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Cost of controlling water pollution and its impact on industrial efficiency

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Contents

Abstract

This paper estimates the cost of effluent discharge regulations for firms located in the lower Kelani River catchment in Sri Lanka. The river provides water for many economic purposes including drinking water and avariety of ecosystem services. Employing multi-input and multi-output translog production technology, we estimate shadow prices of effluents and technical efficiency of firms belonging to eight industries. We also compute total abatement cost for firms under different policy scenarios related to simultaneous reduction in concentration of three water pollutants including current regulatory standards. Wide variations in firm and industry shadow prices (marginal abatement costs) provide a strong case for a comprehensive redesign of environmental policy to control water pollution by industries in Sri Lanka.

Keywords

Shadow prices; Technical efficiency; Environmental regulation; Water pollution; Distance functions; Sri Lanka

Cost of controlling water pollution and its impact on industrial efficiency

1. Introduction

Degradation of water quality of major urban rivers due to point and non-point sources has become a serious challenge in many developing countries (Schaffner, Bader, & Scheidegger, 2009). This is mainly due to rapid urbanization accompanied by population and industrial expansion in these countries where development of water purification infrastructure facilities and policy has lagged behind industrialization (Biswas & Tortajada, 2009; Qin, Su, & Khu, 2011). While the cost of resource degradation is significant to society in these countries, the full cost of environmental externalities has not been accounted for as the monetary value of ecosystem services is not measured or accounted for in regulation.

This study focuses on water polluting industries in the lower Kelani River catchment. The river is the main source of drinking water for Colombo. Apart from provision of drinking water, the river is a source of hydropower generation, industrial and irrigation waters, and is used for washing, bathing, fishing and recreation. Due to population growth and industrialization, water quality in the lower river has deteriorated rapidly over the last 10 years. Therefore, managing river water quality has become a critical issue due to the cost of maintaining drinking water standards and the market and non-market costs of deteriorating ecosystem services. Recent studies report that the river is of poor quality endangering the aquatic life and degrading the ecology of the estuary ecosystem (Herath & Amaresekera, 2007). An urgent need to improve river water quality has, thus, created a strong interest among policy makers to experiment different policy instruments in addition to the existing regulatory standards.

The use of market based instruments to control environmental pollution has been strongly encouraged by economists despite inconclusive evidence in developing and emerging countries where institutional, financial, political and human resource limitations restrict the development of such instruments (Blackman, 2009; Blackman & Harrington, 2000; Kathuria, 2006). These instruments create economic incentives for industries to reduce pollution by imposing implicit or explicit price on emissions. Well-designed and implemented market based instruments have the ability to provide the overall least cost means of achieving desirable levels of emission reductions (Stavins, 2003) by equalizing the marginal or incremental abatement cost across polluters (Baumol & Oates, 1988; Tietenberg, 2006). In many cases, the marginal cost of abatement among firms varies due to size, industrial category, location, price and quality of inputs and differences in abatement technology. The potential cost savings achieved by implementing a market based instrument tends to be high where marginal abatement costs are different across firms (Newell & Stavins, 2003).

However, information on abatement costs is not readily available for policy makers due to the absence of market and observable prices for pollutants. In such cases, among the two main economic approaches to estimate the cost of abatement of undesirable outputs, estimation of firm level efficiency and shadow prices using distance functions has been widely employed over the cost function approach (Hailu & Veeman, 2000; Lee, Park, & Kim, 2002; Lee, 2005). The distance functions characterize environmental production technology in a multi-input and multi-output setting including undesirable outputs where information on regulations and input pricesis not required. Using duality theory from microeconomics, shadow prices can be calculated. The calculated shadow prices with respect to a particular pollutant can be defined as the marginal cost of abatement (MAC) for this pollutant as it represents the additional cost incurred to reduce the pollution by one unit. The MAC provides useful information at firm level linking current emission levels to the cost of reducing one more unit of emission. At policy level, these values can be used as an important tool to determine the economically efficient levels of pollution reductions to maximize societal welfare (Vijay, DeCarolis, & Srivastava, 2010).

Estimation of shadow prices using distance functions has followed three main approaches: non-parametric or Data Envelopment Analysis (DEA), parametric functions estimated using linear programming (PLP) and the parametric Stochastic Frontier Analysis (SFA) (Zhou, Zhou, & Fan, 2014). The DEA is a frontier analysis technique (Cooper, Seiford, & Zhu, 2011) which constructs a piece-wise production boundary combining observed input and output data (Du, Hanley, & Wei, 2015). The advantage of DEA is that it is not necessary to specify a functional form for the underlying production technology (Zhou *et al*., 2014). However, it does not guarantee the differentiability of the estimated distance function which is important in estimating shadow prices.

In contrast, parametric distance function methods have become popular in the literature due to their differentiability which is an essential feature for estimating shadow prices (Zhang & Choi, 2014). PLP methods allow simple imposition of important constraints in the frontier estimation. The only shortcoming of this estimation approach is that it ignores statistical noise andattributes all deviations from the frontier to inefficiency. On the other hand, the stochastic frontier approach allows for measurement errors as well as for hypothesis testing. The inconvenience in setting prior monotonicity restrictions on the parametric function (distance function) still remains the main disadvantage of SFA method (Kuosmanen & Kortelainen, 2012).

