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TRUTHFUL SELF-REPORTING UNDER LIMITED ENFORCEMENT: EVIDENCE FROM INDONESIA

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Introduction

Environmental inspection is the primary channel used by regulators to detect non-compliance of industrial facilities. But limited budgets often constrain regulators as to the number of inspections they can conduct (Russel, 1990; Dion, Lanoie and Laplante, 1997). Consequently, only a small proportion of polluters is subject to random inspections in any given period. To overcome this limitation, regulators often use self-reported environmental data as a substitute for inspections.

Generally, regulations require industrial enterprises to periodically report self-monitoring data to environmental agencies. However, a number of polluters may "under-report"—that is, willfully misrepresent the true state of pollution in the self-monitoring reports. When inspections are infrequent and penalties rare, firms often may not invest the time and money needed to obtain accurate data, choosing instead to understate emissions in their self-reports (Malik, 1993; GAO, 1993). Thus, compliance assessment based on self-reported data tends to result in misleading conclusions. From a regulator's perspective, the situation involves a tradeoff between the benefits of reliable data obtained from expensive inspections against the lower cost of potentially inaccurate data from the self-monitoring reports. However, regulators realize the benefits of lower costs and reliable data when polluters honestly self-report violations.

From the polluter's perspective, the choice self-reporting strategy depends on the benefits and costs of under-reporting. Three main factors must be considered. First, what is the penalty for under-reporting, should it be detected? Secondly, truthful self-reporting could be influenced by internal corporate environmental policies; several enterprises have advanced, fairly strict, in-house standards and procedures for environmental performance. Finally, under-reporting may pose moral dilemmas for individuals associated with this function, making ethical choices a strong factor in truth-telling behavior. The latter two factors could be called non-regulatory incentives, and roughly categorized as organizational and norm effects respectively. While existing literature on self-reporting has examined in detail only the aspect of enforcement incentives, this paper aims to evaluate the extent to which non-regulatory factors influence the self-reporting behavior of industrial enterprises .

Current theory holds that self-reporting of violations depends on the penalty function. To induce polluters to self-report violations, the regulator structures the penalty so that a facility benefits more by reporting the violation honestly to the regulator rather than by being detected during random inspection. Typically, the regulator imposes a fixed fine (F_{SR}) when facilities self-report their violation. However, when a violation is detected through random inspection, a higher fine (F_I) is imposed. To create incentive for honest self-reporting, the regulator must set F_{SR} at a level such that $F_{SR} \leq q\ F_I$, where q is the probability of inspection. Within this framework, if the penalty structure does not discriminate for self-reported violations, non-compliant polluters have little incentive to identify themselves to the regulator.

This paper sets forth an empirical test regarding this penalty-based theory of self-reporting using water pollution data from Indonesia, a country where penalties are not structured to reward honest self-reporting and water pollution control regulations are rarely enforced through the judicial system. Hence, the probability of enforcement is virtually non-existent, and enforcement incentives for truthful self-reporting are absent. According to the penalty-based self-reporting theory, the regulatory conditions of Indonesia should lead to most facilities under-reporting pollution data to the environmental agencies. Yet, some 70 percent of Indonesian facilities honestly report their pollution in the monthly reports. Do non-regulatory factors like norm effect and internal corporate policy significantly influence the environmental behavior of factories?

To understand the mysterious self-reporting behavior of Indonesia's industries, we investigate the characteristics shared by facilities that tend to under-report. According to penalty-based self-reporting theory, facilities with high abatement costs are most likely to under-report their pollution. Surprisingly, we find that some characteristics associated with low pollution abatement costs are also associated with a high likelihood of under-reporting. This underscores the theory that a diverse range of non-regulatory or informal incentives influence the environmental behavior of industrial facilities and that reasons for honest self-reporting are not limited to regulatory sanctions and abatement costs.

The remainder of the paper is structured as follows—we first review the literature on self-reporting, followed by the discussion of Indonesia's approach to industrial water pollution control and the data sources. Then we describe our econometric methodology and the results. And finally, we discuss the implications of these findings for Indonesia's regulatory management and to highlight the weaknesses of the existing models.

Literature Review

Theoretical literature on self-reporting[1] is limited and focuses mainly on questions of welfare implications of including a self-reporting provision in controlling negative externalities, and its role in increasing the probability of compliance. The first question is analyzed in Malik (1993) and Kaplow and Shavell (1994). They show that a self-reporting provision reduces the need for often-costly inspections, thereby reducing the social cost of achieving compliance. Two behavioral elements drive the results in these models—a penalty structure that allows for a guaranteed lower fine when violations are confessed, and the risk preference of polluters. Thus, according to this theory, the penalty function serves as an important determinant truthful self-reporting.

