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Good governance pays? A cross-sectional analysis of export performance and environmental compliance–enforcement

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1. Introduction

Environmental governance research typically studies enforcement design or firm compliance behavior separately. Yet, the two are closely linked: sustainable governance requires aligning state and firm goals. A firm's compliance decision depends on the authority's capacity, and enforcement outcomes depend on which firms actually comply (Gray & Shimshack, 2011; Heyes, 2000). Compliance without effective public oversight and enforcement without genuine compliance both fail to deliver social welfare. This link is especially relevant in developing countries such as Peru, which ranks in the lower-middle range of the Worldwide Governance Indicators (World Bank, n.d.) and where aligning compliance with enforcement remains a persistent challenge. One factor that could connect the two sides is export performance: foreign buyers may reward firms that produce sustainably, while large exporters are also more visible to the regulator. Does firm export performance, measured hereafter by export revenue, help align these two sides of governance, or does it mainly shape how firms are sanctioned once they fail to comply?

The fishing sector's features make this question worth addressing. In 2022, Peru was the world's third-largest marine capture producer, with 5.3 million tons (6.6% of the world total), most of it Peruvian anchoveta (*Engraulis ringens*), and the leading exporter of fishmeal, with nearly one-third of world export value (Food and Agriculture Organization [FAO], 2024). Fishing accounted for only 0.5–0.8% of Peru's GDP at current prices in 2019–2025 (Instituto Nacional de Estadística e Informática [INEI], 2026), but it weighs more heavily in exports: fishing exports earned USD 2.9–4.7 billion a year, 4.4–7.4% of the country's total exports. Fishmeal and fish oil, Peru's 'traditional' fishing exports, accounted for 51–63% of that value in every year except 2023, when the share was 39% (Appendix A, Table A4), and most of the rest came from 'non-traditional' frozen crustaceans, mollusks, and fish and canned products (Banco Central de Reserva del Peru [BCR], n.d.).

Peru's environmental enforcement authority, the Environmental Assessment and Enforcement Agency (OEFA), supervises large-scale sectors, including fishing, under a 'carrot and stick'[1] regime that combines deterrence with incentives. In the fishing sector, OEFA public data (OEFA, n.d.-a, n.d.-b) show that roughly half of inspections likely detected non-compliance with auditable environmental obligations (AEO) of regulated firms ('holders', in OEFA and administrative terminology). Between 2018 and January 2026, 2,204 supervisions were conducted,

[1] Legal basis: Resolution of the Presidency of the Board of Directors N° 035-2013-OEFA/PCD (former fine methodology); Board resolutions (RCD) N° 045-2013, 024-2017, 027-2017, 006-2018, 00030-2022, 00015-2024, 00019-2025, 00005-2026-OEFA/CD (infraction classification, current fine methodology, supervision and sanctioning procedure). Ministerial Resolution N° 167-2014-MINAM; and RCD N° 034-2014, 040-2014-OEFA/CD (incentive and oversight).

1,064 sanctioning procedures were opened, and fines totaling 6,321.95 tax units (UIT)[2] were imposed, by our tabulation of OEFA's summary statistics ('OEFA en cifras', January 2026 update), a broader source than the firm-level files used in our analysis, which run to 2025 (OEFA, n.d.-a, n.d.-b). Some firms have launched sustainability programs, such as conservation and eco-efficiency initiatives, and report them on their own platforms (SNP, n.d.; TASA, n.d.). However, repeat infractions (reiteration or recidivism) still persist (OEFA, n.d.-a, n.d.-b), which suggests that firms' own initiatives and public enforcement are not yet working toward shared goals.

Prior work on environmental enforcement centers on a deterrence-and-optimization framework (Becker, 1968; Polinsky & Shavell, 2000; Stigler, 1970), in which firms' gain from non-compliance (traditionally modeled as an "illicit benefit") and institutional design shape compliance outcomes (Gray & Shimshack, 2011; Segerson & Tietenberg, 1992). Peru lacks firm-level empirical studies linking export performance to both compliance and sanctions; existing research on enforcement still focuses on enforcement design (supervision and sanctions) in other sectors, such as hydrocarbons (Vásquez Cordano & Gallardo Ku, 2006), or on fine methodologies. Given that about 47% of inspections revealed likely non-compliance, and given the limited uptake of official compliance-incentive programs from the enforcement authority (OEFA, n.d.-a, n.d.-b, 2016), firms in the sector likely see compliance mainly as a cost. A growing literature on environmental, social and governance (ESG) performance, corporate social responsibility (CSR) and trade suggests a different view: good sustainability performance can bring financial and non-financial returns, such as higher market valuation, competitiveness and productivity (Barontini & Gioja, 2025; Donaldson & Preston, 1995; Liu et al., 2025; Porter & van der Linde, 1995; Reyes Bastidas et al., 2026; Wanyan & Zhao, 2024; Xie et al., 2023). If such returns also reach firms that comply with environmental regulation, export markets could offer a "sustainable incentive" to comply, in addition to the classical deterrence. We call this channel export-driven sustainability (EDS), a framing drawn from our earlier qualitative fieldwork in this sector (Jaramillo Abad & Uwasu, 2025). Firm-level evidence on this channel is mixed. At the plant level, trade and ownership links with OECD economies did not improve environmental compliance in Mexico, whereas inspections and internal management procedures did (Dasgupta et al., 2000); other studies find that ties to environmentally demanding export markets raise firms' environmental self-regulation (Christmann & Taylor, 2001) and their adoption of voluntary standards such as ISO 14001 (Prakash & Potoski, 2006).

[2] In 2026 (DS N° 301-2025-EF), a tax unit (UIT) is equal to PEN 5,500 (about USD 1,500–1,600)

This paper asks two related questions about large-scale fishing firms in Peru. Does a firm's export revenue, used here as a simple summary measure of its size and export performance, predict (a) the probability that the firm complies with its environmental obligations, and (b) the size of the fine it receives when it does not comply? We answer these questions using a cross-sectional sample of 112 fishing firms, built by matching 2023 export declarations with OEFA's public compliance and sanction records (details in Section 2).

Export revenue is not a measure of profit: it omits production costs, domestic sales, and margins. Still, in heterogeneous-firm trade models, more productive firms are larger, self-select into exporting and earn higher export revenues (Melitz, 2003; Melitz & Redding, 2015). Unlike earlier models with identical firms, in which the gains from trade come mainly from greater product variety (Krugman, 1980), these models explain which firms export. Entering export markets carries fixed costs, including the cost of adapting products to "foreign standards (which include testing, packaging, and labeling requirements)" (Melitz, 2003), so only the more productive firms export, and trade shifts market share toward them. Neither model addresses environmental regulation, but by analogy, larger, more productive exporters would bear the fixed costs of meeting foreign buyers' environmental and certification requirements more easily. Throughout this paper, export revenue is therefore read as a measure of firm scale and export performance: the observable counterpart of the market-based incentive channel to comply (denoted as I^M in Section 2.1) and of a firm's visibility to the regulator. Our analysis rests on a simple model in which a firm chooses its compliance effort by weighing the cost of compliance against expected sanctions and possible sustainable incentives (Section 2.1).

We report three main empirical findings. First, in a simple linear model, export revenue does not consistently predict compliance: the result depends on how compliance is defined (by infraction or by fine record). Second, when we add a squared term, compliance follows an inverted U in the 2023 data: the probability of compliance rises with export revenue among smaller exporters, peaks at about USD 1.3–2.9 million (well below the sample median of USD 7.5 million), and then falls; with 2022 or 2024 exports the curve keeps this shape, but the squared term is not significant at the 5% level (Section 3.6). Third, among firms with a confirmed infraction, larger exporters receive larger fines, mainly at the top of the export distribution; this association, however, weakens and loses statistical significance once we control for activity type and the number of facilities a firm operates (Appendix E.9) or reweight the sample for selection (Appendix E.2).

This paper makes three empirical contributions. First, it provides firm-level evidence for Peru linking export performance to both sides of environmental governance, the probability of compliance and the severity of sanctions, within one audited sample; existing work on the sector has not examined this link. Second, it shows that in the 2023 data the compliance relationship is an inverted U rather than uniformly positive or negative, and that both outcomes change most among the largest exporters. Third, it shows that inferences about compliance are sensitive to how a confirmed infraction with a zero fine is coded, so every specification is reported under both standards. The remainder of the paper is organized as follows. Section 2 sets out the theoretical assumptions, data construction, and specifications; Section 3 reports the results and discussion; and Section 4 concludes with policy implications. The appendices report descriptive statistics, full regression output, diagnostics, predicted probabilities, additional robustness checks, reproducibility notes, and the planned panel specification.

2. Materials and Methods

2.1. Theoretical Assumptions

Firms choose compliance effort *e* to maximize profit, given fixed and variable costs and optimized production Q^*.

$$\max_e \pi_i = R(Q*) - C(Q*) - \text{Full cost on compliance(e)} + \text{Incentives(e)} \quad \textbf{(1)}$$

$$\pi^C = \pi - C_e + q\text{'I} \quad \textbf{(2)}$$

$$\pi^{NC} = \pi - pp'S - p\theta O \quad \textbf{(3)}$$

where π^C, π^{NC} are profits under compliance/non-compliance; C_e is the marginal cost of compliance effort; *q'I* is the expected incentive value for compliance and/or overcompliance performance, with *q'* the probability that compliance is recognized and rewarded and *I* the sustainable incentive earned through compliance performance; *p* is the probability that a violation (infraction) is detected and *p'* is the probability that a detected violation is confirmed and sanctioned (post-detection probability); *S* is the sanction (tangible and intangible), and *O* is the cost of a legal-defense strategy ($\theta = 1$, if the firm decides to appeal).

Thus, we assume the following *compliance condition:* firm *i* complies if and only if $\pi^C \geq \pi^{NC}$

$$pp'S + p\theta O + q\text{'I} \geq C_e \quad \textbf{(4)}$$

Firm *i* complies when expected sanctions, adjusted for post-detection credibility, plus sustainable incentives, exceed the cost of compliance effort.

Two features of this condition matter for the empirical strategy that follows. First, sanction exposure is weighted jointly by the probability of detection (p) and the probability that a detected case is confirmed and sanctioned (p'). Because p' reflects the credibility of enforcement once a violation is detected, it plausibly exerts a different, and potentially stronger, deterrent effect than the raw detection probability p. Second, the incentive term $q'I$ captures any sustainable incentive available to the firm. Sustainable incentives are further understood as a portfolio $I = I^O + I^M + I^R + I^P$, spanning official awards or recognition, market returns, reputational returns, and production/eco-efficiency gains, any of which may complement formal sanction schemes rather than substitute for them. This logic is developed and formalized in a companion theoretical analysis (Jaramillo Abad & Uwasu, 2026). That analysis also derives a "governance multiplier": if the probability of being rewarded rises with post-detection credibility, $q' = q'(p')$, then strengthening institutional credibility (p') amplifies the deterrence and incentive channels at the same time. On this view, institutional credibility, not inspection volume alone, drives compliance gains. This is consistent with evidence that a regulator's sanctioning reputation deters non-compliance well beyond the sanctioned plant (Shimshack & Ward, 2005).

This paper focuses empirically on the market-incentive channel I^M, using export revenue as its observable proxy, and asks whether firm export performance (scale) is associated with (a) the probability of compliance and (b) the severity of sanction once a violation is confirmed. Two further predictions of the broader framework (namely, that post-detection credibility p' should matter more for compliance than detection intensity p alone, and that firm size may moderate this relationship through differences in risk response) are examined only partially, where the cross-sectional data allow. The theoretical framework as a whole (assumptions, derivations, and implications) is developed formally in Jaramillo Abad and Uwasu (2026)[3]. That companion paper contains the full analytical derivations and proofs of the comparative statics, the governance multiplier and the conditions for a non-monotonic relationship; the present paper does not derive the reduced forms it estimates.

Enforcement and compliance co-evolve rather than interact in a simple linear sequence (Beunen et al., 2022): enforcement shapes compliance response, while compliance incentives, such as reputational, market-access, and productivity returns (Barontini & Gioja, 2025; Donaldson & Preston, 1995; Porter & van der Linde, 1995; Reyes Bastidas et al., 2026; Xie et al., 2023), shape performance. We use export revenue as a single summary proxy for

[3] **Note**. The companion paper (Jaramillo Abad & Uwasu, 2026; OSIPP Discussion Paper 26E010, submitted for peer review) derives the p' > p asymmetry and develops the role of risk aversion (decreasing absolute risk aversion, DARA), the incentive portfolio and the governance multiplier (Eq. M-5.4 $\frac{\partial^2 e^*}{\partial I \, \partial p'} > 0$).

both the scale of economic activity and firms' exposure to enforcement scrutiny, consistent with penalty-design and enforcement literature, in which efficient sanctions grow with the scale of potential damages and larger sources and offenses attract more enforcement effort (Gray & Shimshack, 2011; Heyes, 2000; Segerson & Tietenberg, 1992; Stigler, 1970).

Export performance enters the compliance condition (4) through channels that do not all point the same way, so we interpret it broadly as a measure of firm scale, which shapes both market incentives and visibility. (i) *A market-incentive channel*: exposure to foreign buyers and certification requirements raises $q'I^M$ and should raise compliance. Meeting importers' requirements is itself costly. In World Bank survey data on 159 firms in 16 developing countries, the fixed cost of conforming to importers' product standards averaged about USD 425,000 per firm, about 4.7% of value added, and these standards also raised variable production costs (Maskus et al., 2005); a stricter EU food-safety standard was projected to cut African exports of some food products to Europe by 64% relative to an international (Codex) standard (Otsuki et al., 2001). Neither study concerns fisheries or environmental obligations, but by analogy the market incentive I^M is likely to accrue mainly to firms able to bear such costs, so firms of different size should respond differently. (ii) *A visibility channel*: larger, more prominent exporters are more visible to the regulator. A higher p raises expected sanctions in (4) and should strengthen deterrence, but it also raises the chance that any lapse is detected and recorded, which lowers measured compliance. In addition, because OEFA's fine methodology incorporates the illicit benefit and caps fines relative to the infractor's gross income, S rises with scale once an infraction is confirmed. (iii) *An exposure channel*: larger operations run more facilities and carry more obligations, multiplying the opportunities for a recorded infraction and lowering measured compliance. The reduced-form association between export scale and compliance is therefore ambiguous. If market incentives dominate among small exporters while exposure to more obligations and closer scrutiny grow faster at large scale, the association will be inverted-U shaped, whereas sanction severity should rise with scale. Regulatory attention and buyer scrutiny may respond to a firm's relative standing in the market, whereas exposure depends on absolute operations. Separating the two would require a measure of prominence that is not a rescaling of revenue, such as a firm's share within its product segment or destination market, which these data do not provide; Section 3.5 therefore uses market share (stated in the 2023 export records of SNP) only to check the shape of the scale relationship. This motivates two hypotheses: H1, compliance is non-monotonically (inverted-U) related to export scale; and H2, among non-compliant firms, sanction severity increases with export scale.

2.2. Data and Sample Construction

Peru's large-scale fishing sector falls under the competence of the national enforcement agency, OEFA, and it is a significant source of export earnings (Appendix A, Table A4). Building on prior evidence on compliance, firm performance and trade (Dasgupta et al., 2000; Liu et al., 2025; Xie et al., 2023), we test whether export revenue relates to compliance and enforcement outcomes, using cross-sectional data that match a firm's tax identification number (RUC) across export revenue records and OEFA's compliance (supervision and sanction) records. Export data from the year 2023 come from Peru's National Fisheries Society (SNP), which compiles customs records of Peru's National Superintendency of Customs and Tax Administration (SUNAT), and cover 370 firms. Compliance-supervision and sanction data come from three OEFA public sources: the holder registry, supervision-event logs, and the public sanctions database, the Unique Registry of Environmental Offenders Sanctioned by OEFA (RUIAS), which lists confirmed infractions and their fine outcomes. The first two are accessed through OEFA's Interactive Environmental Oversight Portal (PIFA); together the three sources hold cumulative 2018–2025 records for 328 fishing firms under OEFA's jurisdiction (OEFA, n.d.-a, n.d.-b). The unit of analysis is the firm. Each of 370 exporters is observed once, combining its 2023 exports with its cumulative OEFA enforcement record (from 2018 to 2025), so for this study the data have no time dimension. The analytic sample has 112 firms; the fine models use the 90 (confirmed-infraction) or 76 (fine-only) non-compliant firms.

Combining OEFA and SNP records shows whether an exporting firm falls under OEFA's competence, and therefore whether its compliance and sanction status can be observed. A firm is included in the compliance sample only if its status can be confirmed against at least one OEFA source: 112 of 370 firms. We exclude the firms with no record in any OEFA source (258 firms, about 70% of the exporter list, mostly trading intermediaries without their own audited production facility), rather than assuming compliance or non-compliance, since their true status is unknown. Three explicit dummies underlie this restriction: *supervised* (in the holder registry or supervision-event logs; 104 firms), *sanctioned* (in RUIAS with a confirmed infraction; 90 firms), and their union, the confirmed-OEFA-competency population (112 firms) used throughout this paper[4]. Appendix E.1 tests this restriction directly against a firm-scale measure, and E.2 re-estimates the paper's main models under inverse-probability weighting (IPW) to gauge how much this restriction affects the results reported below.

