we need information on agents' moral motivations to comply with regulations, factors which are not directly observable. To address this challenge, we draw on data from a survey and a series of incentivized economic experiments conducted among Norwegian fishers. These data allow us to construct proxies for individual risk preferences as well as compliance attitudes toward different types of regulations.

Norwegian fisheries provide a compelling setting for our analysis for several reasons. First, regulatory enforcement is imperfect: while rules exist, agents do not always comply fully, which creates variation in behavior. Second, the regulatory environment includes both quota-based regulations and technology-based regulations, closely aligning with the structure we analyze in our theoretical model. Third, the institutional framework of the industry requires that vessels are majority-owned by active fishers. As a result, most fishers are owner-operators who make decisions on behalf of their firms. This alignment between decision-maker and owner allows us to directly link intrinsic motivations to firm behavior, in line with our theoretical analysis.

In the following sections, we briefly introduce key aspects of the Norwegian fisheries management system and present our experiment and survey data, which form the basis for testing the model's predictions.

*3.1. Background: the Norwegian fisheries quota system*

Norway's fisheries management has undergone major reforms since the 1960s, transitioning from open access to a system of transferable catch shares. The shift was triggered by the collapse of the Norwegian spring-spawning herring fishery in the late 1960s, which highlighted the need for stronger regulation. Starting with the pelagic fisheries and later extended to others, the management system evolved through several stages: from open access, to regulated open access, and eventually to a catch-share system (Diekert

and Schweder, 2017). Over time, management goals also shifted from preventing overfishing and rebuilding the fish stocks to also addressing excess capacity in the fishing fleet and improving the economic efficiency of the sector (Gullestad et al., 2013).

The government introduced quota consolidation policies beginning in the late 1990s, initially targeting certain offshore fleets. These reforms enabled quotas to be transferred between vessels, provided the vessel transferring its quota was removed from the fishery. This marked a move toward a modern catch-share system. Over the next decade, the government expanded this system to other parts of the fishing fleet, while gradually easing restrictions on quota transfers (Abe et al., 2024).

The current system is known as the 'structural quota system.' It is an individual transferable quota system with specific rules limiting consolidation and transfer of quota. While regulatory details and frictions differ from a perfectly transferable quota system, the Norwegian context retains the key features of ITQs with individually held and tradable vessel quotas.

To balance quota flexibility with policy goals such as fleet structure and regional employment, the system incorporates a set of regulatory constraints on consolidation and transfer. These include consolidation caps, regional constraints on transfers, sunset provisions, and a requirement that only active fishers may hold a majority-ownership share in quota-holding vessels. The latter ensures that the operational and ownership responsibilities typically rest with the same individual, making the Norwegian fishery particularly relevant to our study.

A key feature of the structural quota system is the ability to transfer quotas between vessels, although several restrictions apply. This rule enables consolidation of fishing rights but also introduces transaction costs. First, while a vessel's initial quota allocations are permanent, transferred (i.e., consolidated) quotas are subject to sunset provisions that limit their duration. Second, transfers that consolidate quota on fewer vessels trigger a quota deduction: a portion of the transferred quota is removed and reallocated among all quota holders within the relevant regulatory group. Previously, quotas were vessel-specific, requiring buyers to operate the quota on the original vessel, which effectively prevented consolidation.<sup>4</sup>

These deductions vary by region and direction of transfer. During the study period, transfers within northern Norway or from the south to the north were subject to a 5% deduction. Transfers within the south faced a 15% deduction, while transfers from north to south were subject to a 40% deduction. This asymmetry was designed to promote employment and settlement in coastal communities in northern Norway, which are more economically dependent on fisheries. In contrast, firms in southern Norway have shown a higher willingness to pay for additional quotas, putting upward pressure on prices.

Importantly, fishers can avoid both sunset provisions and quota deductions by acquiring vessels with quota and operating them separately, rather than consolidating the quota on an existing vessel. Thus, while consolidation caps, sunset restrictions, and other constraints raise the costs and complexity of consolidating quotas, they do not limit a fisher's ability to expand total quota holdings through the purchase of more vessels. This feature is central to understanding how incentives to invest in quotas and vessels, regulatory constraints, and individual compliance motivations interact in practice. For a more detailed discussion of the structural quota system, see Abe et al. (2024).

During our study period, consolidation caps in the coastal fleet, which comprises most of our sample, were raised in 2013, and there is no firm-level cap in this segment. In offshore fleets, firm-level caps apply within specific regulatory groups but are set at levels that only bind the largest companies. Because these caps are defined per regulatory group, a firm that reaches the limit in one group can still expand its overall quota holdings by acquiring quotas or vessels in other groups. In practice, however, few firms approach the caps in any segment (Nøstbakken and Wold, 2025). Thus, for almost all owners in our sample, the legal possibility of expanding quota holdings was not meaningfully constrained by consolidation rules.

In addition to quota allocations and transfer rules, Norwegian fisheries are subject to a comprehensive set of technical regulations that govern how fishing is conducted. These include gear restrictions, such as minimum mesh sizes, sorting grids, and escape panels, as well as vessel-based limitations tied to vessel length and type. For example, vessels over 11 meters fishing for cod north of 62° N must use fishing nets with a minimum mesh size of 130 mm in the retention section, a rule designed to reduce bycatch and protect juvenile fish. Minimum fish size regulations similarly prohibit landing of undersized fish, with species-specific limits enforced for cod, haddock, and other commercially important species. Norway is also notable for having introduced a discard ban in the late 1980s, making it one of few countries to prohibit the discarding of bycatch at sea (Gullestad et al., 2015). Spatial and temporal closures further influence fishing behavior by seasonally or permanently closing certain areas to specific gear types or vessel classes to protect spawning grounds, juvenile stocks, or vulnerable habitats. These rules are updated regularly and enforced through monitoring and reporting requirements, including inspections at sea by the Coast Guard and at landing sites by the Directorate of Fisheries. Collectively, technical regulations impose operational constraints and compliance costs across fisheries, and it is violations of these regulations that we refer to as technological violations in our theoretical model.

### 3.2. Dataset and summary statistics

We use data from a set of experiments and a survey that we conducted among Norwegian fishers; see Diekert et al. (2023) for details on survey design. In total 253 fishers participated in the survey, of whom 164 were identified as vessel owners – the sample we use in this paper.

The first part of the survey consists of questions about the demographic and socioeconomic backgrounds of respondents. The average respondent is 45.5 years old and 20% are above the official retirement age for fishers at the age of 60 (DAge60). Personal

<sup>4</sup> Here, consolidation refers to combining quotas on fewer vessels, not consolidation on fewer owners. Even before inter-vessel transfers were permitted, owners could still expand their quota holdings by acquiring and operating additional vessels with quota.

