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Measuring the CO_2 shadow price for wastewater treatment: A directional distance function approach

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HIGHLIGHTS

- The shadow price of CO_2 informs about the marginal abatement cost of this pollutant.
- It is estimated the shadow price of CO_2 for wastewater treatment plants.
- The shadow prices depend on the setting of the directional vectors of the distance function.
- Sewage sludge treatment technology affects the CO_2 shadow price.

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ABSTRACT

The estimation of the value of carbon emissions has become a major research and policy topic since the establishment of the Kyoto Protocol. The shadow price of CO_2 provides information about the marginal abatement cost of this pollutant. It is an essential element in guiding environmental policy issues, since the CO_2 shadow price can be used when fixing carbon tax rates, in environmental cost-benefit analysis and in ascertaining an initial market price for a trading system. The water industry could play an important role in the reduction of greenhouse gas (GHG) emissions. This paper estimates the shadow price of CO_2 for a sample of wastewater treatment plants (WWTPs), using a parametric quadratic directional distance function. Following this, in a sensitivity analysis, the paper evaluates the impact of different settings of directional vectors on the shadow prices. Applying the Mann–Whitney and Kruskal–Wallis non-parametric tests, factors affecting CO_2 prices are investigated. The variation of CO_2 shadow prices across the WWTPs evaluated argues in favour of a market-based approach to CO_2 mitigation as opposed to command-and-control regulation. The paper argues that the estimation of the shadow price of CO_2 for non-power enterprises can provide incentives for reducing GHG emissions.

1. Introduction

One of the biggest global challenges related to environmental pollution is the climate change induced mainly by anthropogenic emissions of CO_2, methane and other greenhouse gases (GHG) [1]. The construction and operation of water utilities, while it is not the main source of GHG emissions, contributes to climate change [2]. In particular, the energy consumed and, consequently, the indirect GHG emitted by wastewater treatment plants (WWTPs) has grown considerably in the recent past as a result of increases in the volume of wastes treated and because of the implementation of new processes aimed at achieving higher effluent quality [3].

It is certainly true that some governments have already realised the important role that the wastewater treatment industry might play in the reduction of GHG emissions. For example, it is likely that the water industry in Canada will become subject to a carbon levy (a carbon tax is already in place in Quebec and British Columbia). Because the reduction of the carbon footprint of WWTPs is not just an environmental issue but also an economic one, a carbon cost levied on electricity derived from fossil fuels will create an

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incentive for WWTP operators to implement systems that aim to balance several sustainability objectives including minimising carbon emissions and minimising operational costs [2].

Infrastructure investments in sanitation and wastewater treatment are almost always the responsibility of governments. To facilitate an efficient use of resources, any investment should be preceded by a cost-benefit analysis (CBA) [4]. A CBA considers all the benefits and costs derived from a project, including those without a market value. According to the Water Framework Directive (EU Directive 60/2000/EU), CBA is the approach to be followed for assessing the economic feasibility of projects related to water management. In this context, previous studies have identified and quantified the positive environmental externalities of wastewater treatment, using different methodologies [5–8]. However, WWTPs also involve negative environmental externalities, such as the GHG emissions associated with electricity consumption. The economic value of these emissions must be integrated into the CBA or there will be an over-estimation of the benefits of wastewater treatment. This necessarily involves the quantification of the value of CO_2.

The estimation of CO_2 values has become a major research topic since the United Nations Framework Convention on Climate Change (UNFCC) established the Kyoto Protocol in 1997 [9]. Two main approaches have been used to derive a carbon emissions value: a direct approach, which is based on the establishment of the costs of the social damage of emitting an extra tonne of carbon, and an indirect approach, where the value is derived from an estimation of the shadow price of the carbon, in the form of the marginal abatement costs of cutting CO_2.

The social cost of carbon (SCC) is the marginal present value of the future costs caused by additional GHG emissions [10]. In other words, the SCC compares the damage done by one more tonne of CO_2 emissions with a baseline context in which those emissions do not increase [11]. In recent years, many studies have attempted to estimate the SCC using a range of approaches [12]. The approach that estimates the shadow price of CO_2 assumes that policies already implemented create a cost per unit of emission for regulated agents [4]. Economic theory suggests that the equilibrium permit price in a well-functioning carbon market should be equivalent to the marginal abatement cost [13].

After a systematic review of the direct and indirect approaches to estimating CO_2 values, Mandell [4] concluded that, although both approaches are necessary, the indirect approach (i.e., shadow price estimation) should be the primary tool for the CBA of infrastructure projects. Hence, our study is focused on the estimation of the CO_2 shadow price for the wastewater treatment industry.