[4] **Note**. Each of the 112 firms in the sample is a fishing-sector holder with a 2023 export record that falls under OEFA's jurisdiction. A firm is coded compliant only if it has a positive confirming record from at least one OEFA source, so no firm is assigned compliant status on the basis of an absent record alone; non-compliant status relies on the RUIAS record of infraction or fine.

Main explanatory variable. Export performance is measured by each firm's 2023 export revenue (free on board FOB, thousand USD) as reported by SNP. It is strongly right-skewed: across all 370 exporters the mean is USD 8.08 million and the median USD 0.55 million; within the 112-firm sample, USD 23.1 and 7.5 million, respectively. It therefore enters every model as Ln(export revenue), computed as ln(revenue + 1) with revenue in thousand USD; in the 112-firm sample this differs from ln(revenue) by at most 0.03. As set out in Section 2.1, it is read as a measure of firm scale and export-market exposure. Section 3.5 uses two alternatives from the same report: export volume (tons), as a second scale measure, and the firm's share of total fishing exports, which is revenue rescaled by a constant and therefore checks only the functional form. Fines, the second dependent variable, are also right-skewed (among the 90 firms with a confirmed infraction, mean 26.4 and median 3.9 UIT) and enter as Ln(fine+1) because 14 of these firms have a zero fine.

A firm with a confirmed infraction but a monetary fine of exactly zero (e.g., a warning, a fine reduced to zero on appeal, or another administrative decision) admits more than one defensible coding. We therefore report two compliance standards side by side throughout this study: a **confirmed-infraction standard** (non-compliant if any infraction is on record, regardless of the eventual fine; 90 of 112 firms coded non-compliant) and a **fine-only standard** (non-compliant only if the verified fine is nonzero; 76 of 112 firms coded non-compliant). The two standards disagree for 14 firms; one of these was a firm with a documented reconsideration appeal on record, which might explain a zero fine despite a recorded infraction. The two standards are nested: every firm that is non-compliant under the fine-only standard is also non-compliant under the confirmed-infraction standard. In terms of condition (4), we may say that the confirmed-infraction standard reflects detection (p), while the fine-only standard also requires that a detected case end in a monetary sanction, which is closer to post-detection credibility (p').

2.3. Data-Quality Audit

Because the compliance and fine variables are the paper's dependent variables, we subjected the firm-RUC linkage underlying this sample to an explicit data-quality audit rather than relying on manual name-matching alone. In practice, the audit re-derived each firm's RUC from OEFA's own records, recomputed each firm's fine and infraction count from the sanctions registry, and corrected data-entry errors; the code and files are part of the replication package (Appendix F). The audit re-derived the linkage directly from the underlying OEFA/SNP source files (2023 export declarations, the OEFA holder and supervision registries of 2018–2025, and two complementary OEFA fine sources from the PIFA and RUIAS platforms). We also independently re-matched all 370 exporting

firms against the OEFA supervision registry and the RUIAS sanctions list, both of which have usable RUC identifiers[5]. The audit thus makes the provenance of the data transparent to readers.

2.4. Model Specification

We estimate a logistic model (5) of compliance on Ln(export revenue), with a quadratic extension, and an Ordinary Least Squares (OLS) regression model (6) of Ln(fine+1) on Ln(export revenue) among non-compliant cases, which is also extended with export-size tercile interactions to test slope heterogeneity. We run each specification under both compliance standards. Section 3.5 adds export market share as a second regressor, which checks only the functional form because market share in the SNP records is export revenue divided by the sector total, and replaces export revenue with export volume (tons) as an alternative scale measure. Appendix E reports further checks on sample representativeness and model specification.

$$Pr(Com_i = 1|\pi) = \beta_0 + \beta_1 Export_i + \varepsilon_i \qquad \text{(all firms in the compliance sample)} \qquad \textbf{(5)}$$

$$Fine_i = \alpha_0 + \alpha_1 Export_i + \varepsilon_i \qquad \text{(for non-complying firms)} \qquad \textbf{(6)}$$

We call specifications (5) and (6), in which Ln(export revenue) enters linearly, the base specifications (a logit model for compliance and an OLS model for sanctions); their quadratic and export-tercile versions are extensions.

Estimator choice. Because compliance is binary and predicted probabilities approach zero in the tails of the export distribution, specification (5) is estimated as a logistic (logit) model rather than a linear probability model, which can produce out-of-range predictions and imposes a constant marginal effect that is incompatible with a turning point. In the quadratic extension, $\Pr(Com_i = 1) = \Lambda(\beta_0 + \beta_1 x_i + \beta_2 x_i^2)$ where $\Lambda(\cdot)$ is the logistic function and $x_i =$ Ln(export revenue), and when $\beta_2 < 0$ the turning point is $x^* = -\beta_1/(2\beta_2)$. We obtain its 95% confidence interval using the delta method and check it with a Fieller interval and a nonparametric bootstrap; the Lind and Mehlum (2010) test assesses whether the slope is significantly positive at the lowest and significantly negative at the highest observed export level (Haans et al., 2016). Because the sample is small and the upper tail is thin, the quadratic model is also re-estimated with Firth (1993) bias reduction, influential firms are identified with Cook (1977) distance in its logistic-regression version (Pregibon, 1981), using the conventional 4/n rule of thumb (on such

[5] **Note**. The re-derived RUC agreed with the original match the sample firms found by name in the supervision log; the exception is COPEINCA, whose supervision records appear under the RUC of CFG Investment, the separate legal entity that acquired it and later files under the COPEINCA name; we keep the RUC of the exporter named in the SNP report.

cutoffs, see Bollen & Jackman, 1985), and the model is re-fitted without the largest exporters (Appendices E.3, E.6 and E.7).

Specification (6) is estimated only for non-compliant firms by design. A fine exists only after an infraction is confirmed, so compliant firms' zero fines are structural zeros rather than censored values of a latent fine. Specifications (5) and (6) are therefore the two parts of a two-part model (Duan et al., 1983): the unconditional expectation of Ln(fine+1) factors as $\Pr(Com_i = 0 \mid x_i) \times E[\text{Ln}(fine_i+1) \mid Com_i = 0, x_i]$, and specification (6) answers the policy question of how severe the sanction is once the regulator acts. A Heckman (1979) correction would in practice require an exclusion restriction (a variable that shifts the probability of infraction without affecting the size of the fine), which this cross-section does not offer, and identification through functional form alone is fragile (Wooldridge, 2010). The fine coefficients are therefore read as conditional associations, with heteroskedasticity-robust (HC_1) standard errors (MacKinnon & White, 1985; White, 1980), quantile regressions (Koenker & Bassett, 1978) and leave-out re-estimations (Appendices E.4 and E.8) as checks.

2.5. Limitations

This cross-sectional sample, like most single-period firm-level analyses, carries a few limitations common to this research design. First, exports (2023) and fines (2018–2025) cover different windows, so the results describe association, not a same-year causal claim, and a firm's compliance record partly reflects supervision intensity built up over years, while export behavior is measured in a single year. The export year was also unusual in its composition: El Niño conditions cut Peru's industrial landings in 2023 by about half relative to 2022 (FAO, 2024), and exports of fishmeal and fish oil fell by 52%, while non-traditional fishing exports rose by 8%, so total fishing exports fell by 27% (BCR, n.d.; see Appendix A, Table A4). With 2022 or 2024 SUNAT exports, the compliance curve keeps its shape, but the squared term is not significant at the 5% level (Section 3.6), so the inverted U should be read as a 2023 pattern. Second, because firm revenue is only reliably observable through customs records (domestic sales are rarely observable), the sample includes only exporting firms, so findings describe variation among the firms that produce, export, and fall under OEFA competence, not exporters versus non-exporters; within this group, export terciles serve as a proxy for firm size. Third, beyond export scale, no other firm-level (specific size, activity, ownership, venues, shocks, production capacity) or infraction-sanction-level controls (type, obligation, punishment, amount, number, repetition) are included in the main specifications, so the main associations reported here are unconditional (Appendix E.9 adds activity type, the number of auditable units and

pre-2023 supervisions as a sensitivity check: the inverted U survives, but the fine-scale slope loses significance). Trade performance itself may also be endogenous to compliance-enforcement performance, since firms that comply may subsequently gain export opportunities through certification or buyer requirements related to production quality or eco-efficiency, reversing the assumed direction of causality.

A future panel extension (Appendix G) with firm fixed effects, year-matched controls, and an instrumental-variables strategy would help address these three concerns directly. Until then, the results should be read as cross-sectional associations, not causal estimates.

3. Results and discussion

3.1. Compliance probability

We regress compliance on Ln(export revenue) under both definitions (Table 1, Figure 1). Under the confirmed-infraction standard, $\beta = -0.104$, $p = 0.396$ ($n = 112$): export revenue is not statistically significant. Under the fine-only standard, $\beta = -0.297$, $p = 0.008$ ($n = 112$), export revenue is a significant negative predictor. Both point estimates are negative, but the fine-only slope is steeper. Appendix E.5 tests the difference with a paired bootstrap that resamples firms once for both standards: the difference (0.193) is statistically significant (95% CI 0.040–0.384; $p = 0.014$), so the two codings (confirmed-infraction and fine-only) agree on direction but not on strength.

Fig. 1 : Compliance probability under both definitions

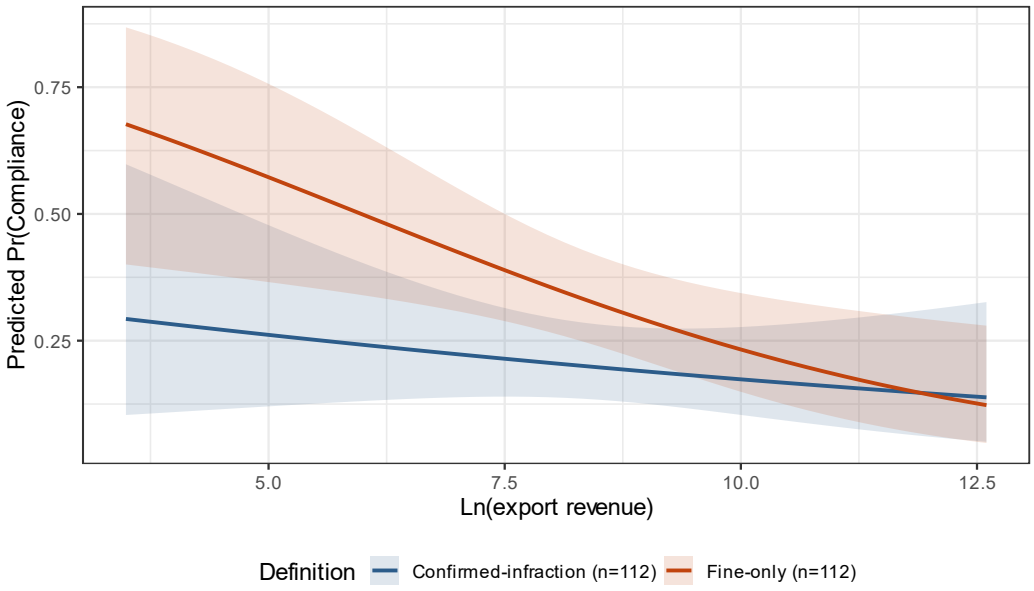


Figure 1. *Predicted probability of compliance Pr(Compliance) vs. Ln(export revenue), under the confirmed-infraction and fine-only definitions (n=112 each); shaded bands are 95% confidence intervals.*

Figure 1 plots the compliance model under both the confirmed-infraction and fine-only definitions. Both curves decline, but the fine-only curve is steeper and its confidence band narrower.

This pattern, null under one standard and significant under the other, neither rules out nor confirms a relationship between export incentives and compliance: with a linear specification and this sample size, power is limited. A quadratic term, Ln(export revenue)^2, is statistically significant under both standards (Table 1): confirmed-infraction standard, β = -0.315, p = 0.0096; fine-only, β = -0.207, p = 0.006 (Figure 2). In both quadratic specifications, predicted compliance probability rises with export revenue, peaks in the lower part of the export range (21st–33rd percentiles), and then declines over most of the export distribution, a pattern a strictly log-linear model would miss entirely. We interpret the squared term because it alone determines whether the curve bends; once included, the linear term has no separate meaning, since the slope at any export level is $\beta_1 + 2\beta_2 \times$ Ln(export revenue). The confidence bands of the two standards overlap in Figure 2, so the shape is similar under both.

The turning points of the two quadratic fits lie at Ln(export revenue) = 7.98, about USD 2.9 million (confirmed-infraction standard; delta-method 95% CI USD 1.5–5.5 million; Fieller interval 0.8–6.1 million), and at 7.16, about USD 1.3 million (fine-only standard; 95% CI USD 0.6–2.9 million; Fieller interval 0.2–2.5 million) (Appendix E.6). Both lie below the sample median of USD 7.5 million, at the 33rd and 21st percentiles of the export distribution, and every interval (delta, Fieller and bootstrap) lies below the median. Compliance therefore declines over most of the export distribution, and the rising segment rests on a minority of smaller exporters (37 and 23 of the 112 firms lie below the respective turning points). The Lind and Mehlum (2010) test nonetheless supports an inverted U under both standards: the slope is significantly positive at the smallest and significantly negative at the largest observed export level (p = 0.007 and p = 0.011).

Table 1. Compliance models: logit coefficients on Ln(export revenue) (standard errors)

	Confirmed-infraction		**Fine-only**	
	Linear	Quadratic	Linear	Quadratic
Ln(export revenue)	−0.104 (0.123)	5.022** (1.998)	−0.297*** (0.112)	2.966** (1.183)
Ln(export revenue)²		−0.315*** (0.122)		−0.207*** (0.075)
Turning point, USD million [95% CI]		2.9 [1.5–5.5]		1.3 [0.6–2.9]
Lind–Mehlum test, p		0.007		0.011
Non-compliant / compliant firms	90 / 22	90 / 22	76 / 36	76 / 36
Observations	112	112	112	112

Log likelihood	−55.13	−49.07	−66.56	−61.10
AIC	114.3	104.1	137.1	128.2

Note. Logit, maximum likelihood. Dependent variable: compliance (1 = compliant). *p < 0.1; **p < 0.05; ***p < 0.01. Turning point and delta-method interval from Appendix E.6. Full output in Tables B1–B2.

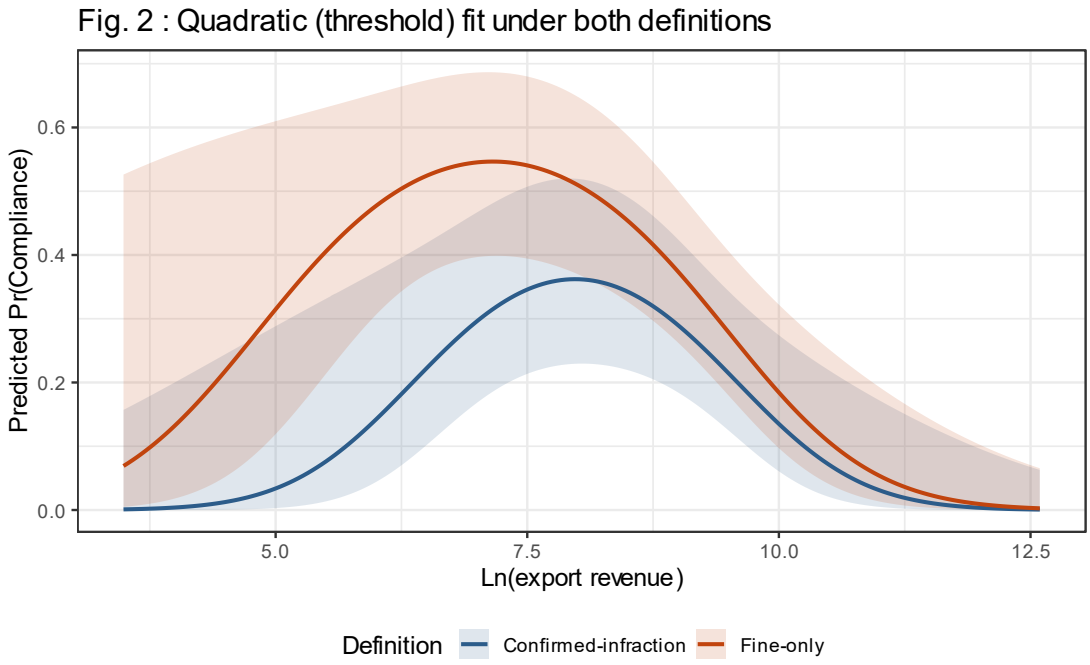


Figure 2. *Quadratic (threshold-type) fit of Pr(Compliance) on Ln(export revenue), under both compliance standards (n=112 each); shaded bands are 95% confidence intervals.*

We read this cautiously: both ends of the export range are sparsely populated, so the far ends of the curve are estimated from few firms. Splitting the sample into export-size terciles gives compliance rates of 26.3% / 21.6% / 10.8% (low/mid/high) for the confirmed-infraction standard (tercile segmentation in Appendix D, Figure D1), and a more pronounced 50.0% / 29.7% / 16.2% under the fine-only standard. Because the quadratic fit's peak falls at the upper edge of the low tercile (33rd percentile, confirmed-infraction standard) or inside it (21st percentile, fine-only standard), this three-way split corroborates the curve's declining segment (mid and high terciles) instead of demonstrating the full rise-then-fall shape by itself; that claim rests on the continuous quadratic model, not the three-bin split alone. Appendix E.3 directly tests the concern that the quadratic decline could be an artifact of a few large firms, using Cook's distance, leave-out-top-2, and Firth bias-reduction. The quadratic term is essentially unchanged when the two largest exporters are excluded and remains significant under a bias-reduced re-estimation designed for exactly this small-sample concern. Appendix E.7 extends these checks: excluding the top 5% of the

exporters leaves the quadratic term and the turning points unchanged, and dropping all firms above the Cook's-distance threshold sharpens the curvature.