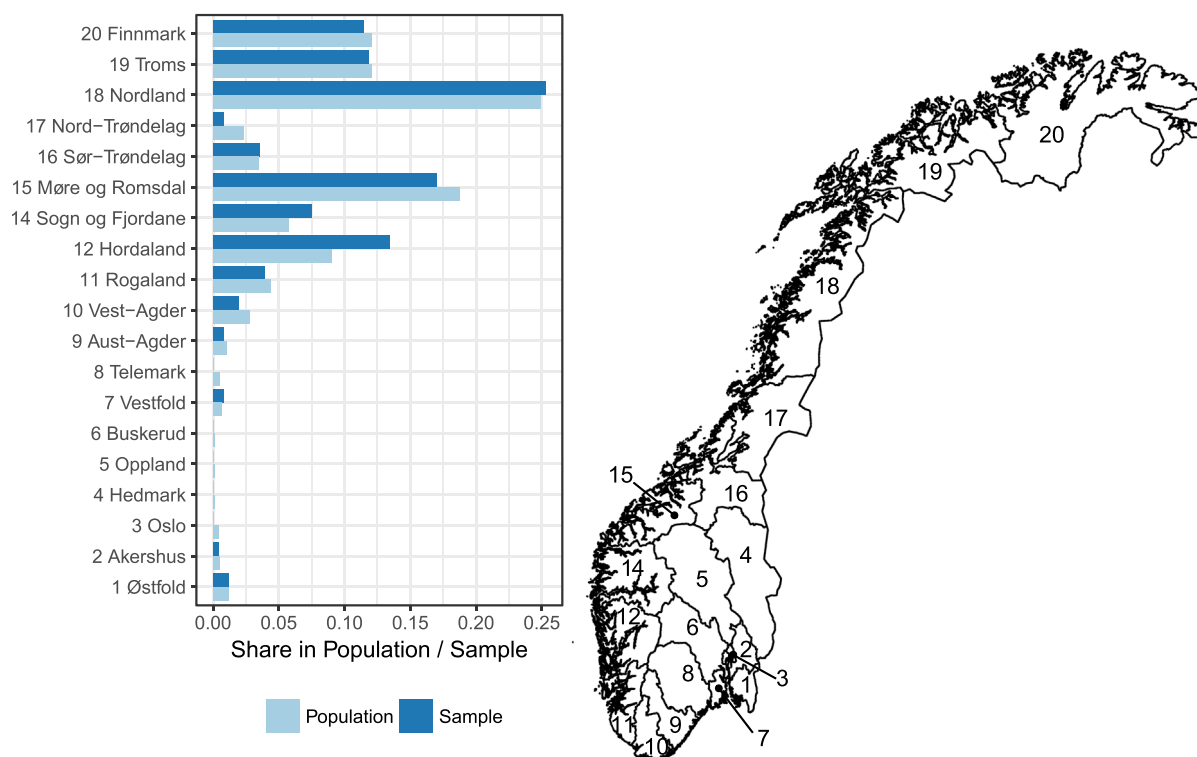


Fig. 1. Geographic distribution of fishers in our dataset and the population of registered fishers in Norway.

income is the self-reported income in 2013, represented in increments of 100,000 Norwegian krone (NOK). In addition, we measure the population share of registered fishers in the respondent's respective home municipality (*ShareFisher*)<sup>5</sup> and whether the fisher lives in the north or south of Norway as geographical control variables (*DNorth*). Overall, our respondents represent the population of Norwegian fishers rather well along key dimensions such as geographical distribution, age, and sex. Fig. 1 shows that the geographic distributions of fishers in our dataset ( $n = 253$ ) and in the entire Norwegian fishing industry ( $n = 11,130$ ) are similar. In addition, Fig. A1 in the Appendix compares the age and gender distributions of our sample to those of the population of registered fishers.

Next, we carried out a series of incentivized experiments to elicit individuals' risk, time, and loss preferences. We conducted pairwise lottery-based experiments in a form similar to that of Tanaka et al. (2010) and Liu (2013).<sup>6</sup> For details on estimating these preference parameters, see Diekert et al. (2023). Risk tolerance ( $r$ ) reflects the concavity of the utility function, where a higher value of  $r$  indicates that the participant is more tolerant of risk. Loss aversion is measured by the parameter  $\lambda$ , where larger values of  $\lambda$  imply a stronger aversion to outcomes framed as losses. Probability weighting is characterized by the coefficient  $a$ , where smaller values of  $a$  indicate that participants place less weight on small probabilities. To elicit discount rates, participants make a set of choices between receiving a fixed amount of money today and an (increasingly) larger amount in eight months. The switching point between the immediate and delayed option provides an individual measure of impatience.<sup>7</sup> After the experiments, we asked respondents to complete a second part of the survey. In that part, we asked additional questions about the respondents' family backgrounds, work values, and views on political issues, in addition to a set of fisheries related questions including their investment decisions over the years 2008–2013 and their attitude to compliance with different regulations. The survey responses on investment and compliance attitudes and behavior allow us to test the theoretical predictions we derived in Section 2. We summarize the survey responses on compliance attitudes in the next subsection, before we present other key variables from the experiment and survey dataset and explain how we use our data to test the theoretical predictions on compliance and investment.

<sup>5</sup> Note that the variable *ShareFisher* is calculated as the share of registered fishers (part-time and full-time) in the respondent's home municipality, multiplied by 10,000. For example, a value of 1239 corresponds to a true share of 0.1239 (or 12.39%).

<sup>6</sup> Tanaka et al. (2010) present the methodology to elicit risk, time, and loss preferences with a series of lottery-based experiments with Vietnamese villagers and examine determinants of these preference parameters. Liu (2013) use a similar method to elicit risk and loss preferences of Chinese farmers and study their effects on farmers' adoption decisions of cotton.

<sup>7</sup> We note that this switching-point measure may conflate the long-run exponential discount rate with present bias, and should therefore be interpreted as a reduced-form indicator of time preferences rather than a structural discount rate estimate. Since both exponential discounting and present bias may affect investment behavior, the measure remains a relevant control variable.

**Table 1**  
Compliance attitudes: main reason for compliance (share of responses).

Violation	Formal punishm.	Should follow law	Stock dev., future inc.	Unfair	Reputation	Other
Gear/season/zone	8.5	52.4	28.0	5.5	4.3	1.2
Minimum size	4.0	40.2	48.2	0.6	3.0	3.7
Discards	2.0	35.4	50.0	2.4	3.7	6.1
Unreported sales	11.0	53.7	15.2	8.5	1.8	9.8
Under/misreporting	14.0	48.2	23.2	2.4	4.9	7.3

### Compliance attitudes and behavior

In the following, we give a brief overview of fishers' attitudes toward various technology and quota violations. In our theoretical model, intrinsic costs affect investment decisions indirectly through non-compliance behaviors. However, individuals' intrinsic costs are unobservable, and we usually cannot observe non-compliance behaviors either.

We asked fishers three types of questions about a set of fisheries-related violations to learn more about their compliance attitudes and behavior. For each violation, we asked respondents whether they think the violation can be justified, what their main reason for complying with the regulation is, and how they consider their own compliance behavior compared to that of the average fisher. We asked respondents about the following five violations: (i) using illegal gear, fishing outside the legally mandated season or fishing area, (ii) catching fish below the minimum size, (iii) discarding fish, (iv) unreported fish sales, and (v) under- or misreporting of catches. Violations of minimum size regulations are technological violations because they typically involve using gear with too small mesh sizes, enabling the vessel to catch more fish with the same effort. Unreported sales of fish represent quota violations, as they involve fishing without deducting the catch from the vessel's quota. Other violations we ask about in the survey – discarding, violating gear/season/zone regulations,<sup>8</sup> and misreporting of catches – are more ambiguous since they can be the result of both technological violations and quota violations.

When asking the respondents to select the main reason for **why they comply**, we gave them the following options: “fear of formal punishment,” “one should follow the law,” “stock development,” “it is unfair relative to others,” “it is bad for my reputation,” and “other.”

The decision to violate or abide by a norm is multifaceted and several aspects play a role. This is why we chose to ask about the *main* reason, thereby restricting respondents to only select one option. Moreover, asking about the main reason to follow a given regulation allows us to analyze norm-based differences in motivations as well as the variability of motivations across and within respondents.

Table 1 summarizes the stated motivations for why the fishers comply with the various rules and regulations. Across violation types, the most commonly cited reason for compliance is the normative belief that one should follow the law, followed by concerns about the sustainability of the fishery and the future development of stocks and fishing income. Far fewer respondents report “fear of formal punishment” as the main reason for complying, while even fewer point to other reasons. Table 1 also shows that the reasons for compliance depend on the type of regulation. This is particularly evident for minimum size regulations and the discard ban, which is reasonable as violating these rules has the most direct negative effect on the fish stocks. We do not see that fear of formal punishment is systematically lower or higher for those regulations that are most acceptable to violate.