Shephard (and radial) and directional distance function have been used in the literature. Both can be specified as flexible forms – radial as translog and directional as generalised quadratic, allowing for the global imposition of linear homogeneity and translation properties, respectively. Many recent studies have tended to use the directional distance function that can allow for increases of desirable output(s) while contracting the undesirable output(s). Nevertheless, the shadow price estimates vary depending on the directional vector which is used to expand or contract the input and output set. Therefore, the choice of an appropriate directional vector plays a key role in shadow price estimations (Zhou *et al*., 2014). However, there is no consensus regarding the choice of directional vector. Further, the use of a direction that implies a radical change in input or output mix is akin to assumption of a structural change that is more consistent with long-run rather than short-run possibilities. Therefore, the use of shadow prices based on a radial distance functions can be more appropriate as these functions maintain quantity mixes at observed levels (Ma & Hailu, forthcoming, 2015)

A few studies have calculated shadow prices using distance functions in developing and emerging country context (Dutta & Narayanan, 2011; Mandal, 2010; Murty, Kumar, & Dhavala, 2007; Murty & Kumar, 2003; Murty, Kumar, & Paul, 2006; Van Ha, Kant, & Maclaren, 2008; Xu, Hyde, & Ji, 2010). To our knowledge this is the first study carried out in Sri Lanka to estimate shadow prices of water pollutants in manufacturing industries. In this study, we calculate firm and industry specific shadow prices for Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD) and Total Suspended Solids (TSS) using input distance functions estimated by PLP (Coelli, Gautier, Perelman, & Saplacan-Pop, 2013; Hailu & Veeman, 2000). Given the importance of cost information on policy decisions, we simulated total abatement cost for different policy scenarios based on simultaneous reduction of pollutant concentration to different levels including those consistent with the current regulatory standards.Our choice of input distance functions in this study is based on the following three reasons: (1) In the presence of undesirable outputs, an input-based efficiency measure is easy to interpret as it represents the proportional change in inputs with both desirable and undesirable outputs held constant (Hailu & Veeman, 2000; Murty *et al*., 2006); (2) Input based efficiency is more appropriate as most firms have more control over inputs than outputs; (3) Shadow price estimates using input distance function do not depend on the choice of a direction vector as it is the case of directional distance functions.

The paper is organized as follows. Section 2 presents the current policy context and Section 3 explains the theoretical concepts behind the methodology we used. Section 4 describes the data and Section 5 reports and discusses the empirical results. Section 6 concludes the paper.

2. Policy Context

Sri Lanka uses command and control regulatory measures administered by the Central Environmental Authority (CEA) to control industrial pollution. The key regulatory measures adopted by CEA are Environmental Protection Licencing (EPL) and concentration standards[3]. The CEA issues Environment Protection Licenses (EPLs) to firms, a mandatory provision to start a new business in Sri Lanka. These licenses are renewed for existing businesses, annually for high polluting industries[4] and triennially for medium to low polluting industries, after checks and verification on whether the wastewater quality meets the existing emission standards. Apart from the government decision on not allowing high polluting industries upstream of the water extraction point in the Kelani River, there are no any river specific policies to manage water quality.

Water quality evidence in Sri Lanka suggests that the current approach to pollution regulation in rivers is ineffective (AECEN 2006; Vasantha 2008). Firstly, emission standards are based on discharge concentrations which do not restricttotal pollution loads. Secondly, EPLs provide no incentive to reduce pollution by industries with varying emission levels as all industries under the same pollution category are charged a uniform fee irrespective of their emission levels. Thirdly, CEA has limited regulatory and weak enforcement powers. The number of cases handled by the legal unit of the CEA was about 252 in 2012 where 64 were new cases related to industrial pollution (CEA, 2012). Fourth, budgetary constraints have resulted in limited resources within CEA. The lack of a well-managed information system is also a hindrance to effective monitoring and enforcement. In addition, the lack of public pressure on polluting industries because of limited public awareness and ineffective public complaint processes has resulted in poor compliance.

Recently, the CEA has been exploring new options[5] such as market-based instruments for effective control of industrial wastewater pollution (Vasantha, 2008). In 2007, CEA proposed a Wastewater Discharge Fee (WDF) program in Sri Lanka. However, implementing such a program presents a number of challenges due to overlapping legal and institutional functions and lack of procedures to design and collect fees. In addition, a lack of technology to measure pollution levels at the firm level and the absence of systematic up-to-date industrial pollution database make implementation of this program difficult. In many cases, it is difficult for government agencies such as CEA to set appropriate fees on industrial emissions due to unavailability of empirical information. This study is an initial attempt to fill this information gap on abatement costs. Thus far there have been no studies estimating abatement costs and technical efficiencyof water polluting firms in Sri Lanka.

3. Methodology

Shephard (1953) was the first to introduce distance functions. The functions can be employed to describe multi-input and multi-output production technology in order to estimate technical efficiency and productivity measures without resorting to specific behavioural assumptions such as profit maximization and cost minimization (Coelli, Rao, O'Donnell, & Battese, 2005). There are two types of distance functions, output and input. An output distance function characterizes production technology by considering maximum proportional expansion of the firm's output vector for a given set of inputs. An input distance function represents the production technology by looking at the maximal proportional contraction of the input vector for a given output vector.

In this paper, we use input distance function which provides meaningful and explicit measure of production efficiency as it considers proportional savings of inputs (costs) while keeping both desirable and undesirable outputs constant. In the case of output efficiency measures, efficiency is defined in terms of proportional expansion

[3] The national concentration standards for water pollutants discharge into inland water bodies are given as 30mg/l for BOD, 250 mg/l for COD and 50 mg/l for TSS.