The inverted U partly contrasts with the qualitative fieldwork (Jaramillo Abad & Uwasu, 2025) where some stakeholders asserted that firms comply to improve their standing in the competitive overseas market (I^M, the EDS channel), upgrading production to meet buyers' standards (cf. the production channel, I^P), suggesting that compliance is shaped by incentives beyond deterrence (Barontini & Gioja, 2025; Donaldson & Preston, 1995; Porter & van der Linde, 1995; Reyes Bastidas et al., 2026; Xie et al., 2023). A panel specification with controls is needed before drawing a firmer conclusion.

This inverted-U pattern is consistent with a framework in which market-based (sustainable) incentives co-move with compliance among smaller firms, though cross-sectional data cannot separate this from firm-level capacity or differential regulatory scrutiny. It also invites an alternative reading: if the compliance-incentive association weakens once firm size and production volume are controlled for, export-driven sustainability may reflect firm capability rather than a genuine incentive mechanism. Section 3.5 cannot settle this concern because market share in these data is export revenue rescaled by a constant; the closer test is Appendix E.9, where the inverted U survives controls for activity type and the number of auditable units. Whether export-driven sustainability reflects an incentive beyond firm capability therefore remains open in these data. This distinction is developed formally, including a corresponding falsification condition, in a companion theoretical analysis (Jaramillo Abad & Uwasu, 2026).

If firm capability, rather than a sustainable incentive, drives the patterns, two explanations are plausible. The first is strategic: in models of environmental disclosure under the threat of an audit, firms selectively reveal favorable information; by analogy, firms anticipating inspection may take preparatory actions, so that observed compliance partly reflects preparation rather than consistent performance (Lyon & Maxwell, 2011). The second is organizational: firms differ in internal structure and management, so facilities facing comparable external pressures, including from regulators, can adopt quite different environmental practices (Delmas & Toffel, 2008).

Trade theory and the evidence on product standards can account for the rising segment of this curve but not for its decline. If meeting buyers' requirements involves fixed costs that larger, more productive firms bear more easily (Maskus et al., 2005; Otsuki et al., 2001), the capacity to comply should rise with export scale and keep rising among the largest exporters, the firms best able to absorb such costs. The decline among those firms is better

explained by visibility and exposure channels set out in Section 2.1. One reading is that the peak, between the 21st and 33rd percentiles of export revenue (about USD 1.3–2.9 million), marks firms large enough to meet buyers' requirements but not yet prominent enough, or with enough facilities, to attract close scrutiny. Because the evidence on standards concerns product requirements in importing countries rather than domestic environmental obligations, it can motivate this reading but not test it.

3.2. Sanction severity

Among confirmed non-compliant cases, Ln(fine+1) rises significantly with Ln(export revenue) under both compliance definitions (Table 2, Figure 3): confirmed-infraction standard, $\alpha = 0.352$, $p < 0.001$, $R^2 = 0.218$, Pearson r = 0.47, n = 90; fine-only standard, $\alpha = 0.291$, $p = 0.003$, $R^2 = 0.164$, Pearson r = 0.40, n = 76. A doubling of export revenue is associated with roughly 28% higher fines (measured as fine + 1) for the confirmed-infraction standard ($e^{(0.352 \ln 2)} \approx 1.28$) and roughly 22% higher fines (measured as fine + 1) for the fine-only standard ($e^{(0.291 \ln 2)} \approx 1.22$); evaluated at each standard's own sample median and mean export levels, predicted fines would rise from about 5.8 to 9.4 UIT for confirmed-infraction standard and from about 8.6 to 11.8 UIT for fine-only standard. Both gaps are economically meaningful but modest relative to the largest fines observed in the data, remaining within the "smaller fines" range (under 100 UIT) that dominates the sample, rather than reflecting severe sanctions.

Table 2. Fine-severity models: OLS coefficients on the export-scale measure (standard errors)

Specification	Confirmed-infraction (n = 90)	Fine-only (n = 76)
Base: Ln(export revenue)	0.352*** (0.089); R² 0.218	0.291*** (0.096); R² 0.164
High-tercile interaction (Sect. 3.3)	1.256*** (0.396); R² 0.419	0.941** (0.414); R² 0.430
Ln(export revenue), market share added (Sect. 3.5)	0.117 (0.099); R² 0.344	0.038 (0.102); R² 0.320
Ln(export volume) instead of revenue (Sect. 3.5)	0.324*** (0.074); R² 0.233	0.260*** (0.084); R² 0.157
Ln(export revenue), firm controls added (App. E.9)	0.156 (0.102); R² 0.452	0.109 (0.109); R² 0.445

Note. Dependent variable: Ln(fine + 1), non-compliant firms only. *p < 0.1; **p < 0.05; ***p < 0.01. All rows use HC1 robust standard errors. Firm controls: activity type, Ln(1 + auditable units) and Ln(1 + supervisions 2018–2022). Full output in Tables B3–B5 and E9b.

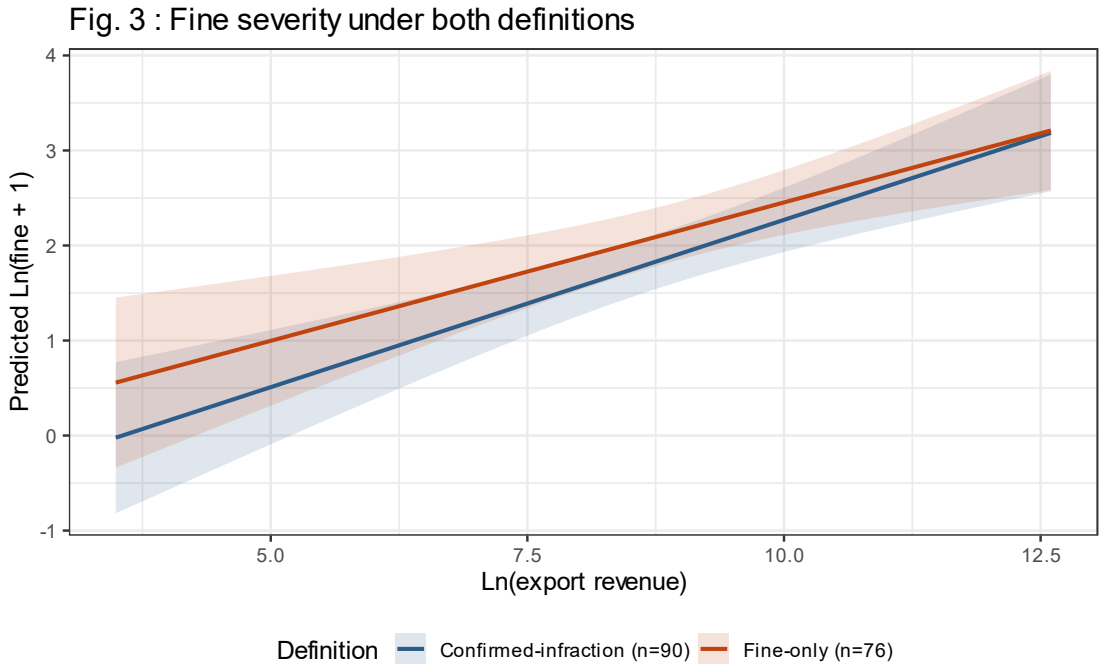


Figure 3. *Predicted Ln(fine+1) vs. Ln(export revenue) among non-compliant firms, under both compliance standards (n=90 and n=76, respectively).*

A Breusch-Pagan test finds no evidence of heteroskedasticity under either compliance definition (confirmed-infraction model: BP = 0.132, p = 0.717; fine-only model: BP = 0.463, p = 0.496), and HC1 robust standard errors, which this paper reports for all fine-severity models, are somewhat larger than the ordinary ones (by about a quarter) but leave the conclusions unchanged under both (confirmed-infraction: $\alpha = 0.352$, robust SE = 0.089 vs. ordinary SE = 0.071, both $p < 0.001$; fine-only: $\alpha = 0.291$, robust SE = 0.096 vs. ordinary SE = 0.076, robust p = 0.003 and ordinary $p < 0.001$; full comparison in Appendix C). Both models' residuals nonetheless show the same curved rather than random pattern, more positive at low and high export levels and negative in the mid-range (Figures 4a and 4b). A Ramsey RESET test confirms this misspecification under both definitions (Appendix C, which also reports the Q-Q plot and Shapiro-Wilk test), and it motivates the heterogeneity check in Section 3.3.

The sanction severity patterns found in this section are consistent with penalty-design literature (Becker, 1968; Gray & Shimshack, 2011; Polinsky & Shavell, 2000; Segerson & Tietenberg, 1992), in which optimal sanctions rise with the harm caused and the violator's gain and capacity to pay, and enforcement outcomes depend on institutional and firm-level context. Still, our earlier qualitative fieldwork (Jaramillo Abad & Uwasu, 2025) found that some stakeholders perceive that enforcement focuses disproportionately on minor violations or documentation infractions rather than direct environmental harm, which may align with the right-skewed distribution of fines

found in the subsample (n=90; mean 26.4, median 3.9 UIT), so most firms have relatively small fine records. This will be explored further using additional controls, such as infraction and sanction type, in the planned panel specification (Appendix G).

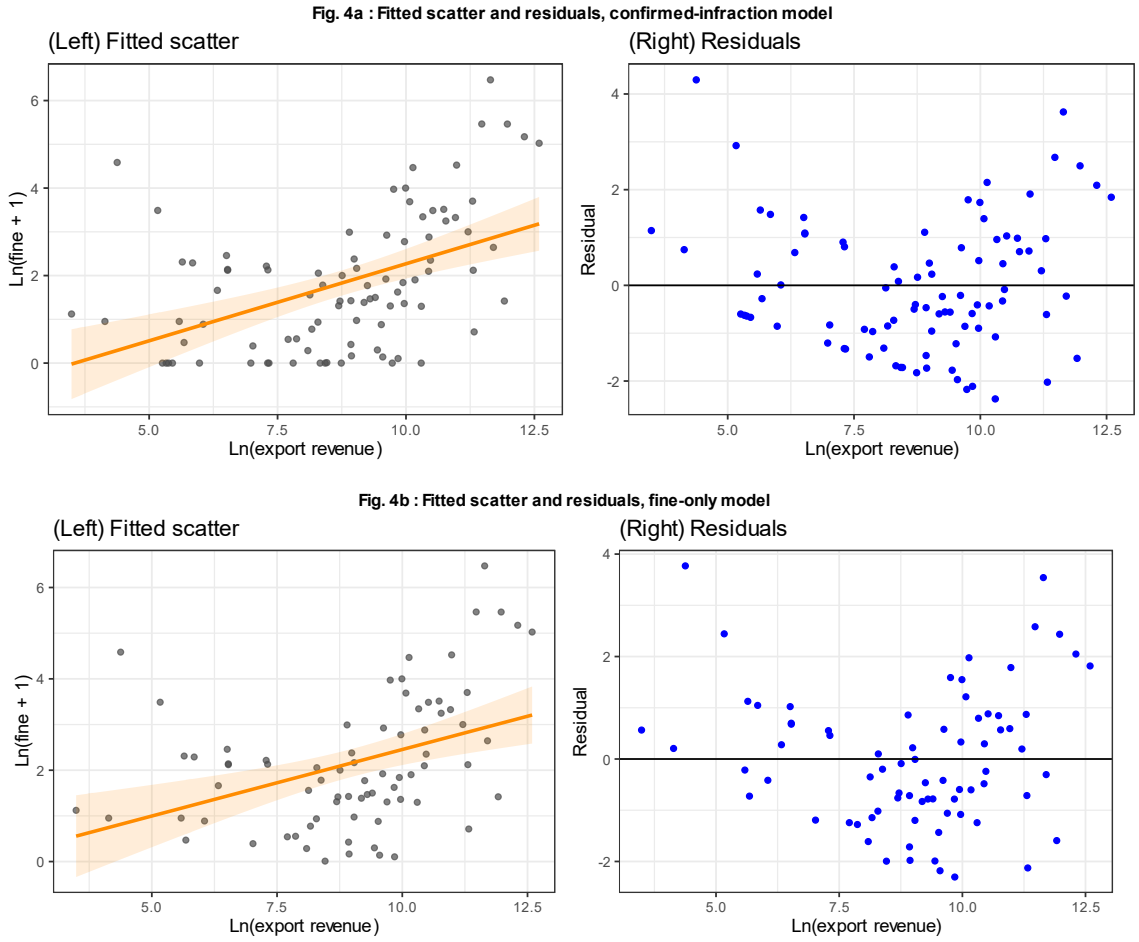


Figure 4. *(Left) Fitted scatter, predicted Ln(fine+1) on Ln(export revenue); (Right) Model residuals against Ln(export revenue): (**a**) confirmed-infraction model (n=90), (**b**) fine-only model (n=76).*

3.3. Heterogeneity and Threshold Effects

The curved residual pattern in Figures 4a and 4b, present under both compliance definitions, motivated a direct heterogeneity test: does the export-fine slope itself differ across firms of different export size?

Splitting the non-compliant-firm sample into export-size terciles and interacting export revenue with tercile reveals substantial heterogeneity under both definitions (Figures 5a and 5b): the slope is flat or slightly negative for the smallest exporters, and steeply positive for the largest exporters. This pattern is compatible with, but does not test, the prediction developed in Jaramillo Abad and Uwasu (2026) that smaller and larger firms respond differently to

enforcement risk because of differences in risk tolerance (decreasing absolute risk aversion, DARA). In the case of the confirmed-infraction standard (n = 90), the high-export interaction term is $\beta = 1.256$, $p = 0.002$, and model fit improves markedly (R^2 rises from 0.218 pooled to 0.419 by tercile). In the other case, the fine-only standard (n = 76), the high-export interaction term is $\beta = 0.941$, $p = 0.026$; the results show a similar pattern with somewhat less statistical strength (R^2 rises from 0.164 to 0.430).

Because the largest exporters also carry the highest leverage, specification (6) was re-estimated without them (Appendix E.8, Table E8). The slope falls modestly but remains positive and significant without the two largest exporters (confirmed-infraction $\alpha = 0.309$, $p = 0.001$; fine-only $\alpha = 0.243$, $p = 0.014$), without the top 5% of exporters (0.295, $p = 0.003$; 0.228, $p = 0.023$), and without firms above the Cook's-distance threshold (0.307 and 0.242, both $p < 0.001$), all with HC1 standard errors. The fine–scale association is therefore concentrated among, but not produced solely by, the largest exporters.