The second question is analyzed in Livernois and McKenna (1996), primarily as a competing explanation offered by Harrington (1988). Harrington explains the phenomenon of a high compliance rate when the expected penalty is low through a model in which regulators can target inspection at different rates based on whether or not a polluter is a high-risk violator. Conversely, Livernois and McKenna explain that by lowering fines when violations are self-reported, the rate of detection of noncompliance increases, enabling regulators to enforce compliance more quickly. One feature driving the result is the abatement cost characteristics of polluters. According to Livernois and McKenna, facilities that are in the medium abatement cost range are most likely to self-

[1] A detailed discussion of the self-reporting literature is in Cohen (1998)

report violations, while the facilities with high compliance costs are most likely to under-report their pollution. The mechanics of Livernois and McKennna model is briefly discussed.

Let the abatement level required for compliance be a^* and the abatement level of the non-compliant polluter be a_1 such that $a_1 < a^*$. Let the marginal cost at abatement levels a^* and a_1 be $MC(a^*)$ and $MC(a_1)$ respectively. Let the constant marginal penalty when polluter declares violation to regulator be F_{SR}. Let the constant marginal fine for violation when discovered by regulator through random inspection be F_1 and the probability of inspection be q. Then the price of compliance when polluter self reports violation will be the sum of marginal compliance cost and the fixed marginal fine, given as $MC(a^*) - MC(a_1) + F_{SR}$. Similarly, the price of compliance when violation is detected through random inspection is given by $q \bullet \left(MC(a^*) - MC(a_1) + F_1\right)$. Polluter will choose to self-report violation if:

$$MC(a^*) - MC(a_1) + F_{SR} < q \bullet \left(MC(a^*) - MC(a_1) + F_1\right) \qquad (1)$$

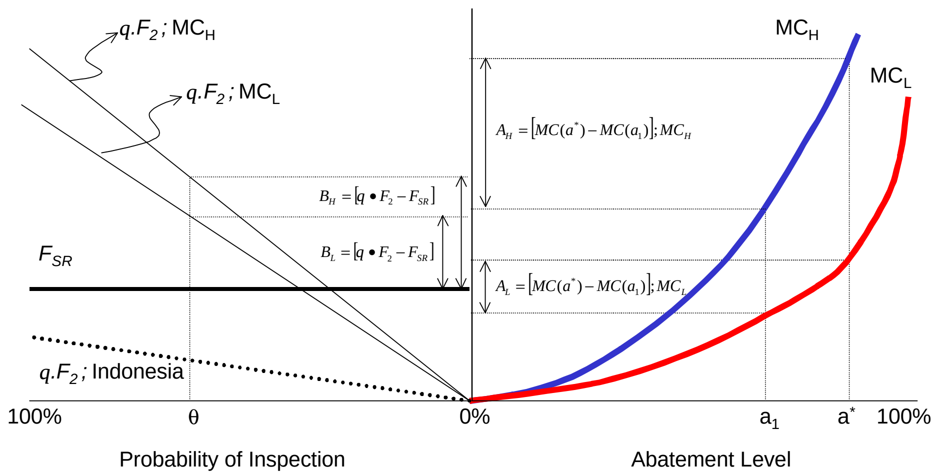
The previous equation can be expressed as:

$$MC(a^*) - MC(a_1) < q \bullet F_2 - F_{SR} \qquad (2)$$

where $F_2 = \left(MC(a^*) - MC(a_1) + F_1\right)$. This formulation allows us to graphically evaluate the relationship between regulatory variables and abatement cost characteristics.

As shown in Figure 1, for a polluter with lower marginal abatement cost (MC_L), the condition in equation (2) holds as illustrated by $A_L < B_L$. While for the polluter with higher marginal abatement cost (MC_H), the condition is reversed as illustrated by $A_H > B_H$. Therefore, it is optimal for the higher abatement cost polluter not to self-report violation. It is clear graphically, that for a given set of regulatory and cost variables, polluter with high abatement cost is less likely to self-report violation. Also, as stated by Livernois and McKenna, there is a critical marginal abatement cost schedule $MC^*(a_i)$

Figure 1



such that $MC_L(a_i) < MC^*(a_i) < MC_H(a_i)$. This condition defines the cut off point for whether or not polluters will self-report violation. Polluters in around $MC^*(a_i)$ comprise what Livernois and McKenna call medium cost polluters.

Also, within this framework, Indonesia's regulatory situation can be represented by the dotted line showing that penalty for violation is extremely low because judicial enforcement is non-existent and F_{SR} =0. Clearly, condition of equation (2) will not hold in most cases and therefore most factories are less likely to self-report violation.

The only empirical evidence of Livernois and McKenna's theory that we are aware of is in Helland (1998) [2]. Using the US data on industrial wastewater discharges, Helland finds that intermediate abatement cost plants are more likely to self-report violations compared to firms facing high compliance costs.

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[2] Brehm and Hamilton (1996) analyze compliance with the reporting requirement in the US-EPA's TRI program. In TRI, self-reports provide data for the public release of the facility level toxic load. They find that the facilities that fail to submit their reports often do it due to ignorance and not necessarily willful evasion.