[4] Industries have been categorised by the CEA based on their level of pollution under three main categories; A-high polluter, B-medium level polluters and C-small scale polluters.

[5] CEA also initiated a program in 2011 to increase the voluntary compliance named as the national Green Award Scheme. This program recognizes and publicizes private and public sector institutions that operate in environmental friendly manner.

of both desirable and undesirable outputs but the net welfare gain from such an expansion cannot be determined. The net welfare gain or loss depends on the difference between benefits gained from the expansion of desirable output and the damage caused by simultaneous expansion of undesirable outputs. Therefore, interpretation of radial output efficiency changes is ambiguous in the presence of undesirable outputs (Hailu & Veeman, 2000; Murty *et al.*, 2006). In addition, the use of input distance function is preferred as the firms in our sample have more control over inputs than the outputs.

3.1 The technology set and input distance function

The production technology of each water polluting firm can be described using input sets, $L(u)$, representing the set of all input vectors $x \in \mathfrak{R}^{N}+$ that produce output vector $u \in \mathfrak{R}^{M}+$ with the output vector consisting of both desirable and undesirable outputs (for example water pollutants). The input distance function can be defined against the input requirement set as follows:

$$D_i\,(x, u) = ⟦\mathrm{Max}_\rho \{\, \rho : (x/\rho,) \in L(u)\,\}\ \forall\ u \in \mathfrak{R}^{M}+ \qquad (1)$$

That is the input distance function indicates the maximum amount by which an input vector x can be deflated or contracted given the output vector and the production technology.

The input distance function is linearly homogenous, non-decreasing and concave in x and non-increasing and quasi-concave in u(Coelli *et al.*, 2005). The value of the distance function is equal to 1 (if x is located on the inner boundary of the frontier) or greater than 1 if x is able to produce u. In other words, the distance function provides a complete representation of the production technology.

$$D_i\,(x, u) \geq 1 \text{ if } x \in L(u) \qquad (2)$$

3.2 Derivation of Shadow prices

We employed input distance function to calculate shadow prices of pollutants following (Hailu & Veeman, 2000). Shadow prices of pollutants can be derived from the cost function (3) and (4) using the behavioural assumption of cost minimization and the duality between cost function and input distance function. A formula for shadow price can be derived using envelope theorem on the first order conditions of the cost minimization problem defined against a distance function representation of the technology as shown in Eq.(5) and (6) below.

$$C\,(u, p) = Min\{p.\,x : x \in L(u)\,\} \qquad (3)$$

$$C\,(u, p) = Min\{p.\,x : D(u.\,x \geq 1),\, x \in \mathfrak{R}^{N}+\} \qquad (4)$$

$$\nabla_u\, C\,(u, p) = -\,\pi(u,p).\ \nabla_u\, D\,(u, x) \qquad (5)$$

$$\nabla_u\, C\,(u, p) = -C(u, p).\ \nabla_u\, D\,(u, x) \qquad (6)$$

where π is the Lagrangian multiplier and equals the value of optimized cost function, allowing us to derive (6) from (5). Using (6), the ratio of shadow prices of outputs can be written as:

$$\frac{r^{*}_{i}}{r^{*}_{j}} = -\,\frac{\dfrac{\partial D(u,x)}{\partial u_i}}{\dfrac{\partial D(u,x)}{\partial u_j}} \qquad (7)$$

This ratio reflects the trade-off between two outputs in the production technology. For example, if i is an undesirable output and j is desirable output, the ratio represents the number of units of desirable output j that would be forgone to reduce the emission of one unit of pollutant j is the producer shadow price for i^{th} pollutant.

If we assume (as is commonly done) that the market price for the desirable output equals its shadow price (Fare, Grosskopf, Lovell, & Yaisawarng, 1993; Färe, Grosskopf, Noh, & Weber, 2005; Hailu & Veeman, 2000; Shephard, 1970), then the shadow price for undesirable output r_i^{*} can be witten as:

$$r^{*}_{i} = - \frac{\frac{\partial D(u,x)}{\partial u_i}}{\frac{\partial D(u,x)}{\partial u_j}} \bullet r_i^{*} \qquad (8)$$

The shadow price of undesirable output is positive as the input distance function is non-decreasing in pollutant outputs and the derivatives have opposite signs. We use Eq. (8) to calculate shadow prices for three water pollutants (BOD, COD and TSS).

3.3 Estimation of parametric input distance function

The input distance function is homogenous in inputs. The flexible functional form that allows us to improve this property globally is the translog form. We estimate the translog parametric input distance function frontier with linear programming techniques.

$$\begin{aligned} \ln D_i(u, x) = {} & \propto_0 + \sum_{n=1}^{N} \propto_n \ln x_n + \sum_{m=1}^{M} \beta_m \ln u_m \\ & + (0.5) \sum_{n=1}^{N} \sum_{n'=1}^{N} \propto_{nn'} \ln x_n \ln x_{n'} \\ & + (0.5) \sum_{m=1}^{M} \sum_{m'=1}^{M} \beta_{mm'} \ln u_m \ln u_{m'} \\ & + \sum_{n=1}^{N} \sum_{m=1}^{M} \Upsilon_{nm} \ln x_n \ln u_m \end{aligned} \qquad (9)$$

Aigner and Chu (1968) were the first to use mathematical programming techniques to estimate parameters of production function. This method minimizes the sum of deviations of the values of the function from the unknown frontier that is being estimated subject to monotonicity and homogeneity restrictions as specified in Hailu and Veeman (2000). For this study, the ability to impose inequality constraints is very important as we need to treat desirable and undesirable outputs asymmetrically in the specification of technology.