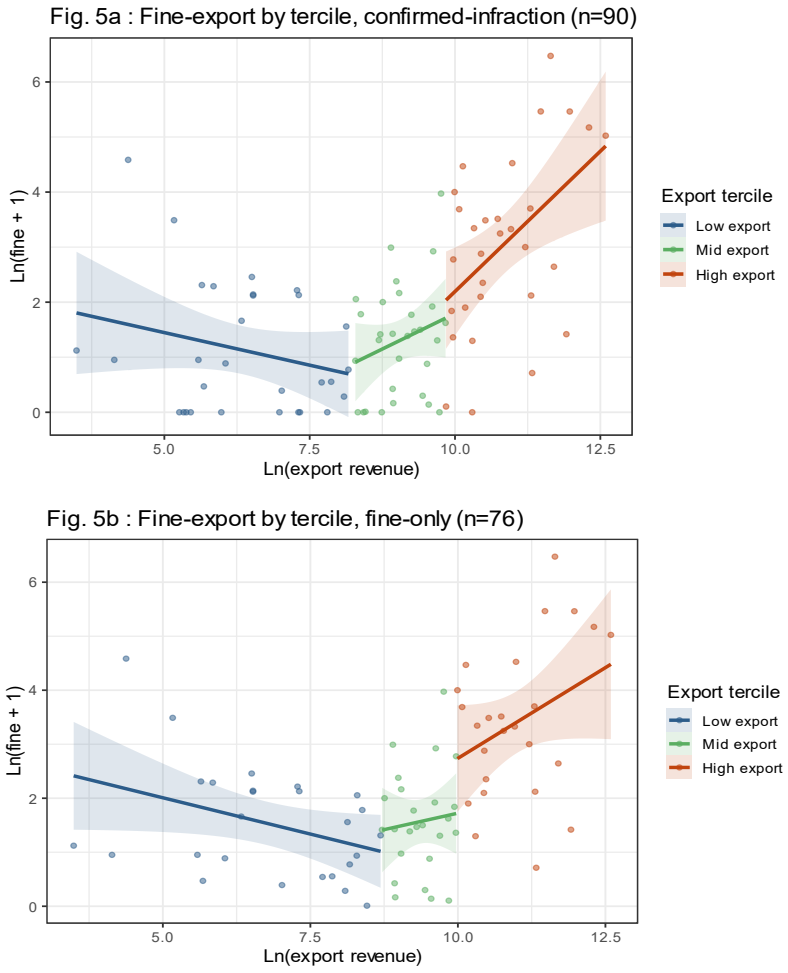


Figure 5. *Fine-export relationship by export-size tercile: (**a**) confirmed-infraction standard (n=90); (**b**) fine-only standard (n=76).*

Read together with Section 3.1, both relationships depend on firm scale: compliance declines above a low turning point and fines rise most steeply among the largest exporters, a firm-scale channel more than a uniform, economy-wide one, consistent with evidence that enforcement responses and the costs and returns of compliance differ with firm size (Dasgupta et al., 2000; Gray & Shimshack, 2011; Segerson & Tietenberg, 1992; Wanyan & Zhao, 2024). Moreover, financial constraints may also play a role: for smaller unlisted firms, environmental responsibility is associated with easier access to finance (Ullah, 2025), which may strengthen the incentive to comply at the lower end of the size distribution. Thus, firm heterogeneity may be shaped by two channels: size-related differences in risk tolerance (DARA) and financial constraints.

3.4. Governance matching (Compliance-Enforcement)

Sections 3.1 to 3.3 do not support a symmetric 'break-even' pattern between compliance and enforcement under either compliance definition considered in this paper. Export revenue's association with compliance probability here is definition-sensitive (not statistically reliable under the confirmed-infraction standard; though significant and negative under the fine-only standard, Section 3.1), while it is significantly and positively associated with higher sanction severity among confirmed non-compliant firms under both definitions (Section 3.2). In the unweighted models without firm controls, export performance is therefore most clearly associated with sanction severity, although this association loses statistical significance after reweighting (Appendix E.2) and is largely absorbed by the number of auditable units (Appendix E.9; Section 3.6); its association with the probability of compliance itself depends on which defensible coding of "compliant" is used, so both readings are reported.

Once non-linearity is allowed, both sides of governance are shaped by firm scale, but not in the same direction. The quadratic fit (Figure 2) shows compliance probability rising then falling with export scale, while the tercile interaction (Figure 5a and 5b) shows fine severity rising most steeply among the largest exporters; the market-share models (Section 3.5) point the same way, because they give more weight to the largest exporters. These large firms are not simply "more compliant" or "less compliant" in a static sense. Instead, they represent the segment where scale, productivity, and visibility most strongly shape governance outcomes in either direction. This is consistent with heightened regulatory attention and enforcement at that end of the size distribution (Gray & Shimshack, 2011; Helland, 1998; Heyes, 2000), and with the idea that firm scale and visibility jointly moderate the strength of both the enforcement and incentive channels – firm size moderates responses to enforcement risk,

while post-detection credibility amplifies both channels by a "governance multiplier", expanded in a companion theoretical analysis (Jaramillo Abad & Uwasu, 2026).

3.5. Export scale vs. market share: Robustness Checks

The export report (2023) also provides physical export volume (metric tons) and each firm's export market share (%). Physical volume is highly correlated with monetary export revenue ($r = 0.953$ in the full 370-firm sample), so we use it as an alternative scale proxy rather than a joint control; market share is added alongside export revenue. Because SNP computes market share as each firm's export revenue divided by the total for all exporters, it is export revenue multiplied by a constant (correlation 0.99999 in our data). Adding it to a model that already contains Ln(export revenue) therefore enters revenue twice, once in logs and once in levels, and tests the shape of the scale relationships rather than a separate firm attribute. Both are carried through both compliance standards (confirmed-infraction and fine-only).

Adding export market share, a linear rescaling of export revenue, to the model with Ln(export revenue), affects the two outcomes differently. For the compliance model, sign instability appears under both definitions: the export-revenue coefficient turns positive (confirmed-infraction: $\beta = +0.556$, $p = 0.069$; fine-only: $\beta = +0.169$, $p = 0.426$), while market share itself is negative and significant under both standards (confirmed-infraction: $\beta = -3.007$, $p = 0.039$, VIF = 2.88; fine-only: $\beta = -2.263$, $p = 0.040$; Figure 6). For the fine-severity model, the result is consistent with the base model: the market-share (linear revenue) term is positive and significant under both standards (confirmed-infraction: $\alpha = 0.454$, $p < 0.001$, VIF = 1.78; fine-only: $\alpha = 0.447$, $p < 0.001$), while export revenue's own coefficient becomes non-significant in both (confirmed-infraction: $\alpha = 0.117$, $p = 0.241$; fine-only: $\alpha = 0.038$, $p = 0.710$; Figure 7). Read together, these results say that compliance and fines change more steeply among the largest exporters than the logarithmic specification implies; they do not show that market prominence matters separately from scale.

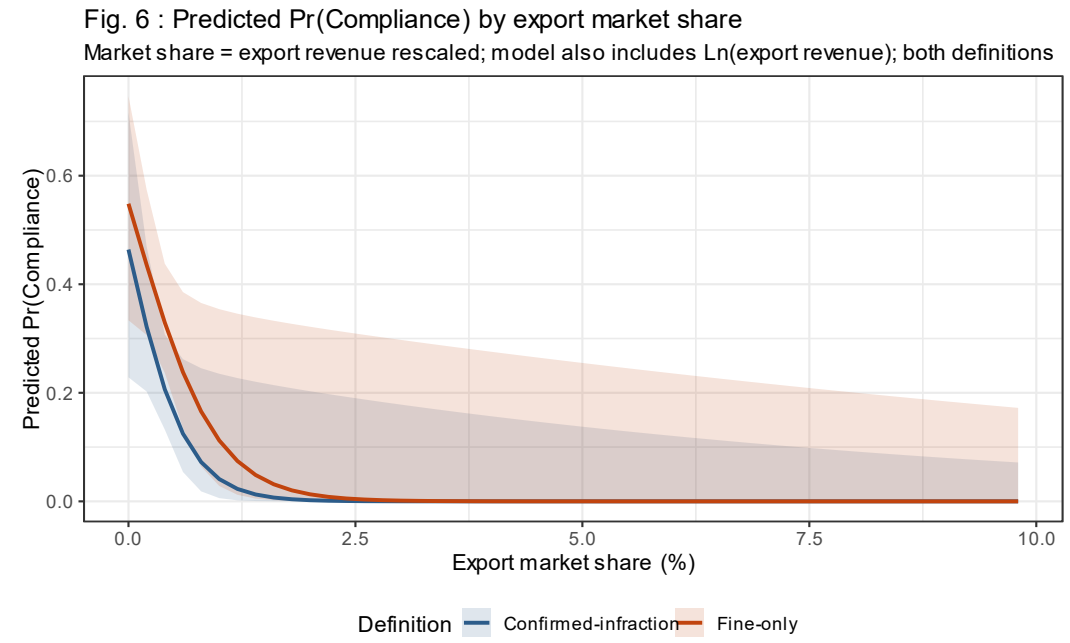


Figure 6. *Predicted effect of export market share (%) on compliance probability Pr(Compliance), from the model that also includes Ln(export revenue), under both compliance definitions (n=112 each).*

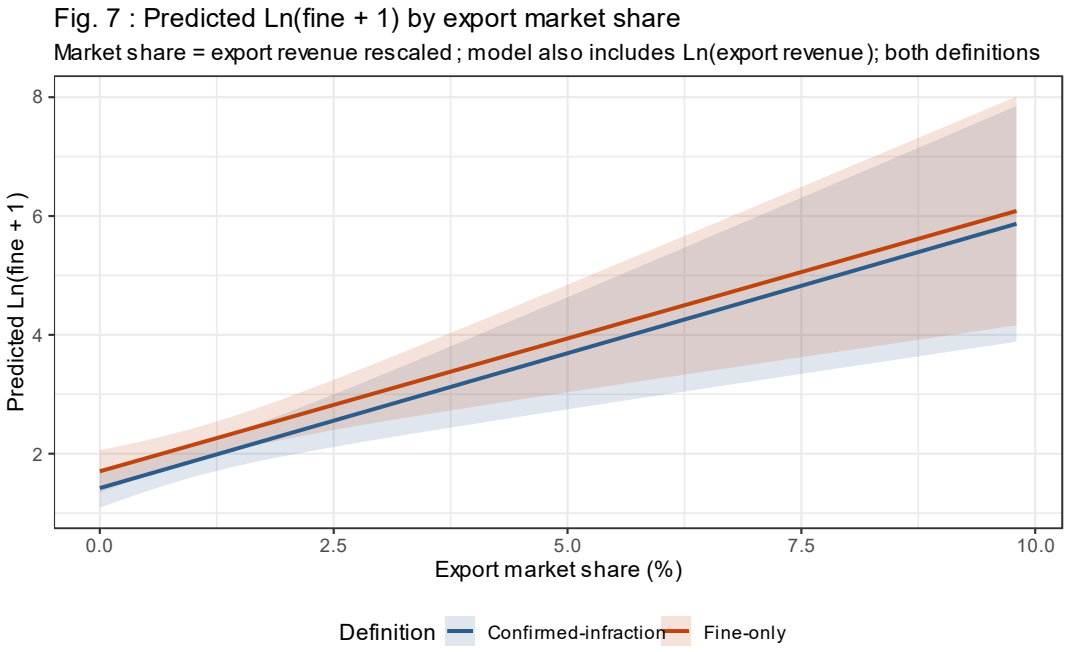


Figure 7. *Predicted effect of export market share (%) on fine severity Ln(fine+1), from the model that also includes Ln(export revenue), under both compliance definitions – confirmed infraction and fine-only (n=90 and n=76, respectively).*

Replacing export revenue with export volume (tons) as an alternative scale measure gives a different picture. For the compliance model (Figure 8), the results are mixed across definitions: under the confirmed-infraction standard the volume coefficient stays negative and statistically unreliable, close to that definition's own base model (β = -0.063, p = 0.569, vs. base β = -0.104); under the fine-only standard it is negative and now statistically significant (β = -0.290, p = 0.004, vs. base β = -0.297), closely tracking rather than overturning that definition's own base-model result. For the fine-severity model (Figure 9), the volume measure closely tracks each definition's own base model under both compliance standards: confirmed-infraction, $\alpha = 0.324$, $p < 0.001$, $R^2 = 0.233$ (vs. base $\alpha = 0.352$, $R^2 = 0.218$); fine-only, $\alpha = 0.260$, $p = 0.003$, $R^2 = 0.157$ (vs. base $\alpha = 0.291$, $R^2 = 0.164$).

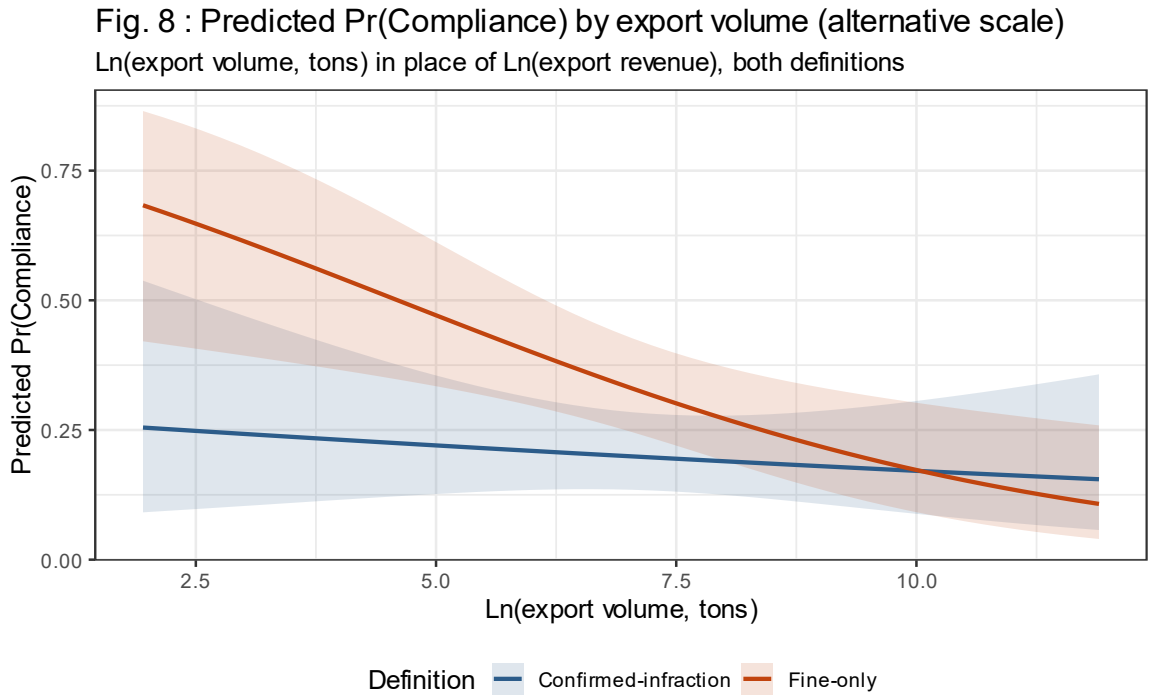


Figure 8. *Predicted compliance probability Pr(Compliance) vs. Ln(export volume, tons), the alternative scale proxy replacing export revenue, under both compliance definitions (n=112 each).*

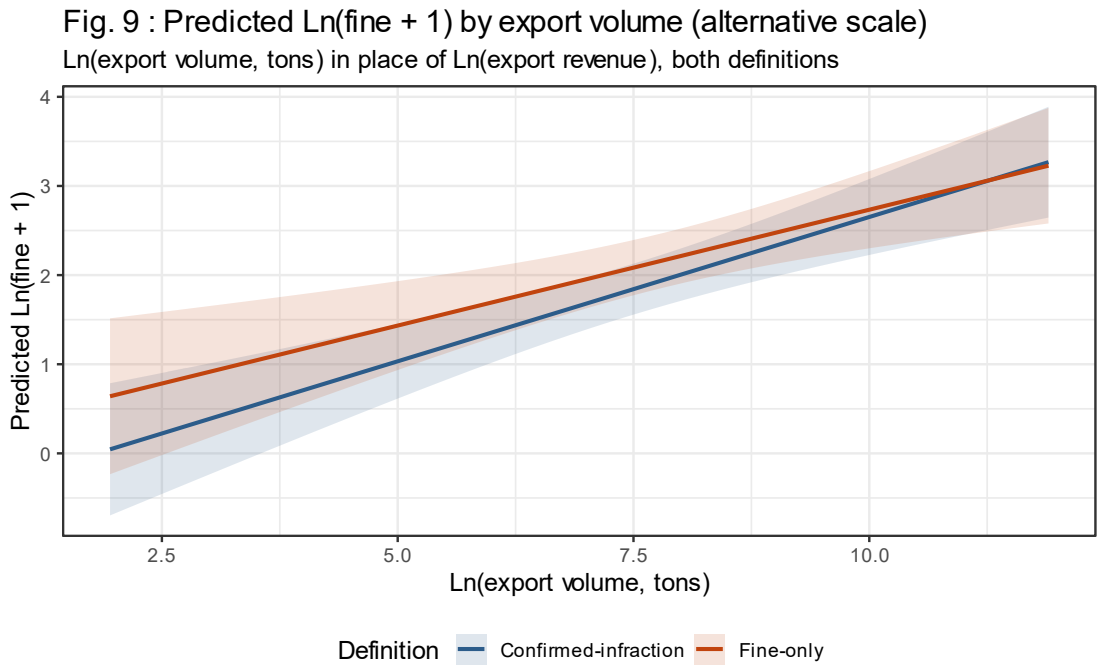


Figure 9. *Predicted sanction severity Ln(fine+1) vs. Ln(export volume, tons), the alternative scale proxy replacing export revenue, among non-compliant firms, under both standards (n=90 and n=76 respectively).*

Across six tested compliance specifications, the cross-sectional data alone do not reliably pin down the compliance-probability relationship, though the fine-only standard returns a negative, significant export-scale association in the linear revenue and volume models, but not once market share is added ($\beta = +0.169$, $p = 0.426$) or after reweighting (Appendix E.2). For fine severity, by contrast, volume coefficient and the market-share (linear revenue) term remain positive and highly significant, supporting robustness to the choice of scale proxy under either coding of compliance. In the unweighted models without firm controls, a firm's export scale, whether measured by export revenue (in logs, or in levels through market share), or by physical export volume, predicts sanction severity more precisely than compliance status. Nevertheless, two caveats apply. Appendix E.2's IPW check shows the result weakens and loses statistical significance (robust $p = 0.165$ and 0.244) once the sample is reweighted for observable selection into OEFA's confirmable universe, so it describes the larger exporters that OEFA's records cover. Appendix E.9 shows that the slope is largely absorbed by the number of auditable units a firm operates (Section 3.6). Other populations under OEFA's competence not covered here (non-exporters, informal holders, or firms in other sectors) may show similar or different patterns, an open question for future work.