When asking fishers **whether different violations can be justified**, we gave respondents the options to answer “never”, “sometimes” or “usually.” Fig. 2 shows the relative share of respondents' answers. Whether respondents think it can be justified to violate, varies considerably by violation. While 90% of the respondents state that it is never justifiable to violate gear, season and zone restrictions, more than 40% state that it can sometimes or usually be justified to under- or misreport fish catches. The responses show that compliance with rules and regulations is not absolute. Rather, rules and regulations are social constructs that are negotiable and there may be circumstances and reasons when violating a norm can be justified.

Finally, we asked respondents about their **own compliance behavior**. For this category, we asked only about the three regulations we expected to have the highest levels of violations; namely, minimum size regulations, discards, and unreported sales. We asked the respondents to state whether they violate these regulations “more,” “less,” or “about the same” as the average fisher.

It is not possible to obtain direct and reliable information on the actual violations of respondents, especially not in a simple survey. Still, to get an indicator of respondents' compliance levels, we asked about their compliance behavior relative to the average. We acknowledge that each respondent may use a different reference point, shaped by local context, peer group, or personal perceptions, when considering the ‘average fisher.’ Thus, this measure reflects subjective perceptions of social norms rather than an objective benchmark.

Fig. 3 shows that the vast majority of respondents think that they violate less than the average. This may be due to over-confidence, sample selection, or social desirability bias. The results remind us of surveys among car drivers where the vast majority of respondents tend to think they drive better than the average (over-confidence). It could also be the case that those who took the time to respond to our survey, tend to behave better than the rest. However, to the extent that such a selection bias indeed prevails, it is not a problem

<sup>8</sup> Our survey measure combines violations of gear, season, and zone regulations into a single category, and does not allow us to identify which specific rule or context is being referenced.

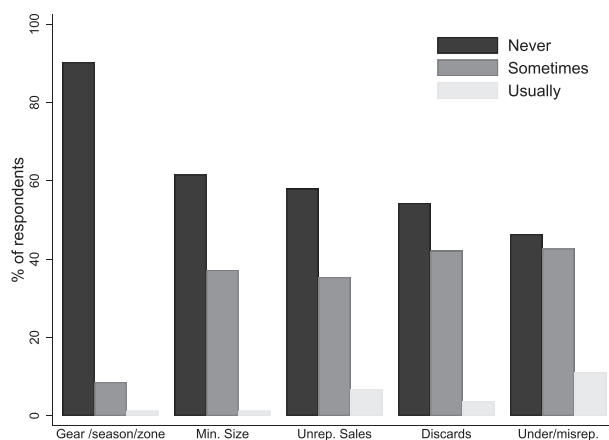


Fig. 2. Compliance attitudes: Can violations be justified?.

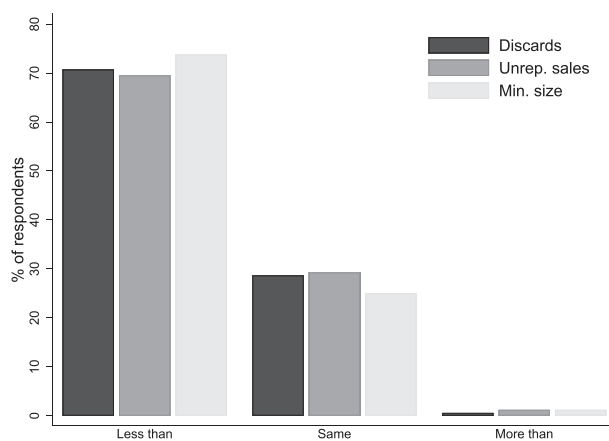


Fig. 3. Compliance attitudes: Own compliance behavior relative to average.

for our analysis, as we are interested in relative differences. Moreover, we do not use this variable in our main regressions; we only report it descriptively to provide context regarding perceived compliance norms.

The ranking of violations based on the share of respondents who report violating less than the average, mirrors the ranking of whether the violation can be justified. More respondents think that violations of minimum size regulations and unreported sales can never be justified compared to discard violations (Fig. 2). Correspondingly, more respondents consider themselves relatively compliant with minimum size regulations and unreported sales than with discard violations (Fig. 3).

In our empirical analysis, we will use responses to the questions of whether respondents believe violations can be justified to proxy their intrinsic costs of violating technological and quota regulations. We assume that respondents who could never justify a given violation have a high intrinsic cost of that violation. We create two dummy variables, “NeverJustTech” and “NeverJustQuota” indicating whether a respondent states that technological or quota violations, respectively, can never be justified (see Table 2 for summary statistics). In addition, we use the individual responses to each of the five violation-type questions separately as explanatory variables in a more disaggregated specification, which allows us to examine which specific violation types drive the results.

We interpret such responses as a proxy for a high intrinsic cost of non-compliance. While this is an indirect and self-reported measure, it captures normative resistance to rule-breaking, which is central to intrinsic motivation. Since true intrinsic costs are unobservable, we view this as the best available empirical proxy, while acknowledging its limitations.

Like all self-reported data, these measures may be subject to social desirability bias, as respondents could overstate their disapproval of non-compliance relative to their actual attitudes or behaviors. While this may inflate the absolute level of measured compliance attitudes, our analysis of relative differences across firms remains informative unless firms systematically differ in their willingness to misreport attitudes in a way that correlates with their quota investment decisions.

#### Quota investments and other key variables

To obtain data on investments, we ask respondents whether they increased their quota holdings or purchased vessels (new or used) in each of the years from 2008 to 2013, and by how much. During the study period, the Norwegian quota system did not allow fishers to sell quotas unless they were bundled with the vessel to which they were registered. We distinguish between cases where the buyer scraps a vessel and transfers the quota to another vessel (consolidation under the structural quota scheme), and the cases

**Table 2**  
Summary statistics.

	Definition	Mean	Std.Dev.	Min	Max
<i>Aggregate moral cost proxies (= 1 if violation never justified)</i>					
NeverJustTech	Tech. violations	0.62	0.49	0.00	1.00
NeverJustQuota	Quota violations	0.58	0.50	0.00	1.00
<i>Disaggregated moral cost proxies (= 1 if violation never justified)</i>					
NeverJustMinSize	Minimum size	0.62	0.49	0.00	1.00
NeverJustGearSeasonZone	Gear/season/zone	0.90	0.30	0.00	1.00
NeverJustSales	Unreported sales	0.58	0.50	0.00	1.00
NeverJustMisreporting	Misreporting	0.46	0.50	0.00	1.00
NeverJustDiscards	Discards	0.54	0.50	0.00	1.00
<i>Outcome and control variables</i>					
NInvQuota	Quota investments (no. years)	0.55	1.05	0.00	5.00
NInvVes	Vessel investments (no. years)	0.76	0.91	0.00	5.00
Risk tolerance ( $r$ )	Higher = less risk averse	0.88	0.55	0.05	1.58
Loss aversion ( $\lambda$ )	Higher = more loss averse	2.34	3.33	0.05	11.66
Impatience ( $\delta$ )	Higher = more impatient	0.05	0.12	0.00	0.57
Prob. weighting ( $a$ )	Lower = more distortion	0.61	0.26	0.07	1.48
DAge60	= 1 if age > 60	0.20	0.40	0.00	1.00
PersonalIncome	Income in 100,000 NOK (2013)	5.21	2.49	0.25	10.00
DNorth	= 1 if Trøndelag or further north	0.27	0.45	0.00	1.00
ShareFisher	Fisher share in municipality ( $\times 10,000$ )	309.75	293.96	1.63	1238.94
Observations		164			

where the buyer keeps and continues to operate the purchased vessel with its quota. In our empirical analysis, we treat the former as an investment in quota only, while the latter is treated as an investment in both quota and vessel.

There are potential limitations to our data on investment decisions. First, we analyze only quota purchases, not quota sales. In the survey, we also asked about quota and vessel sales during the period. However, the number of sales is low due to selection; we sent survey requests to a random selection of registered fishers in 2014. Fishers who sell their quotas, typically leave the fisheries and disappear from the register of fishers. As a result, we observe far fewer sales than purchases, although for every transaction there must be both a seller and a buyer. Second, we asked respondents to report the values of annual investments made over a period of several years prior to the survey, and suspect that the responses could be noisy.<sup>9</sup> An alternative is to use a binary variable indicating whether a respondent invested in a given year, rather than measuring the amount invested.