Surprisingly, given the reliance on self-reports for compliance management, no empirical study so far offers an analysis of *under-reporting*, even for the developed industrial economies. Perhaps, the paucity of simultaneous self-reported and inspected data on pollution makes the analysis of under-reporting behavior difficult. To fill this gap, an analysis of both the self-reported and inspection data for water pollution from industrial enterprises in Indonesia will be a significant contribution to the ongoing research on this topic.

Indonesia's Environmental Management Approach

Like most developing countries, Indonesia’s strategy for industrial wastewater management started with a command-and-control approach. However, Indonesia’s weak public institutions and resource constraints have severely limited effective enforcement of the country’s industrial effluent standards. As a result, even in cases of blatant violation, enforcement of environmental laws by public agencies has failed. Lately, litigation initiated by NGOs has bolstered enforcement efforts, but provincial judges continue to favor the industries. A complex set of political, cultural, and technical factors make it extremely difficult to establish legal precedence for enforcement in Indonesia.

Nevertheless, enforcement failures, specifically those involving high-profile companies, did succeed in bringing environmental issues to public attention. While NGO and media pressures have not effectively altered the probability of formal enforcement, such public activism has shown that it can impose significant transactions costs on polluters (Sonnenfeld, 1998).

The potential for public pressure as a substitute for formal enforcement did not go unnoticed by Indonesia’s regulators. Consequently, Indonesia’s environmental programs explicitly rely on reputation and community pressure to influence the environmental behavior of industries. Thus, public disclosure serves as a dominant feature of pollution control programs in Indonesia.

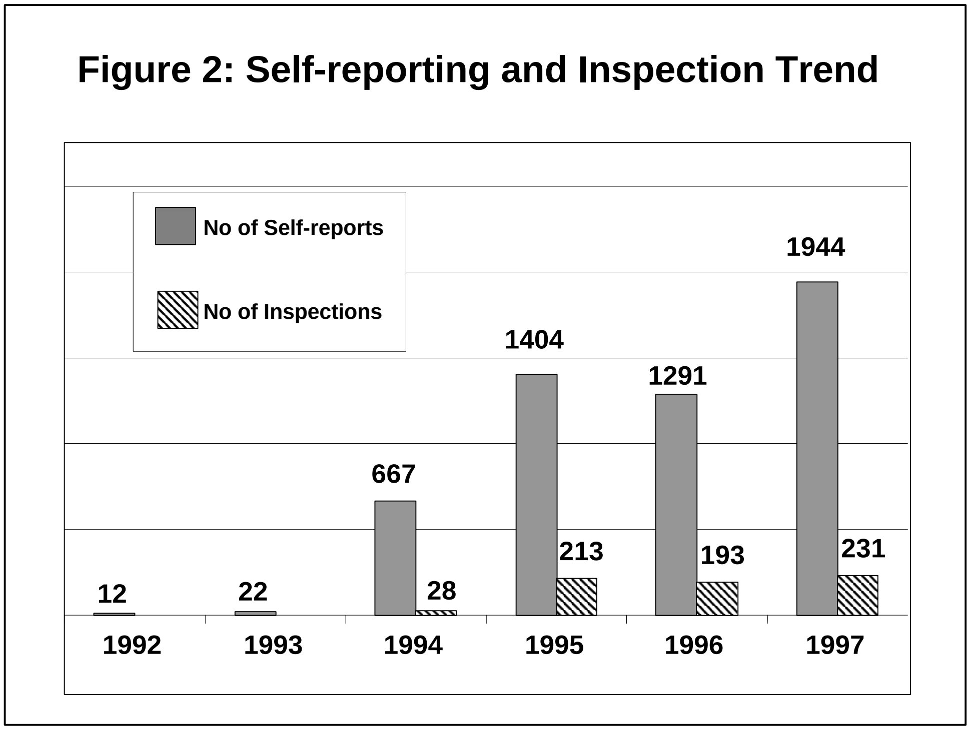
Among the public disclosure programs that Indonesia’s environmental agency implements, the most prominent is the Program for Pollution Control, Evaluation and

Rating (PROPER). Under PROPER, facilities are rated in terms of color codes: Blue, Green, and Gold are for good performance, while Red and Black signal poor performance. To get a Blue rating, facilities must comply with all regulatory requirements. Significant over-compliance is needed to earn a Green rating, while only applicants of clean technology receive a Gold rating. Facilities that have applied some effort to comply but fail to meet all the regulatory requirements get a Red rating. Finally, facilities that have made no effort to comply or that show a pollution level of five times the effluent standard receive a Black rating. The Minister of Environment discloses these ratings to the public through a formal press conference.

The rating criteria clearly indicate that baseline performance is derived from compliance requirements, and the degree of deviation from this baseline determines the relative ratings. Thus, PROPER is closely associated with the command-and-control system, but it relies on public disclosure rather than the judicial process to enforce compliance. Indonesia's regulations stipulate three main requirements for compliance:

- pollution must be less than the effluent standards,
- factories must install a flowmeter and measure the daily discharge, and
- at least one wastewater sample must be sampled per month and reported to the Environmental Management and Impact Agency (BAPEDAL) on a quarterly basis.