This contributes to the analysis of how export 'scale matters': lower observed compliance and higher recorded sanctions are concentrated among the largest exporters, where fines rise more steeply than a straight line in Ln(export revenue) implies (Sections 3.3 and 3.5). This is consistent with larger, more visible market participants facing closer regulatory scrutiny, while their response to market incentives may differ (Dasgupta et al., 2000; Gray & Shimshack, 2011; Helland, 1998; Wanyan & Zhao, 2024). These data cannot separate firm capability from an incentive mechanism (Section 3.1). Whether the marginal effect of compliance history on export revenue or market diversification yields a stronger post-detection response and lower violation rates over time remains open; a panel specification with firm-level controls could test it directly.

3.6. Economic magnitude, confounding, and alternative explanations

Because the compliance coefficient's statistical reliability depends on the definition used (Section 3.1), translating it into a single odds ratio would overstate confidence in either direction. Under the fine-only standard specifically, a doubling of export revenue is associated with about 19% lower odds of compliance (odds ratio $e^{(-0.297 \ln 2)} \approx 0.184$), a concrete significant magnitude that should nonetheless be read alongside the null confirmed-infraction result rather than in isolation. To gauge practical relevance across the export-revenue distribution: moving from the 10th percentile of export revenue (~USD 317.8k) to the 99th percentile (~USD 213.9M), predicted Pr(Compliance) falls from about 24.6% to 14.2% under the confirmed-infraction standard (full percentile table in Appendix D).

On the enforcement side, a doubling of export revenue is associated with about 28% and 22% higher fines under the two standards (Section 3.2). Once market share, which is export revenue rescaled, is added (Section 3.5), the fit improves under either definition (R^2 rises to 0.344 for the confirmed-infraction standard and to 0.320 for the fine-only standard), which indicates that fines rise more steeply among the largest exporters than the logarithmic specification implies, not that market prominence matters separately from scale. The main specifications include no firm-level controls beyond export scale, so these associations are unconditional. When Appendix E.9 adds activity type, the number of auditable units and pre-2023 supervisions, the fine-scale slope loses significance; production capacity and infraction or sanction type remain unobserved here.

Other explanations should also be considered. Firm size and administrative capacity are natural confounders: larger firms plausibly export more, produce more, have greater compliance capacity, and attract more regulatory attention simultaneously, so scale and unobserved capacity may mask the contribution of the export-incentive channel EDS

(I^M) to compliance. The co-movement of reduced compliance probability and higher exposure at higher export levels is not contradictory, since both the incentive channel ($q'I$) and the regulatory-exposure channel ($pp'S$) plausibly scale with firm visibility and size: larger exporters face closer scrutiny when non-compliant alongside stronger incentives to comply, though the incentive channel may weaken relative to the exposure channel once a firm is already highly visible to regulators – a pattern that may reflect a threshold in governance rather than two competing stories. Finally, trade performance itself may be endogenous to compliance-enforcement performance (Volpe Martincus et al., 2010), since firms that comply may subsequently gain export opportunities (e.g., through certification or buyer requirements), reversing the assumed direction of causality. A future panel extension (Appendix G), using firm fixed effects and instrumental variables, would help disentangle these alternative explanations more directly.

A further alternative explanation is temporal: sanctions accumulate over 2018–2025 while export data are measured only for 2023, as noted in Section 2.5. The fine-severity result may be picking up a related but distinct channel – firm scale and productivity – that is more stable across years and therefore better captured by a single cross-section than the compliance result is.

Two further threats concern the enforcement side specifically. First, enforcement targeting: regulators allocate inspections towards firms with past violations and towards politically salient or highly visible plants (Gray & Shimshack, 2011; Helland, 1998). If OEFA supervises large exporters more intensively, it detects more infractions, lowering measured compliance and raising recorded sanctions even if their behavior does not differ; thus, the declining segment of the compliance curve and the positive fine–scale slope may both partly reflect enforcement attention to firm scale and visibility. Second, mechanical fine design: because OEFA's fine methodology incorporates the illicit benefit and caps fines relative to gross income, part of the fine–scale association is built into the penalty formula. Enforcement targeting biases the scale–compliance association downwards and the scale–fine association upwards relative to a behavioral effect; fine design adds a mechanical component only to the scale–fine association; and the reverse-causality channel discussed above biases the compliance association upwards. The planned panel specification (Appendix G), with firm and year fixed effects, credibility and supervision controls and instrumental variables, is designed to separate these channels.

Controls, enforcement history and timing. To address omitted firm characteristics and the different time windows of exports (2023) and enforcement records (2018 onwards), Appendix E.9 adds three controls built from OEFA

records: activity type (fishmeal and fish oil, aquaculture, other processing for direct human consumption), the number of auditable units (plants and concessions) and the number of supervisions in 2018–2022, before the export year. The inverted U holds under every control set, although with all three controls the Firth estimate under the confirmed-infraction standard is only marginally significant ($p = 0.055$): the squared term (standard logit) ranges from -0.34 to -0.41 under the confirmed-infraction standard ($p \leq 0.042$; Firth $p \leq 0.055$) and from -0.24 to -0.28 under the fine-only standard ($p \leq 0.019$; Firth $p \leq 0.027$), while the Firth turning point moves to between USD 0.91 and 2.96 million. The fine-scale association does not survive: with activity type and the number of units, the slope falls to 0.123 ($p = 0.234$) and 0.079 ($p = 0.466$), and R^2 roughly doubles or more (0.218 to 0.417; 0.164 to 0.413); with pre-2023 supervisions alone it stays significant under the confirmed-infraction standard (0.191, $p = 0.021$). The sanction result therefore appears to reflect how many facilities a firm operates under OEFA's oversight, the exposure channel (iii) of Section 2.1, more than export revenue as such. Supervision targeting points the same way: holding pre-2023 supervisions constant, 2023 export revenue is associated with more supervisions from 2023 onwards (0.072, $p < 0.001$). These controls are themselves recorded by the enforcer and may be mediators of scale rather than confounders, so they are reported as sensitivity checks; they cannot rule out reverse causality, which requires dated infraction records or the panel design in Appendix G.

Regarding the timing of the export measure, because the 2023 shock fell mainly on fishmeal and fish oil, due to El Niño, the export revenue of the 18 fishmeal producers in the sample, 16 of them non-compliant under both standards, was roughly halved that year, although they remain among the largest exporters. Excluding them leaves the inverted U in place (squared term -0.294, $p = 0.021$, and -0.199, $p = 0.013$; Appendix E.9). Re-estimating the models with each firm's 2022 or 2024 exports from SUNAT customs records keeps the shape of the compliance curve, but the squared term is no longer significant at the 5% level ($p = 0.06$–0.31), whereas the fine-scale slope remains positive and significant; the inverted U should therefore be read as a pattern observed in 2023, and its stability across years is left to the panel analysis.

Overall, this paper provides evidence on how firm export performance – measured by export revenue – relates to both compliance and sanctions outcomes, and on how these relationships vary with firm scale. Separating compliance under a confirmed-infraction standard from compliance under a fine-only standard offers a complementary, if imperfect, empirical lens on the broader theoretical distinction between detection and post-detection credibility developed in Jaramillo Abad and Uwasu (2026): under either standard, compliance and sanction severity relate differently to firm scale. Because cross-sectional data cannot separate these mechanisms

as cleanly as panel data with firm and year fixed effects could, we report the associations transparently, alongside the alternative explanations they admit, including unobserved factors,[6] and leave a fuller separation of these channels to future research using panel data.

Appendix B tabulates the models underlying Figures 1–9 (Tables B1–B4); Table B5 and Figure B1 compare the twelve specifications that share a single scale coefficient.

4. Conclusions

This paper examined how export revenue, read as a measure of firm scale and a partial proxy for the market incentive I^M (export-driven sustainability, EDS), relates to environmental compliance and enforcement (environmental governance) in a data-quality-audited sample of Peruvian fishing exporters. Among confirmed non-compliant firms, higher export revenue is associated with higher sanction severity, a statistically significant relationship under both compliance standards (confirmed-infraction and fine-only), in a linear specification, and in an export-tercile heterogeneity analysis, although it loses significance after reweighting for sample selection and is largely absorbed by the number of facilities a firm operates. By contrast, export revenue's relationship with the probability of compliance depends on how a zero-fine, confirmed-infraction case is coded: it is not statistically significant under a confirmed-infraction standard, but it is significant and negative under a fine-only standard. Both readings agree that a quadratic extension reveals a significant non-monotonic pattern: rising, peaking, then declining at the highest export levels. The turning points lie below the sample median, so compliance declines over most of the export distribution; the pattern passes the Lind–Mehlum U-test and survives the exclusion of the largest and most influential exporters, but is significant at the 5% level only with 2023 exports, not with 2022 or 2024 exports.

These cross-sectional findings are unconditional associations from a single-year, exporter-only sample, and the compliance-probability finding depends on the compliance-coding choice rather than holding uniformly across specifications. A causal, generalizable claim would require panel data with firm-level controls and an identification strategy, together with continued verification of the compliance and sanction records, including administrative measures and appeals. Because firm controls leave the inverted U in place but absorb most of the fine–scale

[6] **Note**. Unobserved factors such as production capacity, infraction and sanction type, appeal strategy and penalty decision may also drive the observed relationships. We plan to include them in the panel specification (Appendix G).

association, the sanction result may reflect operational scale and enforcement exposure at least as much as export revenue itself.

The choice between the two compliance standards is itself informative. The confirmed-infraction standard counts a confirmed infraction as non-compliance even without a fine, so it is closer to the detection stage of enforcement; the fine-only standard requires a non-zero fine, so it is closer to the post-detection stage, including first- and second-instance decisions after appeal. The two standards may therefore capture different stages of the enforcement process.

These cross-sectional patterns are broadly consistent with a view of environmental governance in which market-based incentives and formal sanctions operate as complements rather than substitutes, and in which the credibility of enforcement – not merely its intensity – shapes firm behavior. This view is developed more fully in a companion theoretical analysis (Jaramillo Abad & Uwasu, 2026).

The robustness checks support the quadratic pattern, the presence of the fine-severity relationship across quantiles, and the common negative direction of the two compliance slopes, although the fine-only slope is significantly steeper. The fine-severity slope survives the exclusion of the largest exporters, but reweighting for sample selection weakens it and reverses the sign of the linear compliance coefficients, so all results describe the larger exporters covered by OEFA's records.

Three policy implications follow from this cross-sectional analysis. They draw mainly on the enforcement-severity finding, which is the most precisely estimated result in the unweighted models, although it depends on sample selection and largely reflects the number of facilities a firm operates. First, observed non-compliance and sanction severity are both highest in the top export tercile: the largest exporters face the most severe sanctions and also show the lowest observed compliance. On average, fines rise less than proportionally with export revenue, though the slope is steepest among the largest exporters; strengthening post-detection credibility and incentive design may matter as much as fine levels, though these data cannot rank such options. Second, because compliance peaks among smaller exporters (around the 21st–33rd percentile), targeted incentive instruments such as official recognition, certification support, or market-access facilitation may be most useful among smaller exporters, precisely the segment where formal sanction exposure is weakest, although this segment includes only a minority of firms and the effect of such programs would need to be evaluated directly. Third, because both outcomes change most among the largest exporters, supervision planning and incentive targeting may need to treat the top of the

export distribution separately rather than apply one rule across all firm sizes; a measure of market prominence distinct from size, such as a firm's share within its product segment, would be needed to say more. These implications should be read as design guidance consistent with the associations documented here, not as causal estimates of program effects. Targeting the largest firms would also reinforce differences in detection, and both deterrence and incentive schemes would need to guard against moral hazard.

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The authors report no conflict of interest. AI assistance: Grammarly and Claude were used for language proofreading, data auditing, and editing R code scripts. All modeling choices, interpretation, and conclusions are the authors' own.

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Appendices

A. Sample and Descriptive Statistics

Table A1. Sample composition

Population	n	Definition
OEFA fishing-sector competence universe (PIFA holder registry)	328	Full population of firms under OEFA's fishing-sector supervisory competence, independent of export status
Full exporter list (SNP, 2023 customs records)	370	All exporting firms in the National Fisheries Society's (SNP) 2023 export report
Confirmed OEFA-competency and exporter-list sample	**112**	Status confirmed against at least one OEFA source (holder registry, PIFA supervision log, or RUIAS records)
Non-compliant, confirmed-infraction standard	**90**	Any infraction on record in RUIAS (regardless of the fine amount)
Non-compliant, fine-only standard	**76**	Verified fine on record in RUIAS (fine amount > 0)

Note. Rows in bold are the analytic sample (n = 112) and the two non-compliant subsamples; the other firms in the sample are compliant (22 under the confirmed-infraction standard, 36 under the fine-only standard). Each of the 112 has a positive confirming record from at least one OEFA source; the 8 firms with no supervision-log record are confirmed non-compliant via RUIAS-OEFA infraction records instead.

Table A2. Fine amount (UIT), analytic sample and non-compliant subsamples

Population	n	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Full confirmed sample (compliant + non-compliant)	112	0.00	0.00	2.68	21.61	9.03	646.45
Confirmed-infraction non-compliant	90	0.00	0.63	3.91	26.42	14.56	646.45
Fine-only non-compliant	76	0.01	1.97	6.12	31.28	18.96	646.45

Source: RUIAS (OEFA), fines 2018–2025; compliant firms have zero fines. In 2026 (DS N° 301-2025-EF), a tax unit (UIT) is equal to PEN 5,500 (about USD 1,500–1,600).

Table A3. Scale-variable descriptive statistics (full 370-firm list)

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Export revenue (Thousands USD)	1.39	68.32	546.68	8,076.28	3,952.10	294,258.35
Export volume (export tons)	0.02	18.78	114.48	3,421.59	1,165.18	151,435.48
Export market share (export %)	0.00	0.00	0.02	0.27	0.13	9.85

Note. Correlation of export revenue vs. export volume: r = 0.953 (full 370-firm sample), the basis for using volume as an alternative scale proxy (Section 3.5) instead of a joint control alongside revenue. Market share was added alongside Ln(export revenue) only as a check on functional form (Section 3.5), because it is export revenue times a constant.

Table A4 places the fishing sector in national context and compares the SNP customs records used for the sample with the central bank's fishing-export figures.

Table A4. Peru's fishing exports and fishing GDP, 2019–2025

Indicator	2019	2020	2021	2022	2023	2024	2025
Total exports (USD million)	47,995	42,822	63,114	66,339	66,963	76,357	93,993

Fishing exports (USD million)	3,543	2,858	3,851	4,025	2,919	3,604	4,650
Traditional: fishmeal and fish oil	1,929	1,542	2,335	2,386	1,142	2,288	2,375
Fishmeal	1,509	1,180	1,806	1,817	904	1,613	1,857
Fish oil	420	363	529	569	238	675	518
Non-traditional	1,614	1,316	1,516	1,639	1,777	1,317	2,275
Frozen crustaceans and molluscs	937	722	809	835	956	615	1,473
Frozen fish	227	231	332	391	355	408	294
Preparations and canned	366	287	257	264	346	224	433
Dried fish and other	84	76	117	149	120	69	74
Fishing exports / total exports (%)	7.4	6.7	6.1	6.1	4.4	4.7	4.9
Traditional / total exports (%)	4.0	3.6	3.7	3.6	1.7	3.0	2.5
Fishmeal export volume (thousand tonnes)	1,052	862	1,209	1,108	526	956	1,272
Fishing GDP / total GDP, current prices (%)	0.6	0.7	0.8	0.7	0.5	0.5	0.5

Note. FOB values. Fishing GDP covers fishing and aquaculture only; fish processing is part of manufacturing. GDP figures for 2022–2023 are provisional and for 2024–2025 estimated (INEI). Components may not sum to totals because of rounding. For comparison, the SNP customs records used for the firm-level sample total USD 2,988.2 million in 2023, close to the BCR figure of USD 2,919.5 million: about USD 1,181 million in traditional and USD 1,807 million in non-traditional products, against USD 1,142.0 and 1,777.5 million in BCR. Sources: BCR (n.d.), series PM40060BA, PM40061BA, PM40069BA–PM40071BA, PM40073BA and PM40128BA–PM40133BA; INEI (2026).