In an ideal world, emission trading could be designed in such a way that allows the achievement of the desirable reduction of emissions [14]. However, there is a range of factors, such as transaction costs and asymmetric information, that complicate the operation of emission trading. These difficulties are relevant for the water industry, for which the CO_2 emissions are relatively low compared with other sectors such as transport or energy production. Hence, other measures to reduce energy consumption and consequently GHG emissions are needed. In this context, information on CO_2 marginal abatement costs across sources is critical for both policy makers and water utility managers. To overcome this limitation, and within the framework of studies into production efficiency, Färe et al. [15] developed a methodology to derive the shadow prices of both desirable and undesirable outputs (emissions), based on the concept of a distance function. The shadow price that is derived reflects the trade-off between the desirable and the undesirable outputs, and can be interpreted as the marginal abatement cost arising from regulations that prevent the free disposal of pollutants.

Several applications have used this approach to estimate the shadow price of different pollutants, such as the sulphur dioxide emissions resulting from the manufacture of electrical appliances [16,17], the waste generated by the ceramics industry [18], water pollutants from several industries [19] and the CO_2 emitted by electrical power plants in Korea [20]. Following the same methodological approach, other studies have utilised a directional distance function (instead of a distance function) to estimate the shadow price of pollutants [21,22,13]. A summary of the existing studies in this field is provided by Zhou et al. [23]. While the distance function assumes a proportional adjustment for all outputs (desirable and undesirable) [24], the directional distance function allows a simultaneous expansion of desirable outputs and contraction of undesirable outputs [25]. Therefore, in the presence of undesirable outputs under regulation, the directional distance function is more suitable for measuring performance [26,27]. The main weakness of this approach is that the shadow prices of undesirable outputs vary crucially with the choice of the directional vectors [28].

With regard to water utilities, some recent studies have utilised both the distance function and the directional distance function to estimate the shadow prices of the main contaminants removed in WWTPs [6]. In this context, a shadow price for the undesirable outputs was considered to be equivalent to the environmental damage that would have been caused by the discharge of such water pollutants into water bodies. Following the same approach, the shadow price of CO_2 can be interpreted as the value of the negative externalities associated with the use of energy for treating wastewater.

Most previous studies estimating the shadow price of CO_2 in this way have focused on coal, fossil fuel and thermal power plants in Korea [29,20], Japan [30], the US [31,32], India [33] and China [13,34]. However, because of the increasing importance of CO_2 emissions, the shadow price of this pollutant has been estimated not just for the energy production industry but also for other sectors such as dairy firms [9], agriculture [35,36] and transport [37].

This paper is the first to estimate the CO_2 shadow price associated with energy consumption in WWTPs. The directional distance function in quadratic form is used to quantify this CO_2 shadow price for a sample of 25 Spanish WWTPs. Subsequently, as a sensitivity analysis, we evaluate the impact of different directional vector settings on the shadow prices. We conclude with an analysis of the factors affecting CO_2 shadow prices.

From a policy perspective, the results of our research are expected to be of great interest and use to decision makers as a decision support tool, since they provide the first CO_2 shadow price estimates in the framework of WWTPs. Being able to assess the marginal abatement costs is an important first step in environmental policy issues, since these costs can be used when fixing carbon tax rates and ascertaining an initial market price for a trading system [15,13]. In other words, information about marginal abatement costs helps in choosing the most efficient burden-sharing rule and abatement mechanism. One of the marked advantages of the approach followed in this study is that it shows the variability of CO_2 shadow prices across facilities. According to Wei et al. [13], "the mean marginal abatement cost could be used to predict an initial permit price, and the variance could be observed by decision makers to determine whether emission trading is worthwhile".

2. Methodology

The estimation of the shadow price of CO_2 was carried out following the methodological approach of Färe et al. [38], which is based on the directional distance function. Hence, we first introduce the directional distance function and then derive the shadow prices.

The directional distance function is a generalisation of Shephard's output distance function [24]. The traditional output distance function expands both desirable and undesirable outputs to the production frontier. On the other hand, the directional distance function allows for the simultaneous expansion of desirable outputs and contraction of undesirable outputs [39].

The directional distance function is introduced as a representation of the production model. We denote the inputs by $x = (x_1, \ldots, x_N) \in R_+^N$, the desirable outputs by $y = (y_1, \ldots, y_M) \in R_+^M$, and the undesirable outputs by $b = (b_1, \ldots, b_J) \in R_+^J$. The technology is represented by the output sets $P(x), x \in R_+^N$ where:

$$P(x) = \{(y, b) : x \ can \ produce (y, b)\} \tag{1}$$

Apart from the standard assumptions of convex, compact and freely disposal inputs, the following additional assumptions are imposed on the output set. First, it is assumed that the undesirable outputs are produced jointly with the desirable outputs. In other words, if a (y, b) combination is feasible and no undesirable output is produced, it must be the case that no desirable output is produced. Formally, if $(y, b) \in P(x)$ and $b = 0$, then $y = 0$. Second, it is assumed that the undesirable outputs and the desirable outputs satisfy joint weak disposability, i.e., if $(y, b) \in P(x)$ and $0 \leqslant \theta \leqslant 1$ then $(\theta y, \theta b) \in P(x)$. This assumption means that any proportional reduction of the desirable and undesirable outputs together is feasible. In other words, any reduction of undesirable outputs involves a cost. Third, it is assumed that desirable outputs by themselves are freely disposable. This means that it is possible to reduce the desirable outputs without reducing the undesirable outputs. Formally, if $(y, b) \in P(x)$, then for $y' \leqslant y, (y', b) \in P(x)$.