Since NGOs and the press closely scrutinize the publicly disclosed ratings, BAPEDAL must make sure that the ratings are credible, since errors will adversely affect the agency's reputation. Without credibility, the agency will fail in its effort to mobilize public pressure on polluters. Therefore, BAPEDAL has subjected self-reported data to close verification through inspections. As shown in Figure 2, the number of self-monitoring reports submitted by facilities has increased significantly since PROPER was introduced. Similarly, the number of inspections by BAPEDAL has also increased substantially. Put together, PROPER provides the ideal data set to evaluate self-reporting behavior.



Framework of Analysis

The evaluation of the likelihood of under-reporting begins with formulating a self-reporting function. Whether or not a facility reports honestly depends on the regulatory system and polluter's compliance cost. Let q be the probability of inspection, F_{SR} be the fine when violation is self-reported and F_I be the fine for violation if detected through inspection. Then the set $\{q, F_{SR}, F_I\}$ captures the main elements of any environmental regulatory system. Also, if F_{SR} exists, then the condition $F_{SR} < F_I$ holds true. At least two other relevant regulatory scenarios emerge for this formulation. If the regulatory system does not discriminate for self-reporting of violations, the regulatory policy is expressed by the set $\{q, F_I\}$. Further, if regulatory agencies conduct inspections but never enforce compliance through the judicial system, regulatory policy is defined by the set $\{q\}$. Or expressed differently, under $\{q\}$, the expected cost of violation is close to zero such that $qF_I \rightarrow 0$. Thus, Indonesia's regulatory policy is best expressed as $\{q\}$.

The development of the compliance cost function occurs in a similar fashion. Let the pollution abatement level be denoted by a and expressed as a percentage such that

$a \in [0,100]$. Let a^* denote the abatement level required for complying with the effluent standard. A plant *i* is in the state of compliance if $a_i \geq a^*$, and the cost of compliance is expressed as $C_{a^*}(\Omega_i)$, where Ω_i is the vector of plant-specific characteristics that determine the pollution control cost. Therefore, the variation in compliance costs across facilities can be explained by plant characteristics.

Let the binary indicator variable *R* take on the values 0 and 1 for honest and dishonest reporting respectively. Then, the self-reporting function for the i^{th} plant can be expressed as:

$$R_i = \begin{cases} \begin{cases} 0 \;\; if \; C_{a^*}(\Omega_i) \leq qF_I \; ....(1) \\ 0 \;\; if \; F_{SR} \leq qF_I \,; a_i < a^* \; ....(2) \end{cases} \\ \begin{cases} 1 \;\; if \; C_{a^*}(\Omega_i) > qF_I \,; \{q, F_I\} ....(3) \\ 1 \;\; if \; a_i \in [0,100); qF_I \to 0 \; ....(4) \end{cases} \end{cases}$$

Equation (1) implies that facilities that are in compliance will report honestly. The second equation applies to the non-compliant plants. These plants will report honestly only if the fine for self-reporting of violations is less costly than the expected cost of non-compliance detected through inspection. Equation (3) shows that it is optimal for plants to under-report pollution when the expected cost of violation is less than the compliance cost, and if the penalty structure does not discriminate for self-reporting. Finally, the last equation implies that, when the expected cost of non-compliance is practically non-existent, as in the case of Indonesia, most plants should under-report.

Following the preceding discussion, a binary choice model can be formulated to analyze a polluter's reporting decision. It is assumed that the plant's decision to under-report pollution or not depends on an unobservable index R_i^*, such that the higher the value of R_i^* the more likely the plant would under-report pollution. More precisely if there is a critical threshold $\overline{R}_i^*$ such that if R_i^* exceeds $\overline{R}_i^*$, then a plant under-reports pollution; whereas if $\overline{R}_i^*$ exceeds R_i^*, it will not. Hence, R_i^* can be expressed as:

$$R_i^* = \beta' W_i + u_i$$

where "W_i" are the plant-specific determinants of R_i^*, and u_i is the error term associated with the unobserved plant characteristics. Then, R_i relates to R_i^* in the following way:

$$R_i = \begin{cases} 1 \; if \;\; R_i^* > \overline{R}_i^* \\ 0 \; otherwise \end{cases}$$

The probability P_i that a plant decides to under-report pollution ($R_i = 1$) can be computed as:

$$P_i = Pr\ (R_i = 1) = Pr\ (R_i^* > \overline{R}_i^*) = 1 - F(\overline{R}_i^*)$$

where $F(\overline{R}_i^*)$ represents the cumulative distribution function.

Next, plant characteristics believed to be important determinants of environmental behavior and hence R_i^* are identified. Recent work on industrial pollution in Asia and Latin America has suggested that plants and firms of different size, sector, ownership, and technological vintage generally assess enforcement probabilities and expected costs in different ways (Wang and Wheeler, 1996; Dasgupta, Hettige and Wheeler, 1997).