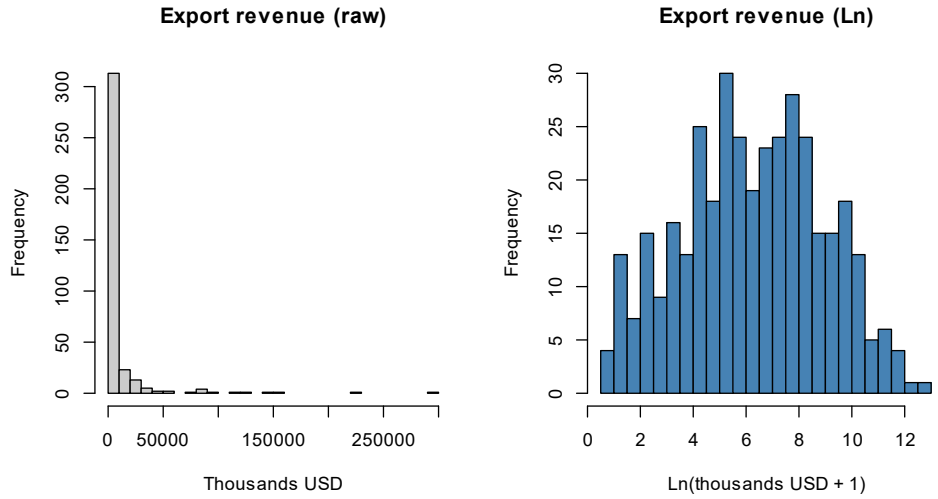


Figure A1. Export revenue distribution, all 370 exporters, raw (left) and Ln-transformed (right).

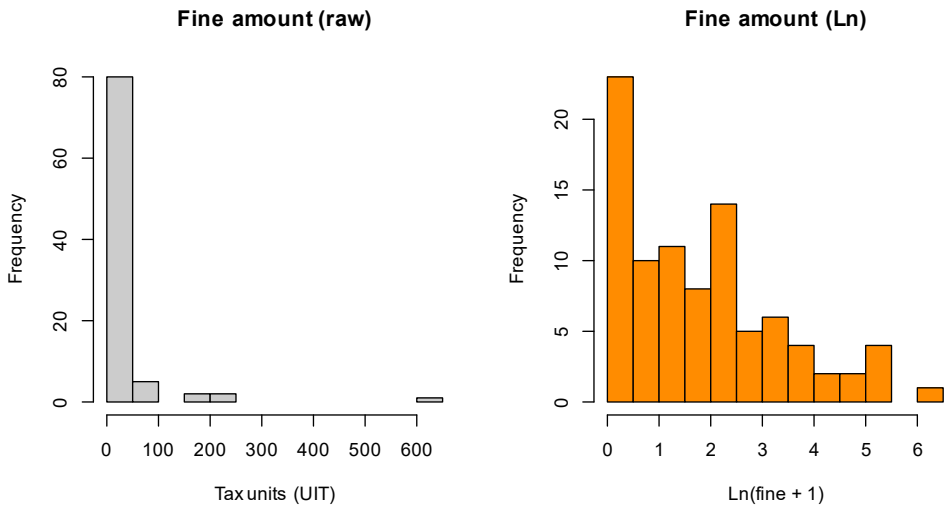


Figure A2. Fine amount distribution, raw (left) and Ln-transformed (right), confirmed-infraction non-compliant sample (n=90).

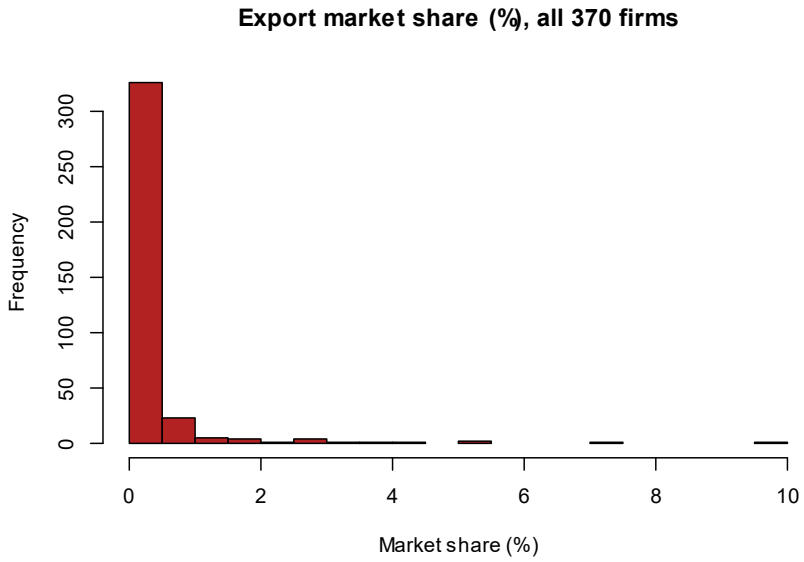


Figure A3. Export market share (%) distribution, all 370 firms.

B. Full Regression Output

Logistic models report the log-odds coefficient; OLS models report the coefficient. Standard errors in parentheses: maximum-likelihood standard errors for the logit models (Tables B1–B2) and HC1 heteroskedasticity-robust standard errors for the OLS fine-severity models (Tables B3–B5), as in the Section 3. The conventional OLS standard errors of the base models are given in Table C1 for comparison.

Table B1. Compliance models, confirmed-infraction standard (logistic; n = 112)

Specification	Coefficient (SE)	p
Linear: Ln(export revenue)	-0.104 (0.123)	0.396
Quadratic: Ln(export revenue)	5.022 (1.998)	0.012
Quadratic: Ln(export revenue)^2	-0.315 (0.122)	0.010
+ Market share: Ln(export revenue)	0.556 (0.305)	0.069
+ Market share: Market share (%) [VIF = 2.88]	-3.007 (1.457)	0.039
Volume (alt. scale): Ln(Volume)	-0.063 (0.110)	0.569

Table B2. Compliance models, fine-only standard (logistic; n = 112)

Specification	Coefficient (SE)	p
Linear: Ln(export revenue)	-0.297 (0.112)	0.008
Quadratic: Ln(export revenue)	2.966 (1.183)	0.012
Quadratic: Ln(export revenue)^2	-0.207 (0.075)	0.006
+ Market share: Ln(export revenue)	0.169 (0.212)	0.426
+ Market share: Market share (%) [VIF = 2.55]	-2.263 (1.102)	0.040
Volume (alt. scale): Ln(Volume)	-0.290 (0.102)	0.004

Table B3. Fine-severity models, confirmed-infraction standard (OLS, HC1 robust SE; n = 90)

Specification	Coefficient (SE)	p	R^2
Base: Ln(export revenue)	0.352 (0.089)	<0.001	0.218
Tercile: Ln(export revenue) [Low, reference]	-0.237 (0.187)	0.208	
Tercile: Mid-export tercile (level)	-5.989 (4.014)	0.140	
Tercile: High-export tercile (level)	-10.628 (3.972)	0.009	
Tercile: Ln(export revenue) x Mid	0.752 (0.463)	0.108	
Tercile: Ln(export revenue) x High	1.256 (0.396)	0.002	0.419
+ Market share: Ln(export revenue)	0.117 (0.099)	0.241	
+ Market share: Market share (%) [VIF = 1.78]	0.454 (0.120)	<0.001	0.344
Volume (alt. scale): Ln(Volume)	0.324 (0.074)	<0.001	0.233

Table B4. Fine-severity models, fine-only standard (OLS, HC1 robust SE; n = 76)

Specification	Coefficient (SE)	p	R^2
Base: Ln(export revenue)	0.291 (0.096)	0.003	0.164
Tercile: Ln(export revenue) [Low, reference]	-0.269 (0.177)	0.132	
Tercile: Mid-export tercile (level)	-4.067 (4.727)	0.393	
Tercile: High-export tercile (level)	-7.331 (4.235)	0.088	
Tercile: Ln(export revenue) x Mid	0.513 (0.521)	0.328	
Tercile: Ln(export revenue) x High	0.941 (0.414)	0.026	0.430
+ Market share: Ln(export revenue)	0.038 (0.102)	0.710	
+ Market share: Market share (%) [VIF = 1.79]	0.447 (0.117)	<0.001	0.320
Volume (alt. scale): Ln(Volume)	0.260 (0.084)	0.003	0.157

Table B5. Model-comparison summary: export-scale coefficient across the twelve comparable specifications

Specification	n	Coefficient (SE)	p	VIF
Compliance – confirmed-infraction: base	112	−0.104 (0.123)	0.396	—
Compliance – confirmed-infraction: + market share	112	0.556 (0.305)	0.069	2.88
Compliance – confirmed-infraction: volume (alt.)	112	−0.063 (0.110)	0.569	—
Compliance – fine-only: base	112	−0.297 (0.112)	0.008	—
Compliance – fine-only: + market share	112	0.169 (0.212)	0.426	2.55
Compliance – fine-only: volume (alt.)	112	−0.290 (0.102)	0.004	—
Fine severity – confirmed-infraction: base	90	0.352 (0.089)	<0.001	—
Fine severity – confirmed-infraction: + market share	90	0.117 (0.099)	0.241	1.78
Fine severity – confirmed-infraction: volume (alt.)	90	0.324 (0.074)	<0.001	—
Fine severity – fine-only: base	76	0.291 (0.096)	0.003	—
Fine severity – fine-only: + market share	76	0.038 (0.102)	0.710	1.79
Fine severity – fine-only: volume (alt.)	76	0.260 (0.084)	0.003	—

Note. VIF is defined only for the four market-share specifications (rows with a second regressor alongside Ln(export revenue)); the base and volume-alternative specifications are univariate on scale, so VIF does not apply there ("—"). Coefficient, SE and p are taken from Tables B1-B4: maximum-likelihood standard errors for the logit rows and HC1 robust standard errors for the OLS rows.

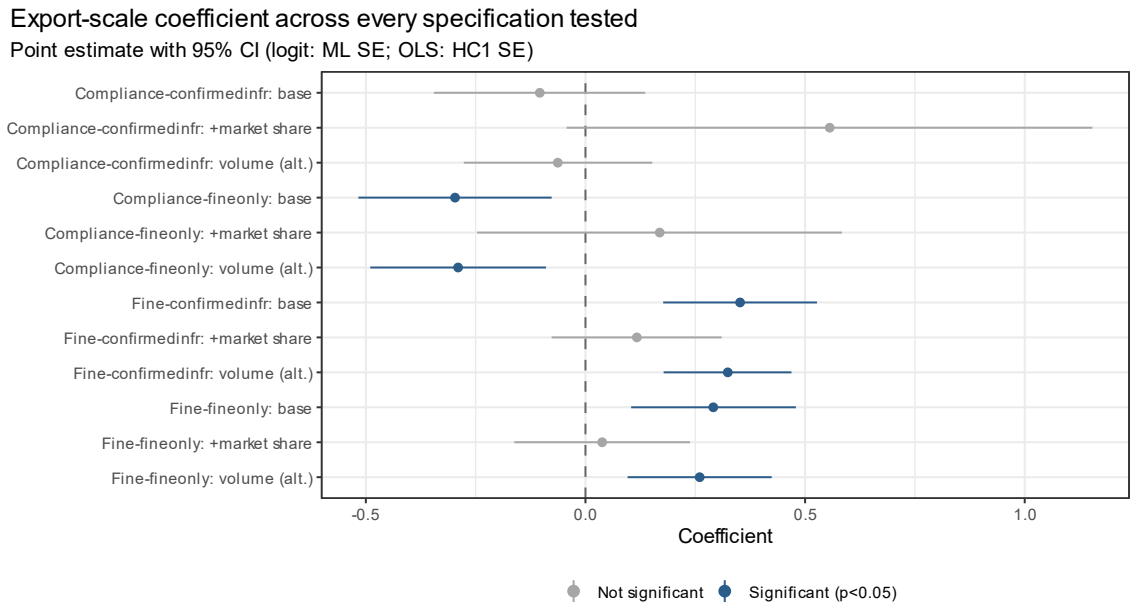


Figure B1. Export-scale coefficient across the twelve specifications in Table B5, plotted as a point estimate with its 95% confidence interval; grey points are not statistically significant, blue points are significant at p<0.05.

Table B5 and Figure B1 above summarize the twelve specifications that share a common form (from Tables B1-B4): a single coefficient on Ln(export revenue), or its volume alternative, which is directly comparable across rows because each row changes only the compliance definition or the added/alternative scale control, holding the functional form fixed. The four **market-share controlled specifications** carry the largest standard errors and, in the two compliance models, a coefficient sign reversed from that definition's own base model. This does not indicate a stronger or separate effect: market share is export revenue multiplied by a constant, so it differs from Ln(export revenue) only in functional

form (VIF 1.78-2.88). Once both are in the same regression, the model splits a single revenue effect between a logarithmic and a linear term, so the linear (market-share) term absorbs most of the explanatory power and export revenue's own coefficient becomes imprecise and, in the compliance models, unstable in sign. The four **volume-alternative specifications**, by contrast, sit close to their own block's base-model coefficient with standard errors of similar size, as expected if volume measures the same scale.

C. Diagnostic Tests

Breusch-Pagan, Shapiro-Wilk, the HC1 robust-SE comparison, and the Ramsey RESET test are reported below for both base fine-severity models (Tables B3 and B4, "Base" rows), confirmed-infraction and fine-only. VIF is diagnostic only for the market-share-controlled models specifically, where multicollinearity is the relevant concern (Table B5); it is not meaningful for a base model with a single predictor, which is why it is not repeated here for the two base models.

Each row of Table C1 checks a different assumption behind a model's ordinary least squares standard errors and p-values, instead of re-testing the coefficient itself. Breusch-Pagan and the HC1 robust-SE comparison both bear on **heteroskedasticity**, whether the residual variance is constant across fitted values; BP is not significant under either definition, and the HC1 robust standard errors, although about 25% larger than the ordinary ones (0.089 vs. 0.071; 0.096 vs. 0.076), leave both coefficients significant at the 1% level; this paper therefore reports HC1 standard errors for every fine-severity model (Table 2 and Tables B3–B5). Shapiro-Wilk checks residual **normality**; the confirmed-infraction model shows a mild, statistically detectable departure (p=0.026), while the fine-only model does not (p=0.083) — neither biases the OLS point estimates themselves, and the confirmed-infraction departure only means its p-values are asymptotically rather than exactly justified at this sample size, a caveat rather than a disqualifying flaw. The Ramsey RESET test checks **functional-form misspecification** directly — whether a nonlinear function of the fitted values would improve the model — and is significant under both definitions (confirmed-infraction and fine-only alike), the formal counterpart to the curved residual pattern visible in Figures 4a–4b: both models' residuals dip in the mid-range and rise at both ends of the export-revenue distribution, the pattern that motivates the tercile check in Section 3.3. Pearson r is a simple bivariate cross-check on the regression coefficient's direction and strength, reported under both compliance definitions. VIF checks **multicollinearity** in the confirmed-infraction market-share-controlled models specifically (Table B5, rows 2 and 8; the fine-only equivalents, rows 5 and 11, are reported there too), and all four values sit well under the conventional VIF>5 threshold, but the VIFs are low only because one term is in logs and the other in levels: market share is export revenue times a constant (correlation 0.99999), so the two regressors measure the same thing. For **visual** purposes, normal Q-Q plots of OLS residuals were included.

Table C1. Diagnostic test results

Test	Statistic	p / result
Breusch-Pagan, confirmed-infraction (heteroskedasticity)	BP = 0.132, df = 1	p = 0.717, no evidence of heteroskedasticity
Breusch-Pagan, fine-only (heteroskedasticity)	BP = 0.463, df = 1	p = 0.496, no evidence of heteroskedasticity
Shapiro-Wilk, confirmed-infraction (residual normality)	W = 0.968	p = 0.026, mild departure from normality; does not bias OLS point estimates
Shapiro-Wilk, fine-only (residual normality)	W = 0.971	p = 0.083, not significant; no detectable departure from normality
HC1 robust SE, confirmed-infraction, Ln(Export) coefficient	α = 0.352, robust SE = 0.089	p < 0.001 (ordinary SE = 0.071, p < 0.001), robust SE about 25% larger; significance at 1% unchanged
HC1 robust SE, fine-only, Ln(Export) coefficient	α = 0.291, robust SE = 0.096	p = 0.003 (ordinary SE = 0.076, p < 0.001), robust SE about 25% larger; significance at 1% unchanged
Ramsey RESET, confirmed-infraction (functional form)	RESET = 13.73, df = (2, 86)	p < 0.001, confirms the curved pattern visible in Fig. 4a
Ramsey RESET, fine-only (functional form)	RESET = 13.19, df = (2, 72)	p < 0.001, confirms the curved pattern visible in Fig. 4b
Pearson r, confirmed-infraction (n=90)	r = 0.467, 95% CI [0.288, 0.615]	t = 4.959, p < 0.001
Pearson r, fine-only (n=76)	r = 0.405, 95% CI [0.197, 0.578]	t = 3.808, p < 0.001
VIF, compliance + market share model	Ln(Export revenue) and market share: 2.88 (confirmed-infraction); 2.55 (fine-only)	below 5 only because one term is in logs and the other in levels
VIF, fine-severity + market share model	Ln(Export revenue) and market share: 1.78 (confirmed-infraction); 1.79 (fine-only)	below 5 only because one term is in logs and the other in levels

The two plots, Figure C1, show the same qualitative right-skewed departure (points lie above the reference line in both tails and slightly below it around the center) but they are not identical: the fine-only residuals (Right plot) have a slightly smaller spread and a narrower range, and their lower tails departs less from the line, consistent with the two models' own differing Shapiro-Wilk results reported in Table C1 above (p=0.026 confirmed-infraction vs. p=0.083 fine-only). Note also that the two fine-severity models are fitted on different samples (n=90 vs. n=76) with different outcome definitions.