Taken into account the above assumptions, the directional output distance function represents the production technology and it is defined as follows [25]:

$$\overrightarrow{D_o}(x, y, b; g_y, g_b) = \max\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \tag{2}$$

where $g = (g_y, -g_b)$ is the directional vector that specifies the direction of the output vector and is always positive ($g > 0$). The directional output distance function contracts b and expands y along the g direction until it hits the boundary of $P(x)$ at $(b - \beta^* g_b, y + \beta^* g_y)$ where $\beta^* = \overrightarrow{D_o}(x, y, b; g)$. The distance β is non-negative ($\beta \geqslant 0$).

The directional distance function inherits its properties from the output possibility set $P(x)$. According to Bellenger and Herlihy [40], these properties include:

(a) $\overrightarrow{D_o}(x, y, b; g_y, g_b) \geqslant 0$ if and only if (y, b) is an element of $P(x)$.
(b) $\overrightarrow{D_o}(x, y', b; g_y, g_b) \geqslant \overrightarrow{D_o}(x, y, b; g_y, g_b)$ for $(y', b) \leqslant (y, b) \in P(x)$.
(c) $\overrightarrow{D_o}(x, y, b'; g_y, g_b) \leqslant \overrightarrow{D_o}(x, y, b; g_y, g_b)$ for $(y, b') \leqslant (y, b) \in P(x)$.
(d) $\overrightarrow{D_o}(x, \theta y, \theta b; g_y, g_b) \geqslant 0$ for $(y, b) \in P(x)$ and $0 \leqslant \theta \leqslant 1$.
(e) $\overrightarrow{D_o}(x, y, b; g_y, g_b)$ is concave in $(y, b) \in P(x)$.
(f) $\overrightarrow{D_o}(x, y + \alpha g_y, b - \alpha g_b; g_y, g_b) = \overrightarrow{D_o}(x, y, b; g_y, g_b) - \alpha, \quad \alpha \in \Re$.

Property (a) states that the directional distance function is non-negative for feasible output vectors. Property (b) is a monotonicity property corresponding to the strong disposability of desirable outputs. Similarly, property (c) is a monotonicity property and means that if undesirable outputs increase, while inputs and desirable outputs are held constant, inefficiency does not decrease. Property (d) corresponds to the weak disposability of desirable and undesirable outputs. The concavity property (e) allows define the sign of the elasticity of substitution of the outputs. Lastly, property (f) refers to translation. This property means that if an undesirable output is contracted by αg_b and a desirable output is expanded by αg_y, the value of the resulting directional distance function will be more efficient by the amount α (α is a positive scalar) [21].

To derive the shadow price the duality relationship between the output-oriented distance function and the revenue function is used [15,38]. Let $p = (p_1, \ldots, p_M) \in R_+^M$ represent desirable output prices and let $q = (q_1, \ldots, q_J) \in R_+^J$ represent undesirable output prices. The revenue function in terms of the directional distance function is defined as [38]:

$$R(x, p, q) = max_{y,b}\{py - qb : (y, b) \in P(x)\} \tag{3}$$

The revenue function determines the largest feasible revenue obtainable when the unit is faced with desirable output prices p and undesirable output prices q. Thus, given a feasible directional vector $g = (g_y, -g_b)$, the revenue function (Eq. (3)) can be written as:

$$R(x, p, q) \geqslant (py - qb) + p \cdot \overrightarrow{D_o}(x, y, b; g) \cdot g_y + q \cdot \overrightarrow{D_o}(x, y, b; g) \cdot g_b \tag{4}$$

The left side of Eq. (4) informs about the maximal feasible revenue. The right side is the observed revenue plus the technical efficiency improvement. The gain in technical efficiency can be decomposed into the gain due to an increase in desirable outputs along g_y and the gain associated to a decrease in undesirable outputs along g_b.

Based on the relationship of duality between the distance function and the revenue function [24], the directional distance function in terms of maximal revenue function are related as shown in Eq. (5):

$$\overrightarrow{D_o}(x, y, b; g) = \frac{R(x, p, q) - (py - qb)}{pg_y - qg_b} = min_{p,q}\left\{\frac{R(x, p, q) - (py - qb)}{pg_y - qg_b}\right\} \tag{5}$$