Based on Pargal and Wheeler (1996), the scale of production, sector, ownership, location, and market linkages with international buyers can significantly influence the environmental behavior of polluters. A brief description of these explanatory variables follows:

<u>Scale of Production</u>: The scale of production influences the compliance behavior in two ways. First, pollution control exhibits economies of scale (Pittman 1981)—large plants are more likely to comply than are smaller units in the same sector. Second, the environmental behavior of large plants is often under close and constant scrutiny by

NGOs, communities, and regulators, since these facilities hold the potential to cause serious damage. Therefore, large plants are likely to be in compliance and report truthfully in the self-monitoring reports.

Sector: Industrial sectors vary considerably in their pollution characteristics. Hence, each sector requires a different kind of pollution control system. Therefore, differences in pollution control costs can logically be expected. Indeed, some empirical work on this topic has found significant variations in pollution control cost across sectors (Dasgupta, Huq, Wheeler and Zhang, 1996; Hartman, Singh and Wheeler, 1997).

Additionally, in sectors exhibiting frequent product changes, pollution characteristics may also vary considerably (PROPER-PROKASIH Team, Afsah, Wheeler, and Laplante, 1995). In such sectors, a higher probability of error in measurement and reporting is likely compared to the industrial sectors where the final product is uniform and standardized. Thus, under-reporting might not be motivated by any willful manipulation, but rather occur from random statistical variation.

Ownership: Regarding ownership, of particular interest are plants that have some foreign ownership share. These facilities often have more advanced technical know-how and corporate environmental policies than do their domestic counterparts. Also, facilities associated with multinational corporations are highly sensitive about their environmental reputations. These features may considerably strengthen incentives for compliance. Accordingly, foreign-owned plants are likely to be in compliance and to report honestly.

International Market Pressure: International buyers, especially in OECD countries, are often particular about the environmental performance of exporters. Therefore, plants with high export shares are expected to be associated with good environmental performance and truthful self-reporting.

Location: In Indonesia, regulatory enforcement does not vary much across different provinces. However, physical environmental conditions at the provincial level can vary greatly. In sensitive areas or locations where rivers are used for domestic purposes, the demand for pollution control could be high. However, no prior expectation exists about the direction of effect that provincial characteristics may have on the environmental behavior of industrial polluters.

Technology vintage also forms an important indicator of compliance performance, but this variable is not included in this analysis because of data unavailability. Interested readers are referred to Pargal and Wheeler (1996) for more information on the impact of this variable.

Data Source and Description

All the data used for these empirical analyses are from the Environmental Management and Impact Agency (BAPEDAL), Government of Indonesia. As part of the PROPER program, BAPEDAL collects not only industrial plant-level environmental data, but also information on a wide range of plant characteristics.

The dataset consists of 280 factories that are currently rated in the PROPER program. These plants collectively represent most of the Indonesian provinces and also the main water-polluting industrial sectors.

The water pollution variable was determined by using plant-level measurements of effluent concentration of the most conventional water pollution indicators: Biological Oxygen Demand (BOD) and Chemical Oxygen Demand (COD). The data sources cover both the self-reported and the matching inspection measurements.

The PROPER database also contains information on plant characteristics, such as employment, ownership, and market orientation. This analysis uses the employment level as the indicator for the scale of production. The information on ownership is structured to categorize each plant as a private domestic, state-owned, or foreign joint venture. Finally, the database also includes information on the share of the plant's output that is exported.

After combining the data on water pollution with plant characteristics, the matched dataset resulted in 153 plants with complete information on all the necessary variables for analysis. The provinces form the main indicator for location characteristics, but for certain clusters of provinces have been grouped as single spatial units. These include:

1) Jawa Barat, Jawa Tengah and Jawa Timur are combined into Jawa,

2) The provinces of Kalimantan Barat, Kalimantan Selatan and Kalimantan Timur are represented as Kalimantan, and

3) Sumatra Selatan and Sumatra Utara become Sumatra.

After this classification, the dataset represents the location characteristics through seven categories of provinces and province clusters.

An additional variable for location characteristics—BAPEDAL's rating of provinces in terms of their effort to clean up their rivers—was also used. This provincial rating is generated as part of BAPEDAL's clean river management program, called PROKASIH. The main criteria used for the ratings include the water quality in the river and the level of effort applied at the provincial level to reduce the discharge of waste into the rivers. This variable is called *PScore* in the econometric model.

Eighteen industrial sectors appear in the data set, with plant sizes varying from 46 to 9,816 employees. Also, 55 factories ship all their products to the domestic markets, while two factories produce only for export markets. The remainder have mix domestic and international sales. Finally, the ownership of the firms varies considerably: 90 are private domestic firms, 18 are completely owned by the government, and 42 are foreign joint venture firms.

An analysis of BAPEDAL's effluent data, as expected, revealed wide variation in plant-level environmental performance. For plants included in our sample, BOD effluent concentration ranges from 3.43 mg/l to 4992.5 mg/l, and COD effluent concentration ranges from 18.46 mg/l to 57706.63 mg/l.