Table 2 presents summary statistics on the individual preference parameters, investment and compliance variables, and a set of individual characteristics of the respondents. The individual preference parameters measure risk and loss preferences, and the individual discount rate (impatience). We calculate these preference parameters from each respondent's choices in the experiments (see Diekert et al., 2023, for details). Our respondents are, on average, risk averse,<sup>10</sup> and have a relatively high discount rate.

The variables *NInvQuota* and *NInvVessel* indicate the number of years between 2008 and 2013 in which each respondent reported making investments in quotas and vessels, respectively. These variables capture the frequency, that is, the number of years in which respondents made such investments, not the total number of investments. Respondents reported investing in vessels more often than in quotas. In addition, the survey data reveal substantial variation in investment behavior: only a minority share of fishers engaged in such investments at all. Specifically, 21% of fishers reported investing in quotas in at least one year over the 2008–2013 period, while 37% reported investing in vessels. A small number of respondents reported investing every year.

As mentioned above, the two variables *NeverJustTech* and *NeverJustQuota* are our measures of the intrinsic costs of violating technology and quota regulations, respectively, based on the survey questions on compliance.

### 3.3. Empirical analysis

Our theoretical analysis predicts a negative relationship between the intrinsic cost of violating technological regulations and quota investments, and a positive relationship between the intrinsic cost of violating quota regulations and quota investments. To test these hypotheses, we empirically analyze the relationships between our two key explanatory variables, the intrinsic costs of violating technology and quota regulations, respectively, and the outcome variable, quota investments.

Recall that we measure the outcome variable as the number of years over a five-year period in which a fisher made investments in quota. Hence, our outcome variable is a count variable. Given that the dependent variable is a non-negative integer count, and

<sup>9</sup> We suspect these self-reported monetary investment values may be subject to greater measurement error than the frequency variable, for several reasons. First, recalling exact investment amounts from up to five years prior is subject to recall bias. Second, fishers may have difficulty distinguishing between expenditures on quota rights and other vessel assets when reporting retrospectively. Third, reported monetary values are likely to involve rounding. By contrast, whether or not an investment occurred in a given year is a more salient binary event and therefore less prone to recall error.

<sup>10</sup> The p-value for  $r \neq 1$  is below 0.0001; two-sided *t*-test.

**Table 3**  
Regression of quota investments on intrinsic costs of violations: negative binomial regression model.

	(1)	(2)	(3)	(4)
NeverJustQuota	0.770*** (0.274)	0.610** (0.288)	0.707** (0.280)	0.678** (0.281)
NeverJustTech	-0.708*** (0.271)	-0.554** (0.278)	-0.476* (0.274)	-0.471* (0.267)
PersonalIncome		0.137*** (0.050)	0.122** (0.052)	0.130** (0.055)
Risk tolerance (r)			-0.270 (0.259)	-0.219 (0.242)
Impatience (δ)			0.636 (1.013)	0.585 (1.002)
Loss aversion (λ)			0.0143 (0.037)	0.0104 (0.036)
Probability weighting (a)			0.124 (0.554)	0.189 (0.546)
DAge60			-1.657*** (0.579)	-1.653*** (0.591)
DNorth				0.428 (0.292)
ShareFisher				-0.000585 (0.000)
Constant	-0.737*** (0.257)	-1.501*** (0.379)	-1.258** (0.524)	-1.316** (0.568)
lnalpha	0.239 (0.318)	0.0831 (0.368)	-0.179 (0.392)	-0.288 (0.444)
Observations	164	164	164	164
Pseudo R <sup>2</sup>	0.040	0.055	0.095	0.101
Log likelihood	-158.2	-155.7	-149.1	-148.1
Chi-squared	14.59	24.41	42.28	44.90

Robust (Huber–White) standard errors in parentheses; lnalpha: log overdispersion parameter.  
\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

given that post-estimation tests confirm overdispersion, we estimate a negative binomial regression model. Specifically, we estimate the following model:

$$\ln(E(NInvQuota_i)) = \beta_0 + \beta_t \text{NeverJustTech}_i + \beta_v \text{NeverJustQuota}_i + Z_i\Gamma + \epsilon_i. \tag{15}$$

The dependent variable,  $NInvQuota_i$ , denotes the number of years in which fisher  $i$  made quota investments. The key explanatory variables,  $NeverJustTech_i$  and  $NeverJustQuota_i$ , capture agent  $i$ 's intrinsic moral costs of violating technological and quota regulations, respectively. Specifically, we measure  $NeverJustTech_i$  using respondents' attitudes toward justifying violations of minimum size regulations, and  $NeverJustQuota_i$  using attitudes toward justifying illegal fish sales (see Section 3.2 for details).

The vector  $Z_i$  includes control variables that may influence quota investment decisions. The error term is denoted by  $\epsilon_i$ . The coefficients  $\beta_t$  and  $\beta_v$  are the parameters of interest, capturing the correlation between the moral costs and quota investment behavior.

We do not seek to identify a causal relationship between intrinsic moral costs and quota investments. Rather, we analyze correlations between our key explanatory variables and quota investments, which can provide empirical support for our hypothesis.

The control variables in  $Z_i$  include a range of factors that could plausibly affect quota investment behavior. First, we account for individual preference parameters – risk aversion, loss aversion, and discount rates – which influence how fishers assess investment opportunities (see Table 2 for definitions). We expect personal income (*PersonalIncome*) to be positively associated with quota investment, as it may proxy individual productivity and access to financing, which may affect the ability to invest in the presence of capital market imperfections. We include age (*DAge60*) to capture life-cycle patterns in investment, given that younger fishers are more likely to be crew members, while older fishers may have accumulated more resources to invest in quotas and vessels. Finally, we include the geographic controls (*DNorth* and *ShareFisher*) to capture regional differences in fishing activity and regulatory conditions.

#### 4. Results

Table 3 reports results from estimating the model given by Eq. (15). Each column includes progressively more control variables. We report heteroskedasticity-robust standard errors in parentheses.<sup>11</sup> In the first column, we report estimates from a regression that controls only for the intrinsic costs of violating quota (*NeverJustQuota*) and technological (*NeverJustTech*) regulations, which are constructed from the compliance attitude responses summarized in Fig. 2. The results show that agents with high intrinsic costs of

<sup>11</sup> Pseudo- $R^2$  values reported at the bottom of each column, measure fit improvement over a null model; low values are typical in cross-sectional count data and do not undermine inference from coefficient estimates.

**Table 4**  
Regression of quota investments on all proxies for intrinsic costs of violations: negative binomial model.

	(1)	(2)	(3)	(4)
NeverJustMinSize	-0.632** (0.273)	-0.511* (0.278)	-0.450* (0.270)	-0.453* (0.266)
NeverJustGearSeasonZone	-0.438 (0.414)	-0.451 (0.398)	-0.376 (0.397)	-0.411 (0.385)
NeverJustSales	0.769*** (0.285)	0.628** (0.305)	0.713** (0.294)	0.676** (0.298)
NeverJustMisreporting	-0.406 (0.290)	-0.292 (0.308)	-0.141 (0.293)	-0.129 (0.293)
NeverJustDiscards	0.246 (0.279)	0.221 (0.282)	0.149 (0.288)	0.192 (0.286)
Constant	-0.361 (0.392)	-1.072** (0.457)	-0.969* (0.560)	-0.982* (0.586)
lnalpha	0.139 (0.320)	0.0188 (0.362)	-0.216 (0.389)	-0.338 (0.440)
Personal income	No	Yes	Yes	Yes
Individual prefs.	No	No	Yes	Yes
Regional chars.	No	No	No	Yes
Observations	164	164	164	164
Pseudo R <sup>2</sup>	0.049	0.062	0.098	0.105
Log likelihood	-156.7	-154.6	-148.6	-147.4
Chi-squared	18.66	27.35	45.14	48.84

Robust (Huber–White) standard errors in parentheses; lnalpha: log overdispersion parameter. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

violating quota regulations, tend to invest more in quotas, while agents with high intrinsic costs of violating technological regulations tend to invest less in quotas. Both coefficients are significant at conventional levels and have the expected signs predicted by our theoretical analysis.<sup>12</sup>

Column (2) adds personal income as a control variable, while column (3) further controls for age and individual preferences – risk aversion, loss aversion, and time preferences. Adding these additional controls decreases the coefficient estimates of our parameters of interest (in absolute terms), and causes a slight increase in the standard errors. The fourth column further adds geographical controls: a north/south dummy and the share of registered fishers in the respondent's municipality.