Eq. (5) is an un-constrained minimisation problem. Assuming that Eq. (2) (directional distance function) and Eq. (3) (revenue function) are differentiable, the first-order condition with respect to desirable output is Eq. (6) and with respect to undesirable outputs is Eq. (7):

$$\nabla_y \overrightarrow{D_o}(x, y, b; g) = \frac{-p}{pg_y - qg_b} \tag{6}$$

$$\nabla_b \overrightarrow{D_o}(x, y, b; g) = \frac{q}{pg_y - qg_b} \tag{7}$$

Assuming that the market price of the mth good output equals its shadow price p_m, the shadow price of the jth undesirable output is derived from the ratio of Eq. (6) to Eq. (7), as follows:

$$q_j = -p_m \cdot \left(\frac{\partial \overrightarrow{D_o}(x, y, b; g)}{\partial b_j} \Big/ \frac{\partial \overrightarrow{D_o}(x, y, b; g)}{\partial y_m}\right) \tag{8}$$

To estimate the unknown parameters, all inputs and outputs variables are normalised. Hence, to compute the shadow price in Eq. (8) one needs to multiply the ratio of the mean value of y by the mean value of b [21].

The directional distance function can be estimated by following either a parametric or a non-parametric approach. The main advantage of the non-parametric methods is that it is not necessary to define the functional form. However, since our study focuses on the shadow price of undesirable outputs, the parametric specification is required because of its differentiability. Moreover, non-parametric approaches have other problems, such as how outliers are dealt with [41]. Because the quadratic function satisfies the translation property and is twice differentiable, it was used to set the parameters for the directional distance function [38,6,13].

The directional vector $g = (1, -1)$ is chosen since we are seeking the simultaneous expansion of good outputs and reduction of undesirable outputs. Assuming $k = 1, \ldots, K$ units (water utilities in our case study), $n = 1, \ldots, N$ inputs, $m = 1, \ldots, M$ desirable outputs and $j = 1, \ldots, J$ undesirable outputs, the quadratic directional distance function for the unit k is:

$$\begin{aligned} \overrightarrow{D_o} &= (x_k, y_k, b_k; 1, -1) \\ &= \alpha + \sum_{n=1}^{N} \alpha_n x_{nk} + \sum_{m=1}^{M} \beta_m y_{mk} + \sum_{j=1}^{J} \gamma_j b_{jk} + \frac{1}{2} \sum_{n=1}^{N} \sum_{n'=1}^{N} \alpha_{nn'} x_{nk} x_{n'k} \\ &\quad + \frac{1}{2} \sum_{m=1}^{M} \sum_{m'=1}^{M} \beta_{mm'} y_{mk} y_{m'k} + \frac{1}{2} \sum_{j=1}^{J} \sum_{j'=1}^{J} \gamma_{jj'} b_{jk} b_{j'k} \\ &\quad + \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{nm} x_{nk} y_{mk} + \sum_{n=1}^{N} \sum_{j=1}^{J} \eta_{nj} x_{nk} b_{jk} + \sum_{m=1}^{M} \sum_{j=1}^{J} \mu_{mj} y_{mk} b_{jk} \end{aligned} \tag{9}$$

Following the work of Aigner and Chu [42], the unknown parameters in Eq. (9) are estimated using linear programming. The parameters of the quadratic function are chosen to minimise the sum of the distance between the frontier technology and each unit evaluated.

$$\begin{aligned} &\mathit{Minimize} \sum_{k=1}^{K} [\overrightarrow{D_o}(x_k, y_k, b_k; 1, -1) - 0] \\ &s.t. \\ &\text{(i)} \quad \overrightarrow{D_o}(x_k, y_k, b_k; 1, -1) \geqslant 0, \quad k = 1, \ldots, K \\ &\text{(ii)} \quad \frac{\partial \overrightarrow{D_o}(x_k, y_k, b_k; 1, -1)}{\partial b_j} \geqslant 0, \quad j = 1, \ldots, J; k = 1, \ldots, K \\ &\text{(iii)} \quad \frac{\partial \overrightarrow{D_o}(x_k, y_k, b_k; 1, -1)}{\partial y_m} \leqslant 0, \quad m = 1, \ldots, M; k = 1, \ldots, K \\ &\text{(iv)} \quad \frac{\partial \overrightarrow{D_o}(\bar{x}, y_k, b_k; 1, -1)}{\partial x_n} \geqslant 0, \quad n = 1, \ldots, N \\ &\text{(v)} \quad \sum_{m=1}^{M} \beta_m - \sum_{j=1}^{J} \gamma_j = -1; \sum_{m'=1}^{M} \beta_{mm'} - \sum_{j=1}^{J} \mu_{mj} = 0, \quad m = 1, \ldots, M \\ &\quad \sum_{j'=1}^{J} \gamma_{jj'} - \sum_{m=1}^{M} \mu_{mj} = 0, \quad j = 1, \ldots, J \\ &\quad \sum_{m=1}^{M} \delta_{nm} - \sum_{j=1}^{J} \eta_{nj} = 0, \quad n = 1, \ldots, N \\ &\text{(vi)} \quad \alpha_{nn'} = \alpha_{n'n} n \neq n'; \quad \beta_{mm'} = \beta_{m'm} m \neq m'; \quad \gamma_{jj'} = \gamma_{j'j} \ j \neq j' \end{aligned} \tag{10}$$

The restriction (i) imposes feasibility, i.e., it requires the output–input vector to be feasible for the k units. The restrictions in (ii) and (iii) impose the monotonicity conditions. The restriction (iv) involves positive monotonicity of the inputs for the mean level of input usage. The restrictions in (v) are due to the translation property.[1] The restriction (vi) imposes symmetry conditions [38].