The objective of our linear programming is to choose a set of parameter estimates that minimize sum of deviations of log values of the input distance function from zero. We impose monotonicity, homogeneity and symmetry conditions as constraints. Also we impose the constraint that estimated input distance value should be equal to one or greater than one. Furthermore, the estimated input distance function is required to be non-decreasing in undesirable outputs (Hailu & Veeman, 2000). To implement the estimation we use APEAR, an R based package for productivity and efficiency analysis (Hailu, 2013).

4. Data

The data used in this paper come from a survey of water polluting industries that we conducted in 2013 in Sri Lanka. We selected a representative sample of water polluting firms categorised under high polluters[6] and medium level of polluters located within 1km of the river (see Fig: 1), from the database of industries available from the environmental agency (CEA). There were 324 water polluting individual firms in total and our sample comprised 74 of them. We interviewed production and administrative managers of the firms to collect information on inputs, desirable outputs and other required firm specific data for the year 2012.

[6] The CEA categorized firms into three categories : high, medium and low polluting firms based on the size, and nature of the pollutants.

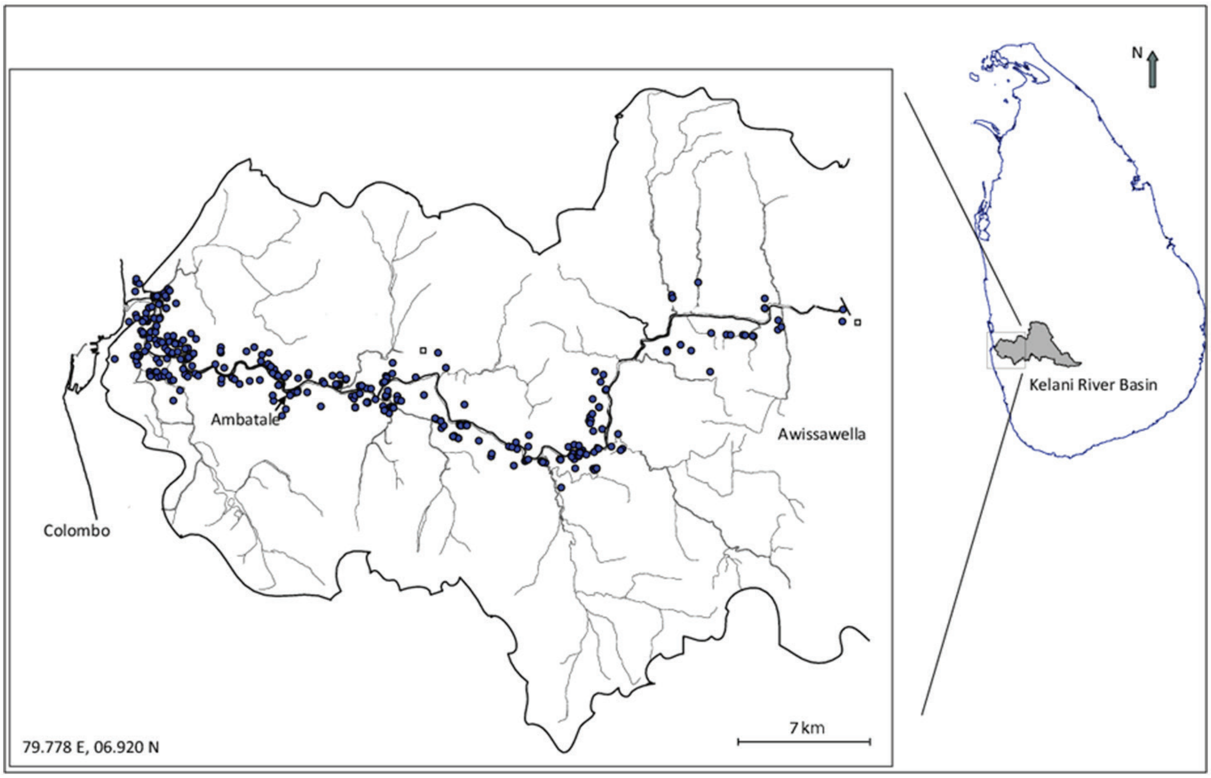

Fig 1: Spatial distribution of water polluting firms within 1km of the lower Kelani River

In addition to desirable outputs, these firms produce wastewater (i.e. undesirable output) in their industrial processes. The wastewater is discharged into the Kelani River either treated or untreated. The quantity of wastewater discharged by each firm was recorded. However, the quality of the wastewater (concentration of BOD, COD and TSS in mg/l) discharged by each firm was not available for the entire sample. Therefore, we extracted water quality data for 25 firms from the latest records available with the CEA. Then, we collected wastewater samples from the rest of the firms by visiting them (without prearranged appointments) with an environmental officer of the CEA and an officer from a private laboratory. Information on undesirable outputs was estimated based on water samples collected from the firms at the survey time. Therefore, we assumed the waste water volumes and concentration levels were not changing throughout the year.