Empirical Analysis

The empirical analysis has three components. After defining what constitutes under-reporting, self-reported and inspected effluent data are compared for each plant. Then, a binary measure of under-reporting using a non-parametric method is constructed. This process statistically identifies the facilities that appear to have under-reported. Finally, the use of probit analysis identifies key determinants of under-reporting.

What constitutes under-reporting? A facility is considered to have under-reported if it shows a statistically significant difference between self-reported and inspected pollution data. Based on this definition, a facility can be identified as an under-reporter irrespective of its state of compliance. As shown in Figure 2, there are potentially three cases when a facility can be considered to have falsified its self-monitoring data.

Figure 2

		Self Reported Data	
		In compliance	In Violation
Inspection Data	In compliance	*Under-reporting*	Not Applicable
	In Violation	*Under-reporting*	*Under-reporting*

Identification of Under-reporting: The complexity of detection of under-reporting emissions is partly due to the stochastic nature of pollution[3] and accompanying uncertainties about their measurement. In the absence of continuous monitoring, the reality of varying emissions—associated with varying production, treatment and production equipment failures (both complete and partial), variations in relevant background conditions such as rainfall and temperature, and imprecise measurement methods and instruments—suggests the need of repeated emissions measurements from different samples. Difficulties in detecting under-reporting are confounded by the fact that even when samples are drawn repeatedly by competent technicians under optimum conditions, sampling variations can still be substantial (PROPER-PROKASIH Team, BAPEDAL, Afsah, Laplante and Wheeler, 1995).

[3] Discharges of pollutants to the environment are best regarded as stochastic, not deterministic (Beavis and Walker, 1983; Vaughan and Russel, 1983)

Taking into consideration the stochastic nature of pollution generation and the accompanying uncertainties about its measurements, this analysis compares self-reported and inspected plant-level effluent data using Wilcoxon rank-sum test. Normally when one is interested in testing the differences in the means of two independent groups of data, the classical two-sample *t* test is generally performed. However, to use the two-sample *t* test, the two independent samples must be randomly drawn from normal populations having equal variances and the data must be measured on an interval scale. The Wilcoxon rank-sum test, on the other hand, makes fewer and less stringent assumptions (Wilcoxon, 1945). The Wilcoxon rank-sum test has also been proven to be almost as powerful as its classical counterpart under equivalent conditions and is likely to be more powerful when the assumptions of the *t* test are not met (Conover, 1980).

To examine the differences between self-reported and inspected emissions, and to detect under-reporting by the Wilcoxon rank-sum test for each plant, the total sample on emissions is first divided into two parts: n_1 self-reported and n_2 inspections. Then, the observations are replaced in the two samples with their combined ranks. The ranks are assigned in such a manner that rank 1 is given to the smallest of the $n = n_1 + n_2$ combined observations, rank 2 is given to the second smallest, and so on until rank n is given to the largest. The Wilcoxon rank-sum test statistic then compares the median ranks of the two samples to test the hypothesis that these two samples are from the same population.

Because interest primarily lies in detection of "under-reporting" pollution, a one-tailed Wilcoxon rank-sum test was performed. The null hypothesis $H_0: M_1 = M_2$ (the median emissions are equal) was tested against the alternative hypothesis $H_1: M_1 > M_2$. The one-tailed Wilcoxon rank-sum test results were then used to construct a binary variable of under-reporting, R_i. The binary variable R_i was given a value one if under-reporting was detected and zero if it was not.

Econometric Model: In order to identify the determinants of a plant's pollution reporting behavior, the binary choice model was then defined with R_i, the binary variable of "under-reporting" constructed from the one-tailed Wilcoxon rank-sum test as the dependent variable. Plant characteristics constructed from BAPEDAL's PROPER database were the main independent variables included in "*W*". Though the model specification of R_i^* is constrained by data availability, the following specification for the R_i^* equation were used:

$$R_i^* = f\left(\overset{-}{Employment_i}, \overset{-}{Ownership}_{foreign}, \overset{+}{Ownership}_{domestic}, \overset{-}{ExportShare_i}, \right.$$
$$\left. \overset{+/-}{Location_i}, \overset{-}{PScore}_{i,location} \right) + u_i$$

The prior for the sign on the coefficients is shown on top of the variable. "+" Implies that the variable increases the probability of underreporting, "-" means that the variable decreases the probability of under-reporting, and "+/-" means that the sign could go either way. Also, the equation assumes that the error term u_i is normally distributed.

While this analysis estimates the probability P_i that a plant decides to under-report emissions, it is also of interest to stud how various explanatory variables affect the probability of under-reporting.

Results

Analysis results are structured into two sub-sections. First, the general results of non-parametric analysis and the findings of the probit model are presented. Second, based on the estimated probit equation, simulations were conducted to evaluate the relative significance of different predictors.