3. Data and variables

The shadow price for GHG – expressed as a CO_2 equivalent – is estimated for a sample of Spanish wastewater treatment plants (WWTPs) that aim to produce effluent suitable for discharge into water bodies. According to Hernández-Sancho et al. [5] and Molinos-Senante et al. [44], Molinos-Senante et al. [6], WWTPs can be considered as carrying out a productive process in which a desirable output (treated water) is obtained from inputs (costs).

The first step in estimating the shadow price of CO_2 is to define the inputs, the desirable outputs and the undesirable output. Three relevant inputs were considered: (i) energy costs (x_1); (ii) staff costs (x_2); and (iii) other costs (x_3). All were expressed in € per year, and the sum of the three inputs is equal to the total costs of the wastewater treatment. In the assessment of the efficiency of the WWTPs, two measurements have previously been used to select the desirable output, namely volume of wastewater treated [45,46] and quantity of pollutants removed from the wastewater [47,48]. In this context, Rodriguez-Garcia et al. [49] illustrated that the cost of wastewater treatment depends on the quantity of pollutants removed. Hence, following Saal and Parker [50] and Saal et al. [51], a quality-adjusted desirable output was used.

We therefore briefly discuss the construction of this quality-adjusted output. The main pollutants removed from wastewater in conventional treatment are organic matter, measured as chemical oxygen demand (COD), suspended solids (SS), nitrogen (N) and phosphorus (P). For each WWTP an effectiveness indicator (EI) (Eq. (11)) was defined based on the removal efficiency (RE) (Eq. (12)) of these four main pollutants:

$$\mathrm{EI} = \frac{\sum_{n=1}^{4} RE_n}{4} \tag{11}$$

$$RE = \frac{[Z]_{inf} - [Z]_{eff}}{[Z]_{inf}} \tag{12}$$

where $[Z]_{inf}$ is the concentration of the pollutant Z in the influent and $[Z]_{eff}$ is the concentration of the pollutant Z in the effluent.

The desirable quality-adjusted output for a WWTP (y_1) is defined by using Eq. (13). It is the volume of wastewater treated (m^3/year) (V) adjusted by the efficiency in the removal of pollutants (EI).

$$y_1 = V * \mathrm{EI} \tag{13}$$

The undesirable output is the indirect emission of GHG expressed in kg of CO_2 equivalents (CO_2) per year. Based on IPCC Guidelines [52] direct CO_2 emissions have not been considered in the assessment. Hence, GHG emissions were quantified based on the energy demand of WWTPs and the Spanish national electrical production mix. Then by using 100-year global warming potential coefficients, these GHG emissions were converted to CO_2 emissions [1]. Specifically, the Spanish Energy White Book [53] reported that GHG emissions per kW h of produced electricity average 0.36 kg of CO_2 equivalent.

The sample used in this empirical application consists of 25 WWTPs located in Spain (Table 1). The statistical information was supplied for the year 2010 by the regional wastewater authority. The volume of wastewater treated in each of these WWTPs varies between 500,000 and 15,000,000 m^3/year. All the facilities feature secondary treatment including the removal of N and P, although they use different technologies: activated sludge, extended aeration and tertiary treatment. Moreover, 10 out of the 25 WWTPs evaluated are subject to seasonality, i.e., they only operate at full capacity during some months (three or four months during holiday periods), and so suffer problems of underuse during the rest of the year[2]. Sala-Garrido et al. [47], Sala-Garrido et al. [54] illustrated the technology of the WWTPs and how seasonality affects their efficiency. Therefore, in order to evaluate whether these features also affect the shadow price of CO_2, the sample data evaluated

[1] For other directions, see Chambers [43].

[2] Supplementary information provides more information about the process scheme of each WWTP.

Table 1
Descriptive statistics of WWTPs evaluated.

		WWTPs	
		Average	Deviation
Inputs (€/year)	Energy (x_1)	278,466	279,638
	Staff (x_2)	285,793	213,171
	Other (x_3)	287,231	261,566
Desirable output	Quality-adjusted wastewater treated (y_1)	2,863,318	3,439,065
Undesirable output (kg/year)	GHG (b_1)	639,224	704,182

embrace WWTPs with different secondary treatments and with different conditions regarding seasonality.

To conclude this section, it should be noted that, in line with the works of Färe et al. [21] and Wei et al. [13], all input and output variables were normalised by dividing them by their mean value. This normalisation means that all input and output variables are converted into an index. The aim is to overcome the convergence problem.