The majority of firms (66 per cent) in our sample are high polluters. Although having an environmental protection licence (EPL) is a mandatory requirement for these industries, only 53 per cent of the firms currently have licences. Little more than half of the firms have end–of-the-pipe treatment plants and only 29 per cent of firms comply with the existing concentration standards for all three pollutants. Even though firms classified as high polluters are monitored annually by the CEA, only 63 per cent of them have treatment plants. In this category, only 53 per cent currently own licenses with an even smaller proportion (49 per cent) complying with existing concentration standards. Among medium level polluters which accounts for 33 per cent of the sample and are monitored once every three years, only 52 per cent possess licences, 40 per cent own treatment facilities and 12 per cent comply with current standards.

For the estimation, we aggregated inputs into four categories: raw materials, labour, power, and services and maintenance as their costs. We also aggregated outputs into four: one desirable output (total sales) and three undesirable outputs (pollution loads of BOD, COD and TSS). Total sales are aggregated in US$ and pollution loads are reported in kilograms. Only some firms had end-of-pipe treatment facilities to for wastewater. For these firms, we recorded the cost of annualized capital and operating cost under treatment costs.

Table 1 : Descriptive statistics of output and input variables (000s)

Variable	Unit	Mean	Standard deviation
1. Total sales	US$	4700.36	17900.00
2. BOD load	kg	3.78	15.67
3. COD load	kg	6.74	26.87
4. TTSS load	kg	3.33	19.39
5. Raw materials	US$	1936.74	11700.00
6. Labour	US$	96.21	267.83
7. Power	US$	65.48	284.48
8. Service and maintenance	US$	42.74	204.44
9. Treatment cost	US$	3.02	6.09

Table 2 shows the cost share of each input by industry. Raw materials account for the biggest cost share in all industries followed by cost of labour, power and service and maintenance and the cost of waste water treatment. The share of waste treatment is comparatively small, 0 to 4.4%; however, figures are available only for the firms that have end-of-pipe emission treatment facilities.

Table 2: Mean cost share of each input by industry

Industry	No of Firms	Raw material	Labour	Power	Service and maintenance	Waste water treatment
Chemical	6	0.607	0.235	0.092	0.065	0.001
Food	12	0.666	0.147	0.133	0.051	0.002
Beverages	5	0.509	0.242	0.123	0.092	0.035
Livestock farms	10	0.674	0.232	0.018	0.032	0.044
Vehicle service	25	0.469	0.375	0.038	0.083	0.034
Textile &leather	8	0.463	0.351	0.090	0.069	0.027
Mineral	5	0.773	0.109	0.093	0.021	0.004
Waste recycling	3	0.434	0.329	0.045	0.192	0.000
Total	74	0.561	0.276	0.070	0.069	0.024

5. Empirical results

In this section we report shadow price estimates, abatement cost estimates under different policy scenarios and the technical efficiency scores obtained from PLP

5.1 Shadow prices

We computed shadow prices for the undesirable outputs (BOD, COD and TSS) using the parameters (Table A.1) of the input distance function estimated by PLP. This was done using the shadow prices ratios as illustrated in the Eq. (8). The shadow price values are based on the marginal rate of transformation between undesirable and desirable outputs. Therefore, these values can be interpreted as marginal cost for pollution abatement for industries. On average, the cost of abatement of a kilogram of undesirable outputs is found to be US$ 25.48 for BOD, US$ 14.76 for COD and US$ 13.39 for TSS (Table 3).

Table 3: Shadow pricesof BOD, COD and TSS (US$/ kg)

Industry	No. of firms	BOD		COD		TSS	
		Median	Mean	Median	Mean	Median	Mean
Chemical	6	16.57	43.26	6.22	15.74	6.61	10.60
Food	12	1.83	13.20	2.02	6.13	2.02	12.73
Beverages	5	.0008	60.11	0.01	65.22	0	0.00
Livestock farms	10	0.825	40.37	5.72	11.13	0.49	1.55
Vehicle service	25	2.51	12.85	5.68	12.52	7.46	19.61
Textile and leather	8	3.86	26.65	2.52	5.66	6.42	13.83
Mineral	5	18.4	42.30	7.24	24.95	7.13	19.31
Waste recycling	3	0.506	5.76	0.01	1.49	1.03	25.73
Total	74	3.02	25.48	4.41	14.76	3.24	13.59

The shadow prices show a wide variation across firms: US$ 0 to 325.5 for BOD, US$ 0 to 251.8 for COD and US$ 0 to 168.37 for TSS. Fig: 2 depicts the distribution of shadow prices for the three pollutants. The graph shows that shadow prices for three pollutants are within the range of 0-20 for majority of firms.