Adding more controls does not substantially alter the estimates of our parameters of interest. Fishers with high intrinsic costs of violating quotas make significantly more investments in quotas, while agents with high intrinsic costs of violating technology regulations tend to invest less. The standard errors are fairly stable across regressions, but since the magnitudes of these effects decline slightly when we add controls for personal income and individual preferences, the significance level also drops.

Few of the additional controls in columns (2)–(4) are statistically significant. The exceptions are personal income, which, as expected, is positively correlated with quota investments, and age: respondents over 60 are less likely to invest in quotas, consistent with the expectation that investment declines as fishers approach retirement.

To test the robustness of our main findings and better understand the role of individual moral attitudes, we estimate an alternative specification using a more disaggregated set of moral cost proxies. Instead of aggregating responses into two indices (for technological and quota violations), we include responses to all survey questions about whether various violations can be justified.

Violating minimum size regulations and using illegal gear, fishing out of season and/or in closed zones are all technological violations, as they allow fishers to harvest a given quantity at a lower cost. In line with our theoretical predictions, the estimated coefficients of never justifying the violation of minimum size regulations (*NeverJustMinSize*) and gear/season/zone regulations (*NeverJustGearSeasonZone*) are negative in all specifications, although only significant for the minimum size regulation reported in columns (1) and (2).

Unreported sales allow fishers to land more than what is counted against their quota, making them clear examples of quota violations. As Table 4 shows, the estimated coefficients on *NeverJustSales* – denoting respondents who say unreported sales can never be justified – are positive and significant across all model specifications. This finding aligns with our theoretical prediction that higher intrinsic costs of quota violations are associated with greater quota investment.

Some violations are ambiguous, as they may involve both types of regulations. In particular, under and misreporting of catches (*NeverJustMisreporting*) and discards (*NeverJustDiscards*) can reflect both technological and quota violations depending on the context. For example, fishers who land more of a species than they report, violate quota regulations, but if misreporting happens as a cover-up after catching undersized fish, it would (also) be a technological violation. The coefficient on the misreporting variable is

<sup>12</sup> One possible concern is that the intrinsic costs of violating technical and quota regulations may be correlated or interact in their effect on quota investments. However, we find that these intrinsic cost measures are only weakly correlated, and including interaction terms in our main specification does not alter the substantive results.

negative, in line with our predictions for technological violations, while the coefficient for *NeverJustDiscards* is positive, as expected if interpreted as a quota violation. However, both estimates are statistically insignificant and smaller in magnitude than those for the more clearly defined violations.

In [Appendix A.3](#), we present robustness checks where the dependent variable is the total monetary value of quota investments (in NOK), rather than the number of years with such investments. These findings largely confirm the robustness of our main results. The coefficients of interest retain their signs across specifications. In [Table A1](#), the coefficient on *NeverJustQuota* becomes statistically insignificant, but in [Table A2](#), which uses the full set of moral cost proxies, the coefficient for *NeverJustMisreporting* remains negative and becomes statistically significant. The other coefficients remain consistent in sign and significance. Despite potential noise in self-reported investment values, the robustness checks strengthen our confidence in the main findings.

Although the sample size of our empirical analysis is relatively modest (164 observations), it is comparable to previous work in experimental economics. Combining incentivized experiments with an in-depth survey is resource-intensive, and we therefore carefully designed our experiments to minimize noise and maximize precision in measurement. Our incentivized experiment and post-experiment survey allow us to obtain high-quality data, mitigating some of the challenges typically associated with smaller samples. Moreover, as noted above, our sample represents a meaningful subset of the target population.

In addition, the statistical power of our analysis appears sufficient to detect the hypothesized effects. The key coefficients of interest – the “Never justify” variables – are statistically significant at conventional levels, supporting the validity of our main hypotheses. The consistency of our robustness checks and the relatively low variance in key variables further reinforce the reliability of the estimates. We therefore argue that the observed significance levels in both the baseline model and alternative specifications reflect a strong relationship between the variables of interest rather than statistical noise.

Across all specifications in [Tables 3](#) and [4](#), the results support both propositions: we find a negative relationship – significant at the 10% level – between the intrinsic cost of violating technological regulations and quota investments ([Proposition 1](#)), and a positive and statistically significant relationship between the intrinsic cost of violating quota regulations and quota investments ([Proposition 2](#)).

## 5. Discussion and concluding remarks

In this paper, we develop a stylized model of imperfectly enforced market-based environmental regulation to investigate how motivations to comply affect behavior in quota markets. We distinguish between two types of non-compliance: technological violations (e.g., illegal gear) and quota violations (e.g., exceeding allowable catch limits). Our theoretical model shows that agents’ motivations to comply with each of these two types of violations have opposite implications for their willingness to pay for quotas.

Specifically, we show that agents with low intrinsic costs of violating technological regulations are more likely to violate such regulations and tend to buy more quota. Under imperfect enforcement, these agents receive higher returns from emissions than their compliant competitors, and therefore produce more and demand more quota. Agents with low intrinsic costs of violating quota regulations, however, are – as one would expect – more likely to violate quota regulations, and less compliant agents will purchase less quota. Hence, a low motivation to comply could lead to either an increase or a decrease in the willingness to pay for quota, depending on the agent’s motivation to comply with quota regulations and technological regulations, respectively.

To test the theoretical predictions, we use data on vessel-owners in Norwegian fisheries through a combination of a survey and a series of incentivized economic experiments. This empirical setting is particularly well suited to our research question: Quota markets in Norwegian fisheries operate under imperfect enforcement, and fishers are subject to both technological and quota-based regulations. Moreover, our data cover owner-operators who typically make all relevant operational and investment decisions for their firms, allowing us to use individual-level measures as proxies for compliance preferences.

Neither individuals’ intrinsic motivations to comply nor their non-compliance behavior is directly observable. To proxy fishers’ intrinsic motivation to comply with regulations, we used their survey responses about whether they deemed it justifiable to violate different types of regulations. We interpret responses that a violation can “never be justified” as indicators of high intrinsic cost of violation. Our empirical analysis corroborates the predictions of our theoretical model: Fishers with a higher intrinsic cost of violating technological regulations are less likely to invest in quotas, while fishers with higher intrinsic costs of violating quota regulations are more likely to invest in quotas.

In our analysis, we conceptualize differences in agents’ motivation to comply as differences in the intrinsic cost of violating regulations. While such intrinsic costs are typically associated with individual preferences, they can also affect corporate behavior. As illustrated by [Simpson \(2002\)](#), personal intrinsic motivations can also affect violations conducted by corporations. In our empirical application, we use data on owners of fishing vessels in Norway, who typically manage small, owner-operated firms. These owner-operators generally make all relevant operational and investment decisions. This setting is therefore particularly well suited to studying the relationship between individual motivations and quota market behavior.

Our paper contributes to the growing literature on environmental regulation and compliance by highlighting how different types of non-compliance interact with market-based mechanisms. In particular, we show that the effect of individual motivation to comply on market outcomes can differ fundamentally depending on whether agents are more motivated to comply with technological or quota-based regulations. This distinction has significant implications for both environmental policy design and the functioning of environmental markets, as we discuss below. It also opens several avenues for future research.