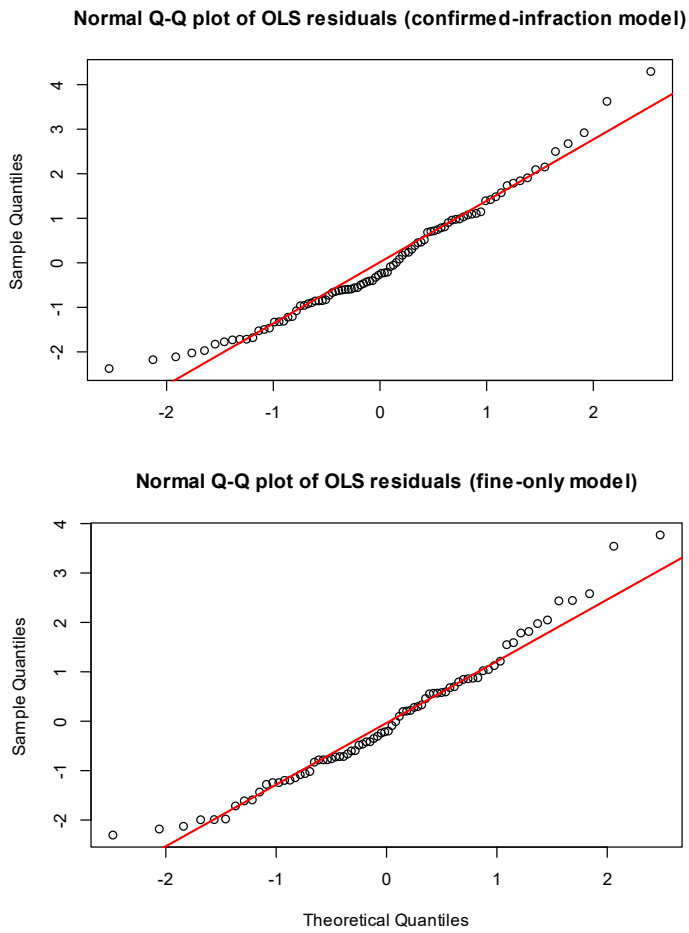


Figure C1. Normal Q-Q plot of OLS residuals: (Left) confirmed-infraction fine-severity model; (Right) fine-only standard in fine-severity model.

D. Practical-Relevance Percentile Table

Predicted compliance probability (confirmed-infraction standard) at selected percentiles of the export-revenue distribution, translating the model in Table B1 ("Linear" row) into concrete probabilities across the realistic range of firm sizes. The linear coefficient is not statistically significant (p = 0.396); the quadratic model, which is the main compliance result, is shown in Figure D1.

Table D1. Predicted Pr(Compliance) at export-revenue percentiles

Percentile	Export revenue (USD thousands)	Predicted Pr(Compliance)
10th	317.8	0.246
25th	1,523.6	0.217
50th	7,535.8	0.190
75th	22,143.5	0.174
90th	58,859.5	0.160
95th	104,281.4	0.152
99th	213,905.5	0.142

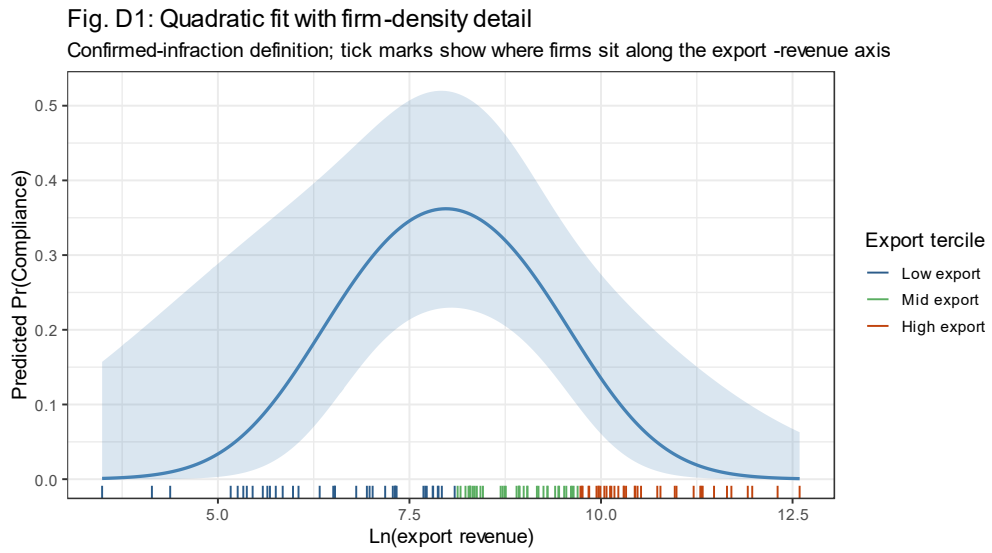


Figure D1. Quadratic compliance fit (confirmed-infraction standard) with a firm-density rug by export tercile along the x-axis.

The rug shows how firms are spread along the curve: because the turning point lies at about the 33rd percentile (Appendix E.6), the rising segment rests on the smaller exporters, and the far right tail, where predicted compliance approaches zero, contains relatively few firms, as cautioned in Section 3.1. The rug is the same for both compliance definitions (112 firms), so the same caution applies to the fine-only curve in Figure 2, and a separate fine-only rug is not shown.

E. Additional Robustness Checks

This appendix reports nine additional checks: a formal balance test on the sample-selection concern raised throughout the paper (E.1; Section 3 and Appendix A); an inverse-probability-weighted (IPW) sensitivity check on the same concern (E.2); a small-sample robustness battery for the quadratic compliance pattern (E.3; Figure 2, and Figure D1); quantile regressions of fine severity (E.4); a bootstrap test comparing the confirmed-infraction and fine-only compliance coefficients (E.5); the turning point of the quadratic compliance model with confidence intervals and the Lind-Mehlum U-test (E.6); re-estimations of the compliance and fine-severity models without extreme or influential firms (E.7–E.8). Finally, it adds firm controls built from OEFA records with a check on supervision targeting (E.9).

E.1. Selection balance: confirmed sample vs. excluded firms

Table A1 reports that 112 of the 370 firms in the full 2023 exporter list have a confirmed OEFA status; the remaining 258 are excluded because no OEFA source could confirm their status either way. Table E1 tests directly whether this restriction is associated with firm scale, using the three variables observed for all 370 exporters (export revenue, export volume, and market share, which is export revenue rescaled).

Table E1. Selection balance: confirmed sample (n=112) vs. excluded firms (n=258)

Variable	Mean (in)	Mean (excl)	Median (in)	Median (excl)	t-test p	Wilcoxon p
Export revenue (Thousands USD)	23,105.18	1,552.10	7,535.78	185.36	<0.001	<0.001
Export volume (export tons)	10,035.82	550.29	1,866.95	45.59	<0.001	<0.001
Export market share (export %)	0.77	0.05	0.25	0.01	<0.001	<0.001

Note. t-test and Wilcoxon rank-sum test both compare the in-sample (confirmed) and excluded groups on each variable independently.

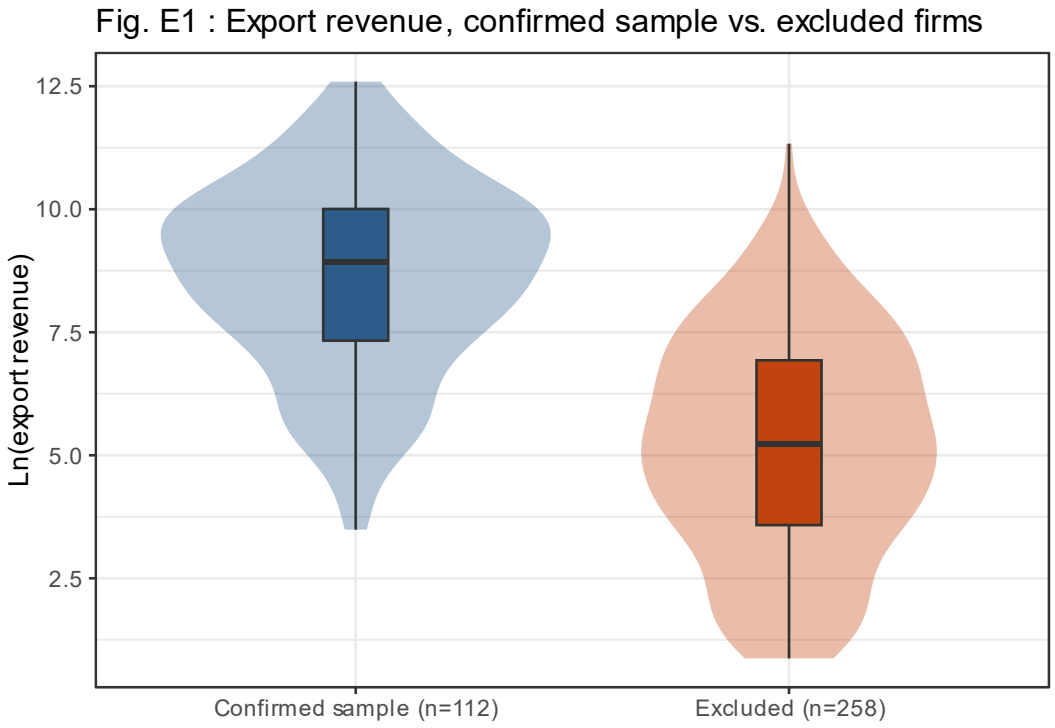


Figure E1. Ln(Export revenue) distribution, confirmed sample vs. excluded firms.

The confirmed sample is heavily skewed toward larger, more visible exporters: mean export revenue (and therefore mean market share, which is revenue rescaled) is roughly fifteen times higher than in the excluded group, with both the parametric and non-parametric tests rejecting equal distributions at $p<0.001$. The cross-sectional associations reported throughout this paper should accordingly be read as describing the relationship among the larger-exporter subpopulation that OEFA's confirmable records happen to cover, rather than the full 370-firm exporter population.

E.2. Inverse-probability-weighting (IPW) sensitivity check

As a complementary check on the same selection concern, a probit selection model was fit on all 370 firms (in-sample indicator regressed on Ln(export revenue), Ln(export volume), and market share, i.e., export revenue in levels), and the resulting propensity scores were used to construct inverse-probability weights ($1/\hat{p}$) for a re-weighted re-estimation of

the four base models reported in Tables B1-B4 ("Linear"/"Base" rows). Because the selection equation and the outcome equations share the same scale variables, this check is identified off functional-form differences rather than a genuine exclusion restriction, and is reported as a transparency and sensitivity exercise, not a causal correction for selection.

Table E2. Ln(export revenue) coefficient, unweighted vs. IPW-reweighted

Model	β (unweighted)	p	β (IPW)	p
Compliance – confirmed-infraction	-0.104	0.396	0.241	0.013
Compliance – fine-only	-0.297	0.008	0.068	0.598
Fine severity – confirmed-infraction	0.352	<0.001	0.119	0.165
Fine severity – fine-only	0.291	0.003	0.107	0.244

Note. β is the coefficient on Ln(export revenue); IPW weights are $1/\hat{p}$ from the probit selection model described above. Across all 370 firms, propensity scores range from 0.001 to >0.999 (mean 0.30), so extreme weights (max ≈41.6) are present: the weights sum to 342 for 112 firms and the effective sample size is about 34 firms. p-values for the IPW columns use heteroskedasticity-robust (sandwich, HC0) standard errors, as is standard for sampling weights. Unweighted p-values are those of Tables B1–B4 (maximum-likelihood standards errors for the logit models, HC1 for the OLS models)

Fig. E2 : Ln(export revenue) coefficient, unweighted vs . IPW-reweighted

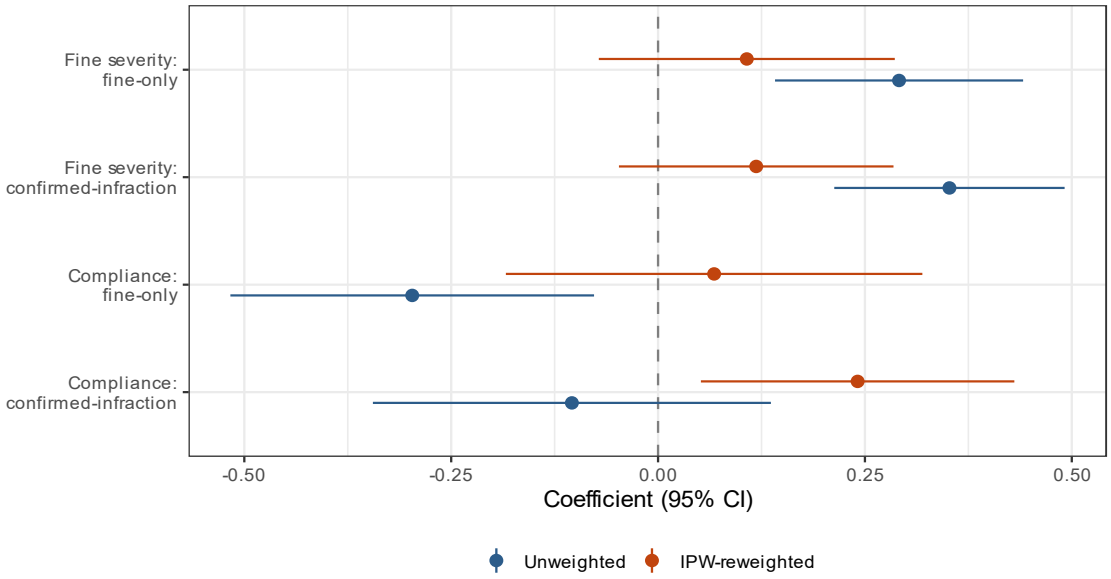


Figure E2. *Ln(export revenue) coefficient, unweighted vs. IPW-reweighted, all four base models.*

Re-weighting turns both linear compliance coefficients positive and changes which compliance standard appears significant – confirmed-infraction becomes significant (p = 0.013) while fine-only becomes insignificant (p = 0.598), the reverse of the unweighted pattern reported in Section 3.1 – and attenuates the fine-severity relationship (Section 3.2's most precisely estimated unweighted result) to non-significance under both definitions (robust p = 0.165 and 0.244). This indicates the definitional sensitivity documented throughout the paper is entangled with, and partly explained by, the sample-selection pattern in E.1, and that the fine-severity relationship, while directionally stable, should be read as describing the larger exporters that OEFA's records cover: once observable selection into the confirmable OEFA universe is accounted for, it is no longer statistically distinguishable from zero, although with an effective sample of about 34 firms this partly reflects lost precision.

E.3. Robustness of the quadratic compliance pattern

Figure D1 (Appendix D) cautions that the far-right tail of the quadratic curve, where predicted compliance approaches zero, rests on relatively few firms. Three checks assess whether this pattern is an artifact of a small number of influential firms or of small-sample maximum-likelihood bias: Cook's distance, a leave-out re-fit excluding the two largest exporters, and a bias-reduced (Firth-type) logistic re-estimation.

Fig. E3 : Cook's distance, quadratic compliance models

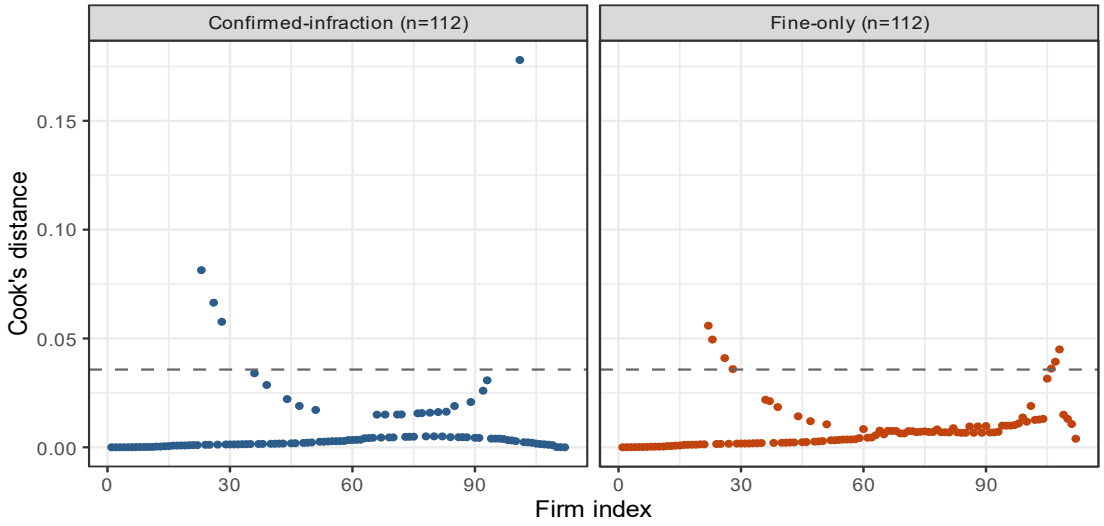


Figure E3. Cook's distance, quadratic compliance models, both definitions.