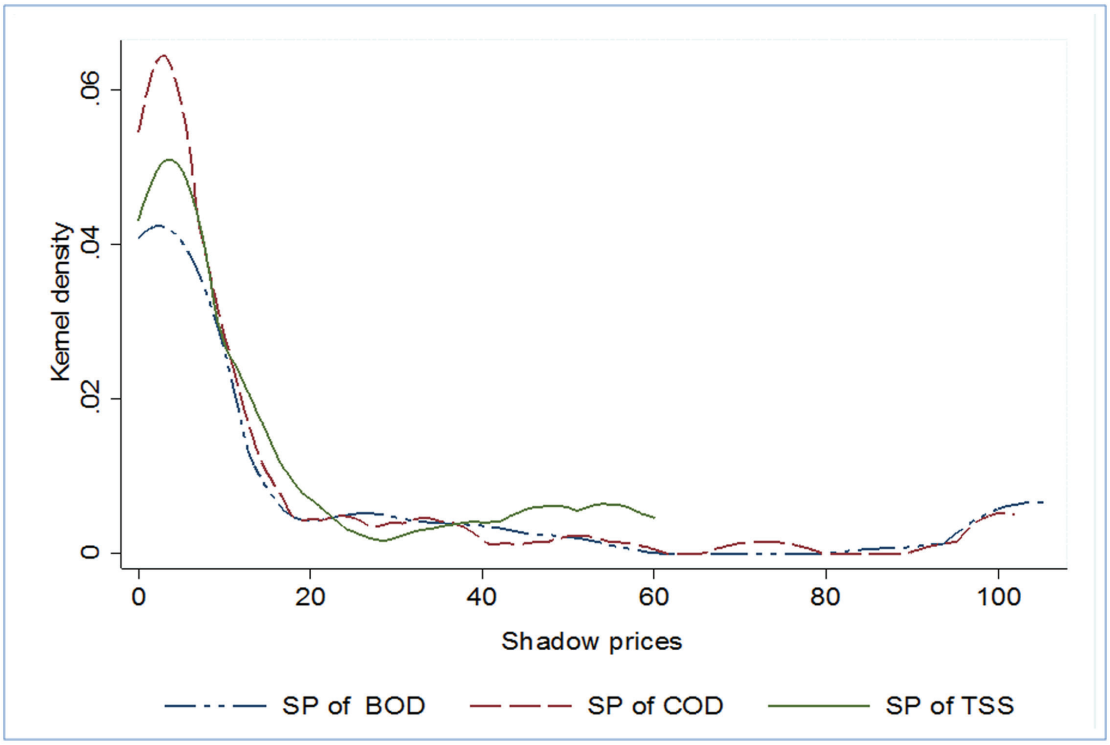

Fig 2: Kernel distribution of shadow prices

We undertook further an empirical analysis to understand the main reasons for variations in shadow prices of BOD (Table B.1). The variation can be explained by the fact that our sample firms comes from different industries. For example, compared to vehicle servicing firms, the shadow price for beverages and livestock firms is significantly higher. The variation of shadow prices of firms within the same industry is due to scale of operations and the compliance to environmental regulations even though all firms are operating under the same regulatory emission standards. Firms with bigger pollution loads tend to have lower shadow prices. However, whether a firm categorised by the CEA as a higher polluter was not found to be statistically significant in explaining the pollution load variations. We undertook similar analyses for COD and TSS and found the same set of variables significantly influencing the shadow prices.

Firms that are already complying with standards have very high shadow prices for all three water pollutants (Table 4). This is partly due to the use of inefficient abatement technologies. The high shadow prices for complying firms imply that further reduction of pollutants is very costly for those firms. The mean shadow price for firms that do not adhere to existing standards is US$ 6.40, US$ 7.32 and US$ 9.75 for BOD, COD and TSS, respectively.

Table 4: Number of firms and shadow pricesby compliance to the existing concentration standards

	Compliant firms			Non-compliant firms		
	BOD	COD	TSS	BOD	COD	TSS
Number of firms (n)	27	40	38	47	34	36
Mean shadow price (US$/ kg)	58.70 (16.25)*	21.10 (6.85)	17.25 (4.55)	6.40 (2.26)	7.32 (2.00)	9.75 (2.71)

* Standard deviations are reported in brackets

5.2 Abatement cost under different policy scenarios

The results presented above provide information on abatement costs at the margin, given existing compliance patterns. It is also possible to use the estimated distance function to derive abatement cost curves under different levels of pollution. The cost curves can be generated for individual pollutants or a simultaneous reduction of pollutants. For each firm, we simulated the marginal abatement cost of simultaneous reductions under the assumption that the firm's efficiency level would remain the same. Given the fact that the current regulation on effluent discharge to the water bodies based on concentration standards, we simulated total cost for firms to meet a range of concentration standards. One of the scenarios considered is a reduction of actual effluent concentration levels to what the current standards require (Scenario 9). The figures for this and eight other scenarios are summarised in Table 5, which includes figures indicating the magnitude of these costs as percentage of total production cost and as a percentage of total revenue for all the firms in the sample. We also record the corresponding loads of BOD, COD and TSS for each concentration level based scenarios.

Table 5: Abatement cost simulations for policy scenarios based on simultaneous reduction of three pollutants.

Policy Scenarios	Concentration levels (mg/l)			Abatement as a % of effluent loads			Overall abatement cost (Million US$)	Abatement as a % of total production cost	Abatement as a %of total revenue
	BOD	COD	TSS	BOD	COD	TSS			
1	200	500	250	72	23	57	0.09	0.06	0.03
2	180	450	200	73	25	59	0.11	0.07	0.03
3	150	400	180	75	27	59	0.12	0.08	0.03
4	130	380	150	76	28	61	0.13	0.08	0.04
5	110	350	130	77	29	62	0.14	0.09	0.04
6	90	320	110	78	30	63	0.16	0.10	0.05
7	70	300	90	79	31	64	0.17	0.11	0.05
8	50	270	70	80	32	65	0.20	0.13	0.06
9	30*	250*	50*	81	33	67	0.23	0.15	0.07

* Indicates the current effluent standards for discharging waste water to inland water bodies

The cost estimates on overall industrial pollution treatment is not available in Sri Lanka. In India, the cost of water pollution treatment would account for 2.5 per cent of the industrial GDP (Kumar & Murty, 2011). A study on rubber industry conducted in Sri Lanka using data from 2003-2005 found that the pollution tax required to bring an average firm to compliance would be 8.7 percent of average annual turnover (Edirisinghe, 2014). Compared with these figures it is apparent that the overall cost for non-complying firms (in our sample) to meet the current regulatory standard is very low (0.15 per cent of total production cost and 0.07 percent of the industrial revenue).