4. Results

4.1. Estimation of shadow price

To solve the linear problem (Eq. (10)) and estimate the parameters of the directional distance function we used GAMS (General Algebraic Modelling Software) with the CPLEX solver. The objective function that we need to minimise is for the 25 WWTPs evaluated. The values of the parameters of the quadratic function are shown in Table 2.

As it is shown in Eq. (8), the calculation of the shadow price of CO_2 for each WWTP involves assigning a reference price for the treated water (desirable output). Unlike drinking water, the value of treated water is not determined by the market unless that treated water is re-used. Hence, following the work of Molinos-Senante et al. [44], a value of 0.345 €/m^3 as the market price of treated water was employed. The shadow price of CO_2 can be expressed as a percentage of the price of the desirable output as shown in the second column of Table 3.

By using Eqs. (2), (8) and (9) described in methodology section, the shadow price of CO_2 for each of the 25 WWTPs estimated. According to Table 3, the shadow price of the CO_2 emitted by WWTPs is rather variable, since the minimum value is 5.0% of the price of the treated water while the maximum value is 34.6%. The average value is 17.7%, with a standard deviation of 8.4%. By considering the price of treated water to be 0.345 €/m^3 and taking into account the weight of CO_2 equivalents emitted by each cubic metre of treated water, the average shadow price of CO_2 is 0.088 €/kg and its standard deviation is 0.139 €/kg.

Traditionally, the shadow price of an undesirable output represents the opportunity cost of reducing the output by one unit in

Table 2
Parameter estimates of directional distance function.

Coefficient	Value	Coefficient	Value
α_0	−0.0625	α_{33}	−2.6587
α_1	−0.1929	$\alpha_{12} = \alpha_{21}$	0.6402
α_2	0.3762	$\alpha_{13} = \alpha_{31}$	0.5572
α_3	0.5290	$\alpha_{23} = \alpha_{32}$	1.5734
β_1	−0.5552	$\beta_{11} = \gamma_{11} = \mu_{11}$	0.0396
γ_1	0.4448	$\delta_{11} = \eta_{11}$	−0.0453
α_{11}	−0.4647	$\delta_{21} = \eta_{21}$	0.0000
α_{22}	−2.5889	$\delta_{31} = \eta_{31}$	0.0000

Table 3
Shadow price of the CO_2 equivalent expressed in% of the treated water price and expressed in €/kg.

WWTP	Shadow price of CO_2	
	%	€/kg
1	25.1	0.087
2	16.8	0.058
3	24.1	0.083
4	15.1	0.052
5	7.9	0.027
6	6.8	0.023
7	12.1	0.042
8	7.5	0.026
9	5.0	0.017
10	24.0	0.083
11	25.6	0.088
12	20.8	0.072
13	19.9	0.069
14	33.0	0.114
15	19.0	0.066
16	15.3	0.053
17	8.6	0.030
18	27.7	0.096
19	16.2	0.056
20	5.7	0.020
21	9.9	0.034
22	21.4	0.739
23	21.6	0.075
24	34.6	0.119
25	17.6	0.061
Average	17.7	0.088
Std.	8.4	0.139

terms of the forgone production of desirable output once inefficient production has been eliminated [16,34]. However, WWTPs involve a special productive process, since their aim is to avoid the discharge of pollutants into water bodies and since they have to treat all the wastewater that arrives at the facility. Because of this, Hernández-Sancho et al. [5] interpreted the shadow price of undesirable outputs as the economic value of the environmental externalities avoided by wastewater treatment. If we assume that the current pollution levels are optimal, the shadow price of CO_2 equivalents can be interpreted as an estimation of the environmental costs of using energy to treat the wastewater. Following this approach, according to the results presented in Table 3, in average terms each kg of CO_2 equivalents that is emitted into the atmosphere as the result of wastewater treatment involves an environmental cost of 0.088 € (17.7% of the value of the treated water).

There are no previous studies estimating the shadow price of the GHG associated with water utilities; most comparable studies have focused on coal, fossil fuel and thermal power plants [23]. Although it is not our intention to report on all the studies performed in this field, some of the results are as follows. Lee and Zhang [55] estimated the shadow price of CO_2 in 30 Chinese manufacturing industries. Their results showed that the shadow prices vary from 18.82 $/ton to below zero, with an average of 3.13 $/ton. Wei et al. [13] investigated the shadow prices of 124 Chinese power enterprises, and found that the mean shadow price for a representative power enterprise is $249 per ton. Du et al. [34] estimated the provincial shadow prices of CO_2 reductions in China. Their results showed an increase in CO_2 shadow prices from 1000 Yuan/ton in 2001 to 2100 Yuan/ton in 2010. Lee [56] estimated the shadow price of CO_2 for 52 power generation plants in the Korean fossil-fuelled electricity generation industry and suggested that, on average, the generators paid $14.63 to decrease CO_2 emissions by one ton. Matsushita and Asano [30] found that the shadow price of CO_2 of the Japanese electric power companies varies between $1.49 and $288.82 per ton of CO_2. In the very different context of agriculture and livestock, Berre et al. [9] found that the shadow price of GHG is 6.73% and 40.86% of the milk price from the perspective of the farmers and society respectively.