Only 4 of 112 firms (confirmed-infraction) and 7 of 112 firms (fine-only) exceed the conventional 4/n influence threshold — the pattern is not driven by one or two isolated points.

Table E3. Quadratic term (Ln(export revenue)²), full sample vs. robustness re-fits

Specification	Confirmed-infr. β (p)	Fine-only β (p)	Method
Full sample (Table B1/B2)	-0.315 (0.010)	-0.207 (0.006)	ML logit
Top-2 exporters excluded	-0.314 (0.010)	-0.206 (0.006)	ML logit
Bias-reduced re-estimation	-0.266 (0.013)	-0.186 (0.009)	Firth-type

Note. "Bias-reduced (Firth-type)" refers to bias-reduction estimation for binomial GLMs, which corrects small-sample/near-separation bias that ordinary maximum-likelihood logit is prone to in thin-tail regions such as the top export tercile.

The quadratic term is essentially unchanged when the two largest exporters are dropped, and remains statistically significant under both compliance definitions after bias-reduction, though its magnitude shrinks somewhat (≈10-16%). The inverted-U pattern reported in Section 3.1 and Figure 2 is not an artifact of one or two firms or of small-sample logit bias.

E.4. Quantile regression on fine severity

As a complement to the mean-based OLS fine-severity models (Tables B3–B4, "Base" rows), median and interquartile quantile regressions were fit on the same continuous Ln(fine+1) outcome. A quantile regression is not informative for the binary compliance outcome (at $\tau = 0.5$ the coefficients and standard errors are exactly zero), so this check is reported for the fine-severity outcome only.

Fig. E4 : Quantile regression of Ln(fine + 1) on Ln(export revenue), by quantile

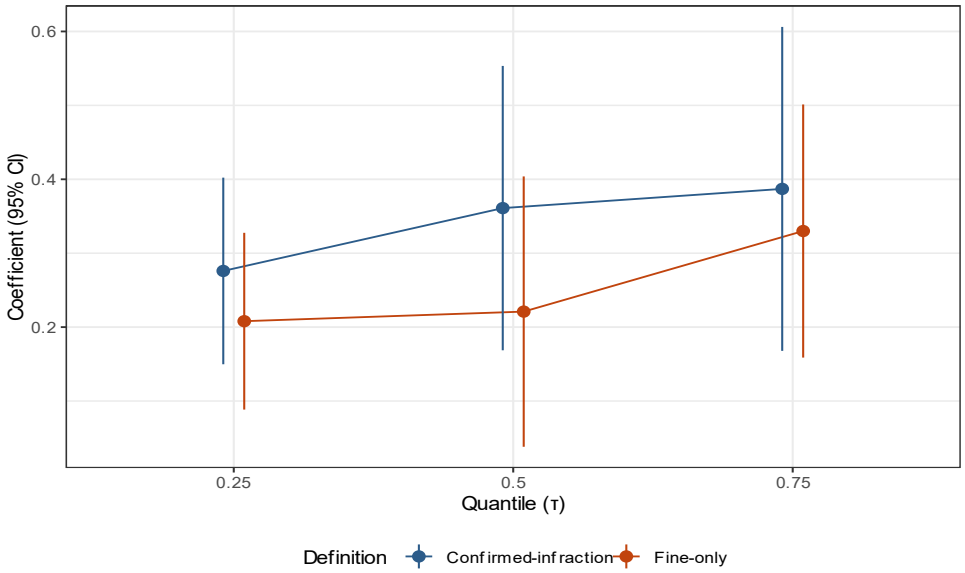


Figure E4. Ln(export revenue) coefficient on Ln(fine+1), quantile regression at τ = 0.25, 0.50, 0.75.

Table E4. Quantile regression, Ln(export revenue) coefficient on Ln(fine+1)

τ	Confirmed-infr. β	p	Fine-only β	p
0.25	0.276	<0.001	0.208	0.001
0.50	0.361	<0.001	0.221	0.021
0.75	0.387	<0.001	0.330	<0.001

The positive export–fine relationship holds at every quantile examined, under both compliance definitions, and strengthens somewhat toward the upper quantiles — evidence that Section 3.2's fine-severity finding is not a mean-driven artifact.

E.5. Formal comparison of the two compliance definitions

Section 3.1 reports that the Ln(export revenue) coefficient in the linear compliance model is insignificant under the confirmed-infraction standard (β=-0.104, p=0.396) but significant under the fine-only standard (β=-0.297, p=0.008). To formally test whether these two point estimates are statistically distinguishable from one another, rather than simply presenting both p-values side by side, a paired bootstrap (1,000 replicates, each replicate resamples the 112 firms once

and refits both models on the same draw, because both standards are coded on the same firms) was used to construct a confidence interval for their difference.

Table E5. Bootstrap comparison of the confirmed-infraction and fine-only linear compliance coefficients

Quantity	Value
Observed difference (confirmed-infr. − fine-only)	0.193
Bootstrap 95% CI of the difference (1,000 reps.)	[0.040, 0.384]
Two-sided bootstrap p-value (H0: difference = 0)	0.014

The 95% CI excludes zero (p = 0.014): the confirmed-infraction coefficient is significantly less negative than the fine-only coefficient. The two codings agree on direction but not on strength: counting zero-fine infractions as non-compliance weakens the export-compliance association. A stacked logit with firm-clustered standard errors gives the same conclusion (interaction, fine-only minus confirmed-infraction slope: -0.193, p = 0.022).

E.6. Turning point of the quadratic compliance model

The turning point of the quadratic logit is $x^* = -\beta 1/(2\beta_2)$ (Section 2.4). Table E6 reports it on the log scale and in USD million, with three 95% confidence intervals: the delta method; the Fieller interval, which is exact for a ratio of coefficients and wider when β_2 is imprecise; and a nonparametric bootstrap (2,000 resamples of firms, all of which produced a concave fit). The Lind–Mehlum test (Lind & Mehlum, 2010) reports the larger of the two one-sided p-values for the slopes at the lowest and highest observed export levels.

Table E6. Turning point, confidence intervals and Lind–Mehlum U-test

Quantity	Confirmed-infraction	Fine-only
Turning point, Ln(export revenue)	7.975	7.158
Turning point, USD million	2.91	1.28
95% CI, delta method (USD million)	[1.54, 5.47]	[0.58, 2.85]
95% CI, Fieller (USD million)	[0.81, 6.06]	[0.18, 2.47]
95% CI, bootstrap (USD million)	[1.52, 5.39]	[0.42, 2.60]
Percentile of the export distribution	33rd	21st
Firms below / above the turning point	37 / 75	23 / 89
Slope at minimum Ln(export revenue) = 3.49 (one-sided p)	2.825 (0.007)	1.520 (0.011)
Slope at maximum Ln(export revenue) = 12.59 (one-sided p)	−2.907 (0.004)	−2.252 (0.001)
Lind–Mehlum U-test, overall p	0.007	0.011

Note. Export revenue in thousands of USD, logged as Ln(x + 1); USD values convert the log-scale bounds back to levels.

Every interval lies below the sample median export revenue (USD 7.5 million), and both turning points fall within the observed data range, so the inverted U is not an extrapolation. Because the turning points lie at the 33rd and 21st

percentiles, the declining segment covers most of the sample; the rising segment rests on the smaller exporters, where the confidence bands in Figure 2 and Figure D1 are wide.

E.7. Quadratic compliance model without extreme or influential firms

Appendix E.3 dropped the two largest exporters. Table E7 extends this to the top 5% of exporters (six firms) and to all firms whose Cook's (1977) distance in the quadratic model exceeds 4/n, and reports the turning point of each re-fit.

Table E7. Quadratic term (Ln(export revenue)^2) and turning point, leave-out re-fits

Specification	Confirmed-infr. β (p)	Turning point (USD m)	Fine-only β (p)	Turning point (USD m)
Full sample (n = 112)	−0.315 (0.010)	2.91	−0.207 (0.006)	1.28
Top 5% of exporters excluded (n = 106)	−0.310 (0.012)	2.92	−0.202 (0.009)	1.28
Cook's D > 4/n excluded (n = 108 / 105)	−0.620 (0.006)	2.81	−0.421 (0.002)	1.69

Note. ML logit. In the last row, n = 108 (confirmed-infraction) and 105 (fine-only), because Cook's distance is computed in each standard's own quadratic model.

Removing the top 5% of exporters leaves both the curvature and the turning points unchanged. Removing the influential firms sharpens the curvature while the turning points stay within the confidence intervals of Table E6. The inverted U is therefore not produced by extreme or influential observations.

E.8. Fine-severity model without extreme or influential firms

Section 3.3 shows that the export–fine slope is concentrated in the top export tercile. Because those firms also have the highest leverage, Table E8 re-estimates the base fine-severity model (Tables B3–B4, "Base" rows) without the two largest exporters, without the top 5% of exporters, and without firms whose Cook's (1977) distance exceeds 4/n, with HC1 robust standard errors throughout.

Table E8. Ln(export revenue) coefficient on Ln(fine+1), leave-out re-estimations (HC1 SE)

Specification	Confirmed-infraction α (SE); p; n	Fine-only α (SE); p; n
Full sample	0.352 (0.089); p < 0.001; n = 90	0.291 (0.096); p = 0.003; n = 76
Two largest exporters excluded	0.309 (0.091); p = 0.001; n = 88	0.243 (0.097); p = 0.014; n = 74
Top 5% of exporters excluded	0.295 (0.095); p = 0.003; n = 85	0.228 (0.098); p = 0.023; n = 72
Cook's D > 4/n excluded	0.307 (0.063); p < 0.001; n = 83	0.242 (0.061); p < 0.001; n = 69

Note. OLS with HC1 robust standard errors.

The slope falls by 12–22% but remains positive and significant in every re-estimation, under both compliance definitions. The fine–scale association is therefore concentrated among, but not produced solely by, the largest exporters; together with the quantile regressions in E.4, this indicates that neither extreme exporters nor extreme fines drive the result.

E.9. Firm controls, enforcement history and supervision targeting

Three firm-level controls are built from the OEFA files used to construct the sample: activity type (fishmeal and fish oil, 18 firms; aquaculture, 24; other processing for direct human consumption, 62; no activity record, 8), Ln(1 + number of auditable units) and Ln(1 + supervisions started in 2018–2022). Table E9a re-estimates the quadratic compliance logit and Table E9b the fine OLS with each control set. Because all eight firms without an activity record are non-compliant under the confirmed-infraction standard, the logit is also estimated with Firth bias reduction. Ln(export revenue) correlates at 0.52 with Ln(1 + units) and at 0.35 with Ln(1 + pre-2023 supervisions).

Table E9a. Quadratic term of the compliance logit with firm controls

Controls	Confirmed-infr.: ML (p)	Firth (p)	Fine-only: ML (p)	Firth (p)
A. None	−0.315 (0.010)	−0.266 (0.013)	−0.207 (0.006)	−0.186 (0.009)
B. Activity + units	−0.339 (0.012)	−0.270 (0.015)	−0.279 (0.004)	−0.241 (0.006)
C. Pre-2023 supervisions	−0.410 (0.009)	−0.349 (0.013)	−0.236 (0.019)	−0.201 (0.027)
D. All three	−0.363 (0.042)	−0.234 (0.055)	−0.268 (0.011)	−0.217 (0.019)

Note. n = 112 in every column. Firth turning points (USD million), confirmed-infraction / fine-only: A 2.77 / 1.21; B 1.97 / 1.41; C 2.96 / 1.27; D 1.07 / 0.91.

Table E9b. Ln(export revenue) coefficient on Ln(fine+1) with firm controls (HC1 SE)

Controls	Confirmed-infraction α (SE); p; R^2	Fine-only α (SE); p; R^2
A. None	0.352 (0.089); p < 0.001; 0.218	0.291 (0.096); p = 0.003; 0.164
B. Activity + units	0.123 (0.102); p = 0.234; 0.417	0.079 (0.108); p = 0.466; 0.413
C. Pre-2023 supervisions	0.191 (0.081); p = 0.021; 0.407	0.145 (0.085); p = 0.092; 0.359
D. All three	0.156 (0.102); p = 0.132; 0.452	0.109 (0.109); p = 0.322; 0.445

Note. n = 90 (confirmed-infraction) and 76 (fine-only). Supervision targeting: regressing Ln(1 + supervisions from 2023 onwards) on Ln(export revenue) and Ln(1 + supervisions 2018–2022) gives 0.072 (HC1 SE 0.019; p < 0.001) for exports and 0.600 (0.051) for past supervisions (n = 112).

The inverted U in compliance survives these controls: the squared term stays negative in every specification and is significant at the 5% level except for the Firth estimate with all three controls under the confirmed-infraction standard (p = 0.055). The Firth turning points move to between USD 0.9 and 3 million, inside the Fieller intervals in Table E6. The fine-scale association is not: it is largely absorbed by the number of auditable units, consistent with the exposure channel and with fines that scale with operations. Because the controls are recorded by the enforcer, they may partly mediate the scale association rather than confound it; these results are sensitivity checks, not preferred specifications. Excluding the 18 fishmeal producers, whose 2023 exports were hit hardest by El Niño, also leaves the inverted U in place: the squared term is -0.294 (p = 0.021) and -0.199 (p = 0.013), with turning points of USD 3.2 and 1.4 million (n = 94).

F. Reproducibility Notes

All coefficients, test statistics, tables and figures in the main text (Figures 1–9) and in Appendices A–E (except Table A4, compiled from BCR and INEI statistics), including the firm-control checks in Appendix E.9 and the timing check with other export years in Section 3.6, are produced by one analysis script, "VDPI_integral_analysis.R". The script reads three input files: "governance_data_final.csv" (the 2023 export list matched to OEFA records, with compliance status and fines), "firm_controls.csv" (activity type, auditable units and supervision history from OEFA files, used in Appendix E.9), and "sunat_exports_2022_2024.csv" (each firm's 2022 and 2024 exports from SUNAT customs records, used in Section 3.6). Three data-preparation scripts (00_extract_snp_table.R, 01_build_governance_data.R and 02_validate_audit.R) build and check these files from the sources described in Section 2 (SNP, OEFA's PIFA and RUIAS, and SUNAT), and 00_run_all.R runs the whole sequence. The scripts and input files are archived as a replication package on Zenodo (https://doi.org/10.5281/zenodo.23983221); the record and its DOI are public, and the files are available on request through the record page.

G. Planned Panel Specification

The structural and reduced-form models below extend the cross-sectional specification with firm-level controls, firm and year fixed effects, and instrumental variable identification. They outline a natural next step for future panel data research; however, we do not estimate them in this paper because current data limitations require us to use only the cross-sectional models above. The structural form (7) restates the compliance condition (4) of Section 2.1, which is developed in the companion theoretical analysis (Jaramillo Abad & Uwasu, 2026); it is not derived further here.

Structural form:

$$\Pr(\mathrm{Com}_i = 1) = \Pr\left(p(e_i)p^{'} S_i + p(e_i)\theta O_{s,i} + q^{'}(e_i) I_i \geq C(e_i)\right) \quad \textbf{(7)}$$

$$\mathrm{Log}(\mathrm{Fine}_i) = f(p_i, p_i^{'}, X) \qquad \text{for non-complying firms (X: vector of controls)} \quad \textbf{(8)}$$

Reduced-form panel specification (firm *i*, year *t*):

$$\mathrm{Com}_{it} = \alpha_0 + \alpha_1 \mathrm{Export}_{it} + \alpha_2 p_{it} + \alpha_3 p_{it}^{'} + \gamma X_{it} + f_i + \tau_t + \varepsilon_{it} \quad \textbf{(9)}$$

$$\log(\mathrm{Fine}_{it}) = \beta_0 + \beta_1 \mathrm{Export}_{it} + \beta_2 p_{it} + \beta_3 p_{it}^{'} + \delta X_{it} + f_i + \tau_t + \varepsilon_{it}, \quad \textbf{(10)}$$

where Export_{it} proxies I^M and firm scale; X_{it} is a vector of firm, obligation, supervision, sanction, and infraction controls; and f_i, τ_t are firm and year fixed effects.