However, given the heterogeneity of firms and MAC, especially small firms and firms with high MAC cost would pay higher cost than the average values suggest.

The total abatement cost is comparatively high in the case of current concentration standards; 0.06 per cent of the total cost and 0.15 per cent of the total revenues for the firms. As scale economies exist in pollution reduction, firms could save if they are allowed to first meet less stringent concentration standards. For example, lifting concentration standards from scenario 1 to 9, would reduce the costssignificantly (Figure 3). The policy scenario 1 shows the pre-treatment standards of some common central waste treatment plants with considerably lower costs compared with existing emission standards. As the industries face higher individual costs in treating waste to very low concentrations, there would be a potential for cost saving if firms treat their waste to pre-treatment standards and direct the discharges to a common treatment plant. This would be a relatively low cost action to improving concentration levels from their current levels. However, currently this option is available only in certain industrial parks and areas of the country.

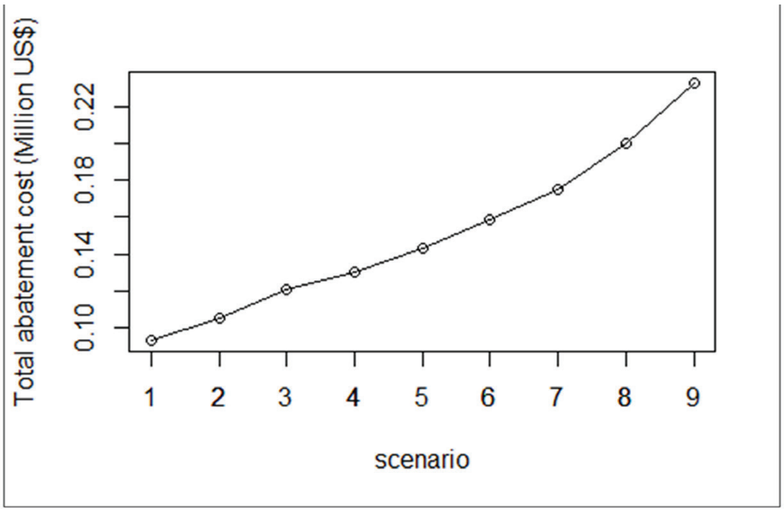

Fig 3: Total abatement cost and the policy scenarios [7]

5.3 Technical efficiency

The measures on technical (input) efficiency using input distance function frontiers are summarized by industry in Table 6. In general, technical efficiency estimates are low for all water polluting industries in the sample, indicating that there is untapped potential for efficiency improvement. The mean technical efficiency is 35 per centimplying that there is a substantial room for cost savings by reducing inputs while keeping the outputs constant.

Table 6: Input efficiency based on parametric input distance functions

Industry	No of Firms	Efficiency	
		Mean	Median
Chemical	6	0.2671	0.1275
Food	12	0.2885	0.1589
Beverages	5	0.3106	0.1863
Livestock farms	10	0.4442	0.2968
Vehicle service	25	0.3938	0.3431
Textile and leather	8	0.1719	0.1322
Mineral	5	0.3438	0.2164
Waste recycling	3	0.6343	0.8259
Total	74	0.3500	0.2366

[7] The scenarios are based on concentration levels of pollutants and corresponding pollution loads, as reported in Table 5.

We carried out an empirical analysis of technical scores with industry categories, pollution category and degree of compliance to current regulation on concentration standards (Table B.2). Compared to vehicle services, food and textile industries found to be significantly less efficient. Higher the degree of compliance, lower the efficiency of firms.

6. Conclusions and policy implications

Controlling water pollution in inland water bodies is one of the key challenges in developing countries given the dependence on surface water for drinking, industrial use, irrigation and recreational uses. Despite continuous deterioration of surface water quality, in many of these countries, environmental regulations are not linked to surface water quality objectives as is the case in Sri Lanka. In this study, we examined existing regulations on industrial water pollution, its cost implications and incentives for compliance by industries.

First, we investigated the cost of pollution for a representative sample of firms belonging to eight types of water polluting industries located in the Kelani river catchment. These industries operate under regulatory standards on emission concentrations but only 29 per cent of them are compliant with the standards. Using parametric input distance functions, we estimated industry and firm specific shadow prices (marginal costs) of water pollutants. Our results reveal a wide variation in shadow prices among firms and also firms within the same industry. The variation of firm-specific shadow prices are due to differences in scale of operation and heterogeneity of pollution abatement technologies. The compliance with existing standards also contributes to the differences. Shadow price estimates for all three pollutants (BOD, COD and TSS) are significantly higher for the compliant firms compared to non-complaint firms implying that further reduction of pollutants is more costly for complying firms.