First, while we model a partial equilibrium setting with fixed quota prices, future work could investigate the general equilibrium effects in quota markets where agents differ in their propensity to comply with quota or technological regulations. One might expect an adverse selection scenario, where agents who have a high demand for quotas due to low propensities to comply with technological regulations bid up quota prices, potentially crowding out other agents. Such interaction could marginalize fully compliant agents

and undermine the efficiency of the market. A comprehensive general equilibrium model could further consider agent heterogeneity along other dimensions, such as capital endowments or constraints. Thus, there remains significant scope for rigorous modeling of environmental markets with heterogeneous non-compliant agents.

Second, our model considers the short run, yet non-compliance likely has long-term consequences, particularly as it affects the composition of active market participants. Increased non-compliance may necessitate a regulatory response such as tightening quota supply to achieve environmental quality targets or preserve depleted resource stocks. Exploring these dynamics explicitly is a promising avenue for future work. In this study, we have taken a first step by demonstrating how motivations to comply with different regulations can distinctly affect quota demand.

Our theoretical results – supported by empirical evidence – suggest that a high demand for quotas may reflect either a strong intrinsic motivation to comply with quota regulations or a weak motivation to comply with technological regulations. Under imperfect enforcement, this gives rise to an adverse selection problem in the quota market. This has policy implications. First, regulators cannot infer agents’ compliance types based on their behavior in the quota market. Second, less compliant agents may have a higher willingness to pay for quota, which could lead to a long-run market equilibrium dominated by agents with weak intrinsic motivations to comply. Finally, while lower intrinsic costs of violations increase the likelihood of non-compliance, technological and quota-based violations affect quota demand in opposite directions. This highlights the importance of accounting for different types of regulatory violations when designing and evaluating market-based environmental policies.

Beyond the scope of the present paper, several dynamic considerations merit future research. First, our model implicitly assumes a steady-state resource stock. If this assumption is relaxed – e.g., if the regulator is unaware of violations and sets quotas too high – quota values would likely decline along with the resource stock. However, such a decline would not necessarily alter the relative incentives for technological versus quota violations, suggesting the core mechanisms of Propositions 1 and 2 may remain relevant in settings – such as Norwegian fisheries and other reasonably well-managed fisheries – where regulators aim to maintain sustainable stock levels. A formal analysis of compliance incentives under more complex stock dynamics remains an interesting avenue for future research.

Second, considering longer time horizons in which the fisher population evolves raises additional dynamics. If entry and exit depend on individual compliance costs, we might observe gradual selection toward fishers who are more compliant with quota regulations but less so with technological regulations. This would affect the composition of the fleet and potentially quota prices, depending on the regulator’s adaptiveness. Fully analyzing these dynamics would require a detailed dynamic model, which we leave for future work.

**CRedit authorship contribution statement**

**Florian Diekert:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Funding acquisition, Formal analysis. **Yuanhao Li:** Writing – original draft, Investigation, Formal analysis. **Linda Nøstbakken:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Investigation, Funding acquisition, Formal analysis. **Andries Richter:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Funding acquisition, Formal analysis.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Appendix A**

*A.1. Kuhn-Tucker analysis of compliance conditions*

The Hessian corresponding to the problem (1) is:

$$H = \begin{bmatrix} \pi_{ee} & \pi_{et} & 0 \\ \pi_{et} & \pi_{tt} - \mu M'' & 0 \\ 0 & 0 & -vN'' \end{bmatrix} \tag{A1}$$

We start by checking second-order conditions. All diagonal elements are negative if  $\pi(\cdot)$  is concave in both  $e$  and  $t$ , i.e.,  $\pi_{ee}$  and  $\pi_{tt} < 0$ , and the intrinsic cost functions are convex, i.e.,  $M'' > 0$  and  $N'' > 0$ . The second-order leading principal minor is  $\pi_{ee}(\pi_{tt} - \mu M'') - \pi_{et}^2$ , which needs to be positive. This condition is likely to fail if the cross-partial derivative,  $\pi_{et}$  is large, i.e., when a marginal increase in technological violation increases marginal return on emissions to a large extent.

The determinant of  $H$  is  $|H| = -[\pi_{ee}(\pi_{tt} - \mu M'') - \pi_{et}^2]vN''$ , which is negative if  $\pi_{ee}(\pi_{tt} - \mu M'') - \pi_{et}^2 > 0$ .

To find the comparative statics, by the implicit function theorem we have:

$$\begin{bmatrix} \frac{\partial F_1}{\partial \mu} & \frac{\partial F_1}{\partial v} & \frac{\partial F_1}{\partial z} \\ \frac{\partial F_2}{\partial \mu} & \frac{\partial F_2}{\partial v} & \frac{\partial F_2}{\partial z} \\ \frac{\partial F_3}{\partial \mu} & \frac{\partial F_3}{\partial v} & \frac{\partial F_3}{\partial z} \end{bmatrix} + H \cdot \begin{bmatrix} \frac{\partial e^*}{\partial \mu} & \frac{\partial e^*}{\partial v} & \frac{\partial e^*}{\partial z} \\ \frac{\partial t^*}{\partial \mu} & \frac{\partial t^*}{\partial v} & \frac{\partial t^*}{\partial z} \\ \frac{\partial v^*}{\partial \mu} & \frac{\partial v^*}{\partial v} & \frac{\partial v^*}{\partial z} \end{bmatrix} = 0$$

Manipulating this expression and substituting in for partial derivatives yields:

$$\mathcal{H} = \begin{bmatrix} \pi_{ee} & \pi_{et} & 0 \\ \pi_{et} & \pi_{tt} - \mu M'' & 0 \\ 0 & 0 & -\nu N'' \end{bmatrix} \tag{A2}$$

Having derived the partial effects, we now interpret their economic meaning. The signs of these derivatives show how the agent’s optimal emissions ( $e^*$ ), technological violations ( $t^*$ ), and quota violations ( $v^*$ ) respond to changes in the intrinsic moral cost parameters ( $\mu, \nu$ ) and the quota price ( $z$ ). To guide intuition, we discuss each parameter in turn.

*Effects of increasing the moral cost of technological violations,  $\mu$*

Applying Cramer’s rule yields (recall that  $\pi_{et} > 0, \pi_{ee} < 0, M' > 0, N'' > 0$  and  $|\mathcal{H}| < 0$  by assumption):

$$\begin{aligned} \frac{\partial e^*}{\partial \mu} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} 0 & \pi_{et} & 0 \\ -M' & \pi_{tt} - \mu M'' & 0 \\ 0 & 0 & -\nu N'' \end{vmatrix} \\ &= -\frac{-\pi_{et} \nu M' N''}{|\mathcal{H}|} < 0 \end{aligned} \tag{A3}$$

$$\begin{aligned} \frac{\partial t^*}{\partial \mu} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} \pi_{ee} & 0 & 0 \\ \pi_{et} & -M' & 0 \\ 0 & 0 & -\nu N'' \end{vmatrix} \\ &= -\frac{\pi_{ee} \nu M' N''}{|\mathcal{H}|} < 0 \end{aligned} \tag{A4}$$

$$\begin{aligned} \frac{\partial v^*}{\partial \mu} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} \pi_{ee} & \pi_{et} & 0 \\ \pi_{et} & \pi_{tt} - \mu M'' & -M' \\ 0 & 0 & 0 \end{vmatrix} \\ &= -\frac{0}{|\mathcal{H}|} = 0 \end{aligned} \tag{A5}$$

An increase in  $\mu$  makes technological violations more morally costly. This directly reduces  $t^*$ . Because emissions and technology use are complementary ( $\pi_{et} > 0$ ), a reduction in  $t^*$  also lowers the marginal profitability of emissions, causing  $e^*$  to fall as well. Quota violations, however, are unaffected since  $\mu$  enters only the cost function for technology violations. Using the definition  $q^* \equiv e^* - v^*$ , we can derive the implied effect on quota purchases:

$$\frac{\partial q^*}{\partial \mu} = \frac{\partial e^*}{\partial \mu} - \frac{\partial v^*}{\partial \mu} \stackrel{s}{=} (-) - 0 < 0, \tag{A6}$$

meaning that greater moral aversion to technological violations leads to lower total emissions and smaller quota demand.