<u>Non-Parametric Analysis</u>: The Wilcoxon rank-sum test results indicate that at a 10 percent level of significance, 48 out of 153 (31%) facilities tracked in BAPEDAL's PROPER program under-reported either BOD or COD concentration in their wastewater stream. Of these 48 facilities, 32 under-reported BOD concentration, and 38 under-reported COD concentration in their wastewater stream.

Descriptive statistics for the sample effluents appear in Table 1. With respect to effluent concentration, the difference between plants under-reporting pollution and the remaining plants is apparent. For the plants under-reporting pollution, median inspected BOD effluent concentration is 93.10 mg/l as compared to the median concentration of 35.45 mg/l for the remaining plants. Likewise, for COD, the median inspected effluent concentration of the plants under-reporting pollution is 239.68 mg/l as compared to the median concentration of 169.88 mg/l of the remaining plants.

Probit Analysis: Table 2 contains the probit results for the under-reporting equation. The first round of estimates include all the variables mentioned in section 2 subject to data availability. Variables were then successively deleted from the full specification until only the significant factors remained. The results clearly indicate that scale, market of company sales, ownership, and sectors of production are significant determinants of a plant's pollution reporting behavior.

Large plants (measured by the employment size) have a higher probability to under-report pollution.[4] As expected, the larger the share of plant's shipments to the international market, the lower the probability that the facility under-reports pollution. But, contrary to expectations, foreign joint venture plants also under-report pollution. Regarding the foreign joint venture, more that 70 percent of these plants are in compliance (Wheeler and Afsah, 1996), so under-reporting is indeed a surprising finding. Perhaps eager for a Green rating to differentiate their environmental performance from domestic plants, these foreign joint ventures may tend to under-report, since doing so has virtually no cost if detected.

Sectoral dummy variables were included in the regression to control for the possibility of sector effects. The results confirm that even after controlling for scale effect, ownership, and market of company sales, polluter's reporting behavior varies significantly across industry sectors. Plants in the textile, rubber, MSG, and pharmaceutical industries are more likely to under-report pollution.

[4] Apart from the scale effect, this may also reflect the fact that if accused of under-reporting, large plants are in a better position to challenge the enforcement agency by an appeal to a court of law.

While it is plausible that the threat of detection and punishment differs for plants located in different regions, none of the dummy variables associated with location, except Kalimantan, were statistically significant at conventional levels. Plants located in Kalimantan had a higher probability of under-reporting emissions. In order to test the impact of enforcement stringency of the provincial pollution control agencies on polluters' reporting behavior, PScore was included as an explanatory variable. Surprisingly, the coefficient of the PSCORE was not statistically significant.

Simulation Results: To identify the relative importance of influential variables, the analysis explored the implications of econometric results with simulations over the existing range of industrial sectors, employment, ownership, and the share of a plant's shipment. Following these econometric results, the four significant industrial sectors (textiles, rubber, pharmaceutical, MSG) were selected, and the remaining sectors were combined into the category 'others'. Dividing each industry observation into two employment groups, group medians were used to define low- and high-employment prototypes. Each employment group had the proportion of plant's shipment to domestic markets ranging from 0–100 percent and different ownership types.

Using low and high measures for employment, the share of a plant's shipment to domestic markets, and foreign joint venture and other ownership types for each industrial sector, simulation results were generated for eight prototype scenarios. Predictions for the probability of under-reporting emissions in each possible scenario used the parameter estimates of Table 2. The results are presented in Tables (Charts) 3a–3e.

For each industrial sector, the 'worst-case' plants were identified. These plants are characterized as large, foreign joint venture plants with 100 percent of their shipments to domestic markets. In textiles, rubber, pharmaceutical, MSG, and 'others', the probability that these plants will under-report emissions are 69 percent, 88 percent, 72 percent, 78 percent, and 81 percent, respectively. As lower values were substituted for percentage of shipment to domestic markets, employment, and different ownership types, the probabilities of under-reporting decreased significantly. With employment and ownership remaining constant, the estimated probability of under-reporting emissions is three times lower for a 100 percent export-oriented plant. At constant levels for employment and shipment to domestic markets, incidence of under-reporting is, on average, 50 percent lower for domestic plants. Lower employment also has strong effects, with an average reduction of 1.5 times in under-reporting incidences. Finally, the 'best-case' plants (small, 100 percent export-oriented, and domestic) in the sample have a predicted probability of under-reporting emissions in the range of 8 percent to 31 percent, depending on their sector of production.

The probit analysis revealed a considerable number of significant variables. Evidence suggests that behavior of under-reporting pollution is systematic, not random, in Indonesia. Finally, the implications of these probit results were explored with simulations and the most influential variables were identified.

Analysis results demonstrate the importance of careful inspection of self-reported data. Given the limited number of empirical analysis in this area, the findings of this paper will broaden understanding about polluters' behavior. Improving the relative accuracy of targeting, these findings will further help regulatory agencies in allocating scarce resources to pollution monitoring and enforcement more effectively.