Although the energy production sector contributed 77% of the Spanish GHG emissions in 2011 [57], to the best of our knowledge, there has been no study assessing the shadow prices of CO_2 for power enterprises located in Spain. It should be noted that the treatment and disposal of waste (including wastewater) accounted for 3.96% of the total emissions. While this is a small percentage of the total emissions, it has increased over time: in 1990 the figure was just 2.59% [57]. Agriculture is also a sector that contributes to GHG emissions. In particular, in 2011 it accounted for 10% of the total Spanish GHG emissions. In this context, Bourne et al. [58] estimated that in agriculture the marginal abatement cost will be €86 per ton of CO_2 equivalents by 2020. Hence, although Bourne et al. [58] estimation and our estimation of shadow price of CO_2 are focused on different topics (agriculture and wastewater treatment), their values are rather similar. Nevertheless, the large standard deviation in both estimations should be taken into account. Moreover, it should be noted that our results are obtained from a sample of 25 WWTPs; therefore, we suggest caution in the interpretation of the CO_2 shadow prices.

4.2. Sensitivity test for directional vectors

Since the estimation of the shadow price is based on the directional distance function, the specification of the directional vector plays an essential role [13]. Two special directional vectors different to our first choice of $g = (1, -1)$ are: $g = (1, 0)$ and $g = (0, -1)$. The former describes increasing the desirable output while keeping the undesirable output constant, and can be expected to lead to lower shadow prices for the undesirable output. In our case study, it is equivalent to increasing the efficiency of removing pollutants while using the same quantity of energy. This approach can be interpreted as implementing a trend currently applied in Europe through the Water Framework Directive (Directive 2000/60/EU), which aims to achieve a good ecological status for water bodies. On the other hand, the directional vector $g = (0, -1)$ implies a reduction of the undesirable output at constant desirable output, and leads to a higher shadow price for the undesirable output than if the directional vector $g = (1, -1)$ is considered. In our case study, this scenario represents the perspective of the managers of WWTPs, since it involves a reduction in energy consumption, i.e., in operational costs, without a reduction in the quality-adjusted volume of wastewater treated.

Fig. 1 shows the variation intervals (represented by bars) in the CO_2 shadow price of each WWTP. It illustrates that the values obtained from the two special scenarios, $g = (1, 0)$ and $g = (0, -1)$, can be treated as the lower and upper boundaries, respectively. Under the directional vector $g = (1, 0)$, the average shadow price of CO_2 is 7.4% of the price of the wastewater treated, while this value reaches 23.5% if more weight is assigned to the contraction of undesirable output, i.e., if the directional vector is $g = (0, -1)$. The variability of the results among the WWTPs in the study, expressed as the standard deviation of the shadow price, is higher when the directional vector is set as $g = (0, -1)$ than when it is set as $g = (1, 0)$. Fig. 1 and Table 4 also illustrate that there is quite a difference in the variability of the shadow price of CO_2 for any particular WWTP. For some facilities, such as those numbered as 9, 13, 16 and 17, the value of the shadow price is quite stable and does not depend on the directional vector selected to estimate it. On the contrary, other WWTPs, such as those numbered 1, 10, 19 and 24, present shadow prices that are highly dependent on the directional vector used. In order to explore which process variables may cause these differences, WWTPs were classified into three groups according the difference in their CO_2 shadow price between the low ($g = (1, 0)$) and up boundary ($g = (0, -1)$): (i) less than 10%; (ii) between 10% and 20%; and (iii) more than 20%. According to the characteristics of the WWTPs (see supplementary information), it is shown that small WWTPs have the lowest variability in their CO_2 shadow price. It means that this group of facilities is the least affected by the selection of the directional vector when CO_2 shadow prices are estimated.

4.3. Factors affecting the shadow price

The shadow price of CO_2 across the WWTPs is highly variable, as shown in Table 3. In order to investigate the determinants of the CO_2 shadow prices, taking into account the available statistical information, we explored the possibility that the shadow prices of CO_2 may be affected by the following factors: (i) wastewater treatment technology; (ii) sewage sludge treatment technology; (iii) size of facility; (iv) age of the WWTP; and (v) seasonality.

Two approaches can be followed to investigate this variability, namely regression analysis and hypothesis testing. In our case study there are two features that limit the performance of the econometric analysis. First, the correlation coefficients between the CO_2 shadow prices and the size and the age of the WWTPs were 0.20 and 0.02, respectively. Second, most of the potential factors that might affect CO_2 shadow prices are qualitative, so it is not feasible to introduce all of them as dummy variables. Hence, to investigate the determinants of the CO_2 shadow prices further, we performed a hypothesis test. To do this, the non-parametric Mann–Whitney U test and its extension, the Kruskal–Wallis test for three or more groups, were applied. WWTPs were grouped according to the different factors that might affect CO_2 shadow prices (wastewater treatment technology, sewage sludge treatment technology, size, age and seasonality). The null hypothesis is that there are no differences in the shadow prices of CO_2 among the groups of WWTPs. If the *p*-value of the non-parametric test is smaller than 0.05, the null hypothesis can be rejected and, therefore the shadow price of CO_2 for the groups of WWTPs is statistically different. The results are shown in Table 5.