*Effects of increasing the moral cost of quota violations,  $\nu$*

$$\begin{aligned} \frac{\partial e^*}{\partial \nu} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} 0 & \pi_{et} & 0 \\ 0 & \pi_{tt} - \mu M'' & 0 \\ -N' & 0 & -\nu N'' \end{vmatrix} \\ &= -\frac{0}{|\mathcal{H}|} = 0 \end{aligned} \tag{A7}$$

$$\begin{aligned} \frac{\partial t^*}{\partial \nu} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} \pi_{ee} & 0 & 0 \\ \pi_{et} & 0 & 0 \\ 0 & -N' & -\nu N'' \end{vmatrix} \\ &= -\frac{0}{|\mathcal{H}|} = 0 \end{aligned} \tag{A8}$$

$$\begin{aligned} \frac{\partial v^*}{\partial \nu} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} \pi_{ee} & \pi_{et} & 0 \\ \pi_{et} & \pi_{tt} - \mu M'' & 0 \\ 0 & 0 & -N' \end{vmatrix} \\ &= -\frac{\overbrace{-N' [\pi_{ee} (\pi_{tt} - \mu M'') - \pi_{et}^2]}^{>0 \text{ by SOC}}}{|\mathcal{H}|} < 0 \end{aligned} \tag{A9}$$

A higher  $\nu$  raises the intrinsic moral cost of quota violations. This directly reduces  $v^*$ , i.e., agents are less willing to exceed their quota. Since emissions and technology use are not directly tied to  $\nu$ , both  $e^*$  and  $t^*$  remain unchanged. The implied quota response

is:

$$\frac{\partial q^*}{\partial v} = \frac{\partial e^*}{\partial v} - \frac{\partial v^*}{\partial v} \stackrel{s}{=} 0 - (-) > 0, \tag{A10}$$

indicating that stronger moral aversion to quota violations increases quota purchases.

Effects of increasing the quota price,  $z$

$$\begin{aligned} \frac{\partial e^*}{\partial z} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} -1 & \pi_{et} & 0 \\ 0 & \pi_{tt} - \mu M'' & 0 \\ 1 & 0 & -vN'' \end{vmatrix} \\ &= -\frac{(\pi_{tt} - \mu M'')vN''}{|\mathcal{H}|} < 0 \end{aligned} \tag{A11}$$

$$\begin{aligned} \frac{\partial t^*}{\partial z} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} \pi_{ee} & -1 & 0 \\ \pi_{et} & 0 & 0 \\ 0 & 1 & -vN'' \end{vmatrix} \\ &= -\frac{-\pi_{et}vN''}{|\mathcal{H}|} < 0 \end{aligned} \tag{A12}$$

$$\begin{aligned} \frac{\partial v^*}{\partial z} &= -\frac{1}{|\mathcal{H}|} \begin{vmatrix} \pi_{ee} & \pi_{et} & -1 \\ \pi_{et} & \pi_{tt} - \mu M'' & 0 \\ 0 & 0 & 1 \end{vmatrix} \\ &\stackrel{>0 \text{ by SOC}}{=} -\frac{\pi_{ee}(\pi_{tt} - \mu M'') - \pi_{et}^2}{|\mathcal{H}|} > 0 \end{aligned} \tag{A13}$$

A higher quota price discourages emissions and technological violations because both raise the need for quota holdings. However, it also increases the incentive to violate quota limits, raising  $v^*$ . The net effect on quota purchases is:

$$\frac{\partial q^*}{\partial z} = \frac{\partial e^*}{\partial z} - \frac{\partial v^*}{\partial z} = (-) - (+) < 0, \tag{A14}$$

so that higher quota prices reduce total quota demand, as agents both emit less and substitute toward unreported (violating) behavior.

### A.2. Additional summary statistics

Fig. A1 compares the age and gender distribution of the sample of owners we use in the empirical analysis to the population of registered, full-time fishers in Norway in 2014.

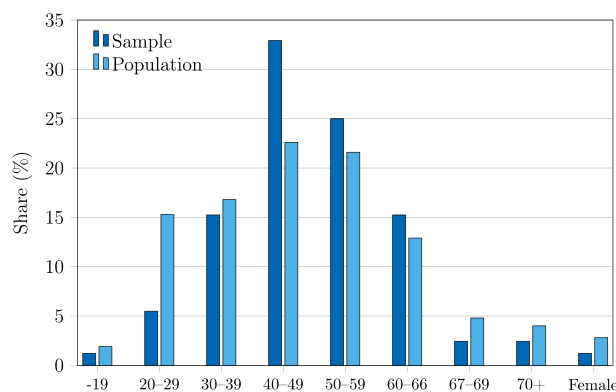


Fig. A1. Comparison of study sample to population of registered fishers: Age brackets and gender.

### A.3. Robustness results

The dependent variable in the robustness regressions presented in this section is the total monetary value of quota investments (in NOK) over the 2008–2013 period, rather than the count of years with positive investments used in the main analysis. Since the dependent variable is continuous rather than a non-negative integer count, we estimate these specifications using OLS with heteroskedasticity-robust standard errors rather than the negative binomial model used in Tables 3 and 4.

**Table A1**  
Robustness results: regression of total sum of investments.

	(1)	(2)	(3)	(4)
NeverJustQuota	1,853,373.6 (3314173.922)	406,450.0 (3331684.262)	810,712.8 (3277675.788)	1,978,306.2 (3192880.578)
NeverJustTech	-9,644,288.2** (3950560.442)	-8,663,424.7** (3828250.336)	-8,181,851.7** (3728325.224)	-8,055,437.8** (3655726.231)
PersonalIncome		1,392,244.3** (574431.134)	1,219,351.4** (569125.167)	1,051,602.7* (576563.856)
DAge60			-5,599,209.3*** (2136825.400)	-6,606,496.2*** (2485563.768)
Risk tolerance ( $r$ )			-2,683,943.0 (2308024.050)	-3,665,568.1 (2635681.749)
Impatience ( $\delta$ )			7,689,019.4 (9222922.767)	6,971,404.4 (9191641.134)
Loss aversion ( $\lambda$ )			391,521.6 (579341.506)	302,578.0 (553691.858)
Probability weighting ( $a$ )			-2,193,142.8 (6146800.615)	-2,202,307.3 (5911852.401)
DNorth				-3,721,102.5 (2531304.528)
ShareFisher				-7324.5** (3438.352)
Constant	10,324,100.8** (4872363.568)	3,308,331.8 (4999838.071)	7,173,337.6 (6955932.791)	11,897,862.7 (8386152.840)
Observations	164	164	164	164
$R^2$	0.058	0.085	0.108	0.129
Adjusted $R^2$	0.046	0.068	0.062	0.072
F-statistic	4.742	4.260	1.982	1.785

Robust (Huber–White) standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table A2**  
Robustness results: regression of total sum of investments on all violations.