Second, we simulated the potential total abatement cost for the firmsunder different policy scenarios for simultaneous reduction of concentrations s including current regulation on three water pollutants. The overall abatement cost to bring non-complying firms to compliance is not very high considered as a percentage of total firm production cost and revenues. However, small firms and the firms with high marginal cost would have to pay high cost for abatement than average values suggest. As marginal cost increases with lower concentration levels, firms with comparatively lower emission concentrations face higher costs. Therefore, having uniform concentrations standards across all firms may not yield optimal results in terms of minimizing cost. Hence, the cost heterogeneity among firms makes a strong case for market based instruments such as effluent discharge tax that equalize marginal abatement cost among all polluting firms and provide least cost solution while achieving pollution reduction targets.

Third, we examine the technical efficiency of firms and found that average efficiency is 35 per cent. This means the manufacturing firms can reduce 65 per cent of their inputs while keeping their current production constant. We also found that the firm efficiency is negatively related to the degree of compliance to current regulation; implying that there is no incentives for firms to comply.

The evidence on poor compliance and wide variations in shadow prices (MAC) makes a strong case for a new design of comprehensive environmental policy to control industrial pollution as an alternative to existing command and control regulations. The shadow price estimates can be used as guidelines to design market based policy instruments such as emission-based taxes or tradeable permits that would cap the level of pollution released into the river. The case for a serious consideration of alternative approaches is made stronger by the evidence of weak enforcement of current regulations. Therefore, setting appropriate economic instruments would provide incentives for firms to control emissions in socially optimum ways without imposinga greater burden on complying firms.

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Appendix A

Table A1 : Parametric estimates of input distance function for water polluting firms in Sri Lanka

Variable	Parameters	Values
lny1	$\propto 1$	-0.7923
lnx1	$\propto 2$	0.4261
lnx2	$\propto 3$	0.1110
lnx3	$\propto 4$	0.0550
lnx4	$\beta 1$	0.4078
lnb1	$\beta 2$	0.0002
lnb2	$\beta 3$	0.0014
lnb3	$\beta 4$	0.0002
lny1y1	$\propto 11$	-0.0932
lny1x1	$\propto 22$	-0.0106
lny1x2	$\propto 33$	0.0336
lny1x3	$\propto 44$	0.0135
lny1x4	$\propto 12$	-0.0365
lny1b1	$\propto 13$	0.0000
lny1b2	$\propto 14$	-0.0003
lny1b3	$\propto 23$	-0.0001
lnx1x1	$\propto 24$	0.0545
lnx2x1	$\propto 34$	-0.0431
lnx3x1	$\beta 11$	-0.0077
lnx4x1	$\beta 22$	-0.0037
lnb1x1	$\beta 33$	-0.0001
lnb2x1	$\beta 44$	0.0004
lnb3x1	$\beta 12$	0.0000
lnx2x2	$\beta 13$	-0.0209
lnx3x2	$\beta 14$	-0.0098
lnx4x2	$\beta 23$	0.0739
lnb1x2	$\beta 24$	0.0001
lnb2x2	$\beta 34$	0.0000
lnb3x2	$\gamma 11$	0.0000
lnx3x3	$\gamma 12$	0.0192
lnx4x3	$\gamma 13$	-0.0017
lnb1x3	$\gamma 14$	-0.0002
lnb2x3	$\gamma 21$	-0.0005
lnb3x3	$\gamma 22$	0.0000
lnx4x4	$\gamma 23$	-0.0685
lnb1x4	$\gamma 24$	0.0003
lnb2x4	$\gamma 31$	0.0002
lnb3x4	$\gamma 32$	-0.0001
lnb1b1	$\gamma 33$	-0.0001
lnb2b1	$\gamma 34$	0.0001
lnb3b1	$\gamma 41$	0.0000
lnb2b2	$\gamma 42$	-0.0004
lnb3b2	$\gamma 43$	0.0002
lnb3b3	$\gamma 44$	-0.0002
Intercept	$\propto 0$	2.4205

Y1 : Total Sales (SLRs. Millions)
b1: BOD (tonnes)
b2: COD (tonnes)
b3: TSS (tonnes)

x1: Cost of raw material
x2: Cost of labour
x3: Cost of power
x4: Cost of service and maintenance

Appendix B

Table B.1

Dependant variable: Shadow price of BOD (USD/kg) **Adjusted R^2 =0.2524**

Variable	Coefficient	Std. Err.	P>t
High polluters (A)	-4.083	15.824	0.797
Water consumption (in 1000 m^3)	-0.009**	0.003	0.002
Industrial category			
Chemical	18.097	25.184	0.475
Food	25.371	19.746	0.204
Beverages	105.770**	33.373	0.002
Livestock	47.466*	20.405	0.023
Mineral	11.773	26.859	0.663
Textile	30.970	23.142	0.186
Waste recycling	24.668	33.580	0.465
Compliance with BOD standard	72.993***	15.621	0.000
Constant	-15.685	14.610	0.287

Table B.2

Dependant variable: Firm efficiency **Adjusted R^2 =0.0557**

Variable	Coefficient	Std. Err.	P>t
High polluters (A)	0.015	0.095	0.872
Industrial category			
Chemical	-0.124	0.138	0.372
Food	-0.325**	0.145	0.029
Beverages	-0.080	0.148	0.589
Livestock	-0.227	0.175	0.199
Mineral	-0.005	0.145	0.973
Textile	-0.326**	0.141	0.024
Waste recycling	0.007	0.216	0.975
Degree of compliance to standards	-0.004 *	0.002	0.050
Constant	0.725 ***	0.162	0.000

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