Conclusions

Self-reported data is an increasingly important source of information for regulators. This paper provides some interesting insights into the self-reporting behavior of industrial polluters. First, it appears that polluters report their environmental data honestly even in the absence of enforcement incentives. This behavior can be explained by norm effects, informal regulation through community pressure, internal corporate environmental policies and the willingness of industries to develop positive relationships with regulators. At the theoretical level, this finding shows that the existing models of self-reporting are incomplete. Perhaps, a need exists to reevaluate the social benefits of self-reporting when firms report honestly because of non-regulatory incentives.

The second set of findings is relevant for Indonesian regulators. Data from Indonesia revealed that nearly two-thirds of the plants report their pollution honestly. This analysis further demonstrated that the behavior of under-reporting pollution is systematic, and not random in Indonesia. Econometric results indicate that plant characteristics have a strong impact on polluters' reporting behavior. Statistically significant correlation was obtained between the probability of under-reporting pollution and plant-scale, market of company sales, ownership, and sectors of production. Simulation revealed a possible large degree of variation in reporting behavior. In summary, 'worst-case' plants have a predicted probability of under-reporting of about 88 percent, while the 'best-case' facilities have a 7 percent probability in this sample.

Econometric work on the determinants of under-reporting pollution is scarce even in OECD economies, and this is apparently the first such study for a developing country. Despite the limited number of empirical analyses in this research, these findings will broaden the understanding of polluter behavior. In addition, they will help regulatory agencies to target inspections more accurately and thus allocate scarce resources in pollution monitoring and enforcement more effectively.

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Table 1: Distribution of Effluent Concentration (mg/l)

Table 1.a: Plants Under-reporting Pollution

		Min	Quartile 1	Quartile 2	Quartile 3	Max
BOD	Inspections	8.13	41.47	93.10	287.93	4854
BOD	Self-reported	2.68	28.38	42.53	80.35	352.58
COD	Inspections	24.51	114.28	239.68	540.7	17133.74
COD	Self-reported	34.58	97.49	134.10	232.95	858.07

Table 1.b: Plants Accurately Reporting Pollution

		Min	Quartile 1	Quartile 2	Quartile 3	Max
BOD	Inspections	5.44	35.45	74.09	166.0	4992.5
BOD	Self-reported	10.30	42.56	74	153.22	1736.55
COD	Inspections	18.47	78.46	169.88	450.0	6228.16
COD	Self-reported	22.68	88.74	174.07	365.28	57706.63

Table 2: Probit Results (Dependent Variable: Under-reported Either BOD or COD Effluent Concentration)

Explanatory Variables	Coefficient	z	Mean $R_i = 1$	Mean $R_i = 0$
Employment	0.0002	2.513	1581	1127
Domestic Sales	0.0105	2.432	0.70	0.63
Foreign Joint Venture	0.5940	2.211	19	23
Textile	0.5818	2.235	17	31
Rubber	1.4768	2.148	11	27
Pharmaceutical	0.8807	1.729	6	10
MSG	0.9415	1.680	4	7
Kalimantan	2.5702	3.413	8	15
PScore	0.0004	0.767	955	1002
Constant	-2.4073	-3.625		
Log-Likelihood = -80.67		Chi – squared = 29.01		
Number of Observations= 153		Prob > Chi- squared = 0.0006		

Table 3: Simulation Results

Table 3a: Textiles

Employment	% of Sales in Domestic Market	Foreign Joint Venture if = 1	Probability of Under-Reporting Emissions
Low	0	0	.08
Low	0	1	.21
Low	100	0	.36
Low	100	1	.59
High	0	0	.12
High	0	1	.29
High	100	0	.46
High	100	1	.69

Table 3b: Rubber

Employment	% of Sales in Domestic Market	Foreign Joint Venture if = 1	Probability of Under-Reporting Emissions
Low	0	0	.31
Low	0	1	.54
Low	100	0	.71
Low	100	1	.88
High	0	0	.32
High	0	1	.55
High	100	0	.71
High	100	1	.88

Table 3c: Pharmaceuticals

Employment	% of Sales in Domestic Market	Foreign Joint Venture if = 1	Probability of Under-Reporting Emissions
Low	0	0	.14
Low	0	1	.31
Low	100	0	.48
Low	100	1	.71
High	0	0	.14
High	0	1	.32
High	100	0	.49
High	100	1	.72

Table 3d: MSG

Employment	% of Sales in Domestic Market	Foreign Joint Venture if = 1	Probability of Under-Reporting Emissions
Low	0	0	.17
Low	0	1	.36
Low	100	0	.53
Low	100	1	.75
High	0	0	.20
High	0	1	.40
High	100	0	.57
High	100	1	.78

Table 3e: Others

Employment	% of Sales in Domestic Market	Foreign Joint Venture if = 1	Probability of Under-Reporting Emissions
Low	0	0	.16
Low	0	1	.35
Low	100	0	.52
Low	100	1	.74
High	0	0	.22
High	0	1	.43
High	100	0	.61
High	100	1	.81