	(1)	(2)	(3)	(4)
NeverJustMinSize	-8,330,550.6** (3367343.612)	-7,420,557.2** (3245639.660)	-6,973,253.0** (3166928.581)	-6,802,265.3** (3107074.518)
NeverJustGearSeasonZone	-6,822,638.6 (9313619.459)	-7,437,401.3 (9284445.653)	-7,142,209.8 (9624011.980)	-8,074,028.3 (9796180.636)
NeverJustSales	2,863,744.9 (2751283.507)	1,463,234.4 (2851987.779)	1,712,238.7 (2819437.230)	2,978,011.9 (2797145.963)
NeverJustMisreporting	-4,719,252.1* (2392910.641)	-3,388,182.3 (2374055.602)	-2,329,147.6 (2333546.359)	-2,557,263.7 (2357631.685)
NeverJustDiscards	289,397.5 (2576389.531)	-240,462.2 (2570527.616)	-1,064,935.9 (2985492.001)	-661,650.5 (2969521.020)
Constant	17,116,689.4 (11371947.096)	10,805,663.2 (11799144.788)	13,488,974.3 (12960845.671)	19,272,801.1 (14838195.228)
Observations	164	164	164	164
$R^2$	0.083	0.106	0.124	0.148
Personal income	No	Yes	Yes	Yes
Individual prefs.	No	No	Yes	Yes
Regional chars.	No	No	No	Yes
F-statistic	2.219	2.691	1.611	1.476

Robust (Huber–White) standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Data availability

Data will be made available on request.

## References

- Abe, K., Nøstbakken, L., Wold, M.F., 2024. Quota consolidation in Norwegian coastal fisheries. *Environ. Resour. Econ.* 87 (5), 1295–1326.
- Arguedas, C., Camacho, E., Zoffo, J.L., 2010. Environmental policy instruments: technology adoption incentives with imperfect compliance. *Env. Resour. Econ.* 47 (2), 261–274.
- Becker, G.S., 1968. Crime and punishment: an economic approach. *J. Polit. Econ.* 76 (2), 169–217.
- Boonstra, W.J., Birnbaum, S., Björkvik, E., 2017. The quality of compliance: investigating fishers' responses towards regulation and authorities. *Fish Fish.* 18 (4), 682–697.
- Burby, R.J., Paterson, R.G., 1993. Improving compliance with state environmental regulations. *J. Policy Anal. Manag.* 12 (4), 753–772.
- Chavez, C., Salgado, H., 2005. Individual transferable quota markets under illegal fishing. *Environ. Resour. Econ.* 31 (3), 303–324.

- Diekert, F., Li, Y., Nøstbakken, L., Richter, A., 2023. Why do fishermen comply with regulations? The role of preferences. In: Bucciol, A., Tavoni, A., Veronesi, M. (Eds.), *Behavioural Economics and the Environment – a Research Companion*, chapter 5. Routledge.
- Diekert, F., Schweder, T., 2017. Disentangling effects of policy reform and environmental changes in the Norwegian coastal fishery for COD. *Land Econ.* 93 (4), 689–709.
- Frey, B., 1997. *Not Just for the Money*. Edward Elgar Publishing.
- Graafland, J., Gerlagh, R., 2019. Economic freedom, internal motivation, and corporate environmental responsibility of SMEs. *Env. Resour. Econ.* 74 (3), 1101–1123.
- Gullestad, P., Aglen, A., Bjordal, Å., Blom, G., Johansen, S., Krog, J., Misund, O.A., Røttingen, I., 2013. Changing attitudes 1970–2012: evolution of the Norwegian management framework to prevent overfishing and to secure long-term sustainability. *ICES J. Mar. Sci.* 71 (2), 173–182.
- Gullestad, P., Blom, G., Bakke, G., Bogstad, B., 2015. The “discard ban package”: experiences in efforts to improve the exploitation patterns in Norwegian fisheries. *Mar. Policy* 54, 1–9.
- Harrington, D.R., 2012. Two-stage adoption of different types of pollution prevention (P2) activities. *Resour. Energy Econ.* 34 (3), 349–373.
- Harrington, D.R., 2023. Technology, management and input choices to increase abatement and output. *Land Econ.* 99 (4), 611–643.
- Hatcher, A., 2005. Non-compliance and the quota price in an ITQ fishery. *J. Environ. Econ. Manag.* 49 (3), 427–436.
- Hatcher, A., Gordon, D., 2005. Further investigations into the factors affecting compliance with U.K. Fishing quotas. *Land Econ.* 81 (1), 71–86. Publisher: University of Wisconsin Press Section: ARTICLES.
- Keeler, A.G., 1991. Noncompliant firms in transferable discharge permit markets: some extensions. *J. Environ. Econ. Manag.* 21 (2), 180–189.
- Kuperan, K., Sutinen, J.G., 1998. Blue water crime: deterrence, legitimacy, and compliance in fisheries. *Law & Society Review* 32 (2), 309–338.
- Lazkano, I., Nøstbakken, L., 2016. Quota enforcement and capital investment in natural resource industries. *Mar. Resour. Econ.* 31 (3), 339–354.
- Leibbrandt, A., Lynham, J., 2018. Does the allocation of property rights matter in the commons? *J. Environ. Econ. Manag.* 89, 201–217.
- Liu, E.M., 2013. Time to change what to sow: risk preferences and technology adoption decisions of cotton farmers in China. *Rev. Econ. Stat.* 95 (4), 1386–1403.
- Malik, A.S., 1990. Markets for pollution control when firms are noncompliant. *J. Environ. Econ. Manag.* 18 (2, Part 1), 97–106.
- Murphy, J.J., Stranlund, J.K., 2007. A laboratory investigation of compliance behavior under tradable emissions rights: implications for targeted enforcement. *J. Environ. Econ. Manag.* 53 (2), 196–212.
- Nøstbakken, L., 2008. Fisheries law enforcement—a survey of the economic literature. *Mar. Policy* 32 (3), 293–300.
- Nøstbakken, L., 2013. Formal and informal quota enforcement. *Resour. Energy Econ.* 35 (2), 191–215.
- Nøstbakken, L., Wold, M., 2025. The Efficiency Costs of Transfer and Consolidation Constraints: Evidence from a Resource Market. SNF Working Paper 07/2025, SNF – Centre for Applied Research at NHH.
- Oyanedel, R., Gelcich, S., Milner-Gulland, E.J., 2020. Motivations for (non-)compliance with conservation rules by small-scale resource users. *Conserv. Lett.* 13 (5), e12725. [eprint: https://conbio.onlinelibrary.wiley.com/doi/pdf/10.1111/conl.12725](https://conbio.onlinelibrary.wiley.com/doi/pdf/10.1111/conl.12725).
- Peeters, M., Denkers, A., Huisman, W., 2020. Rule violations by SMES: the influence of conduct within the industry, company culture and personal motives. *Eur. J. Criminol.* 17 (1), 50–69.
- Rorie, M., 2015. An integrated theory of corporate environmental compliance and overcompliance. *Crime Law Soc. Change* 64, 65–101.
- Shimshack, J.P., 2014. The economics of environmental monitoring and enforcement. *Annu. Rev. Resour. Econ.* 6 (1), 339–360.
- Simpson, S.S., 2002. *Corporate Crime, Law, and Social Control*. Cambridge University Press Cambridge.
- Stranlund, J.K., 2017. The economics of enforcing emissions markets. *Rev. Environ. Econ. Policy* 11 (2), 227–246.
- Stranlund, J.K., Murphy, J.J., Spraggon, J.M., Ziogiannis, N., 2019. Tying enforcement to prices in emissions markets: an experimental evaluation. *J. Environ. Econ. Manag.* 98, 102246.
- Tanaka, T., Camerer, C.F., Nguyen, Q., 2010. Risk and time preferences: linking experimental and household survey data from Vietnam. *Am. Econ. Rev.* 100 (1), 557–571.
- Vidal-Meliá, L., Arguedas, C., Camacho-Cuena, E., Zofío, J.L., 2022. An experimental analysis of the effects of imperfect compliance on technology adoption. *Env. Resour. Econ.* 81 (3), 425–451.
- Villegas-Palacio, C., Coria, J., 2010. On the interaction between imperfect compliance and technology adoption: taxes versus tradable emissions permits. *J. Regul. Econ.* 38 (3), 274–291.
- Viteri, C., Chàvez, C., 2007. Legitimacy, local participation, and compliance in the Galapagos Marine Reserve. *Ocean Coast. Manag.* 50, 253–274.