The first explanatory factor studied was the wastewater treatment technology (see Table 5). The WWTPs were classified into three groups: (i) activated sludge (AS); (ii) extended aeration; and (iii) tertiary treatment.[3] While the mean CO_2 shadow price of the WWTPs using tertiary treatment is slightly higher than the shadow price of the facilities that just carried out secondary treatment, the Kruskal–Wallis test results did not enable a rejection of the null hypothesis. Moreover, the results showed that the mean CO_2 shadow prices of the facilities with different secondary technologies are very similar.

The sludge produced in WWTPs can be treated using different technologies which involve different energy consumption and consequently different costs. To evaluate whether the CO_2 shadow price is affected by this factor, the 25 WWTPs were classified into three groups: (i) mechanical dewatering (MD); (ii) aerobic digestion (AD); and (iii) anaerobic digestion (AnD). As was expected, the CO_2 shadow price of WWTPs using AnD is lower than that for facilities treating the sludge with the other two technologies considered. AnD is widely used as a renewable energy source since, besides CO_2, the process produces hydrogen and/or methane that could be suitable for energy production [59]. The differences in shadow price observed between the three groups of WWTPs are statistically significant. Hence, it can be concluded that the specific technology used to treat sewage sludge affects the CO_2 shadow price of the WWTP.

[3] Not all the wastewater treated in secondary treatment is regenerated through tertiary treatment.

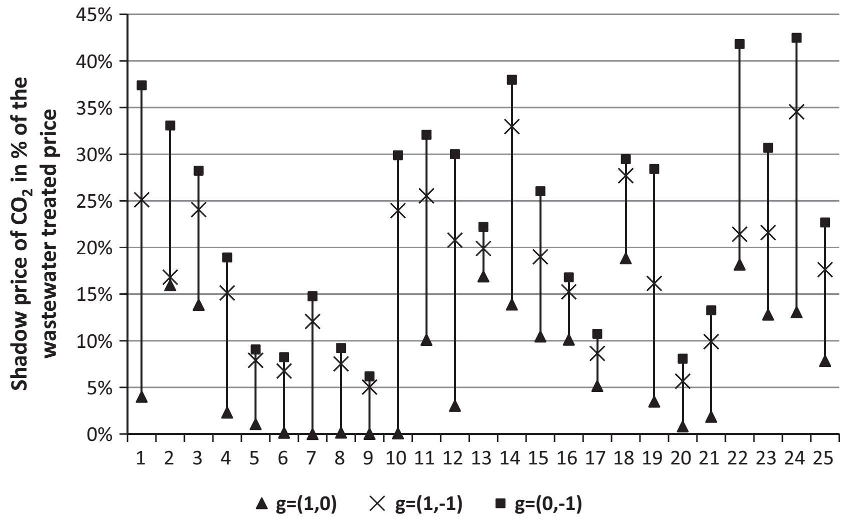

Fig. 1. Shadow price of CO_2 in% of the wastewater treated price for the three directional vectors.

Table 4
Shadow price of CO_2 in% of the wastewater treated price for the three directional vectors.

WWTP	Shadow price of CO_2 (%)		
	$g = (1,0)$	$g = (1,-1)$	$g = (0,-1)$
1	4.00	25.13	37.41
2	15.96	16.83	33.09
3	13.86	24.07	28.25
4	2.31	15.14	18.93
5	1.07	7.91	9.07
6	0.15	6.76	8.24
7	0.02	12.08	14.77
8	0.15	7.53	9.23
9	0.03	5.04	6.18
10	0.08	23.96	29.90
11	10.12	25.55	32.09
12	3.04	20.80	30.02
13	16.90	19.90	22.23
14	13.90	32.97	37.99
15	10.47	19.01	26.04
16	10.13	15.25	16.80
17	5.17	8.65	10.76
18	18.85	27.71	29.48
19	3.48	16.16	28.43
20	0.82	5.67	8.09
21	1.86	9.91	13.27
22	18.18	21.43	41.83
23	12.81	21.61	30.70
24	13.08	34.56	42.49
25	7.85	17.63	22.69
Average	7.37	17.65	23.52
Std.	6.58	8.35	11.33

Another potentially significant variable for explaining CO_2 shadow price differences is the size of the WWTP, expressed as the volume of wastewater treated annually. It is well known that the costs of WWTPs are characterised by economies of scale [60], and therefore we test to see if this is also the case for the shadow price of CO_2. To investigate this hypothesis, the WWTPs were categorised into three groups:[4] (i) less than 1,000,000 m^3/year; (ii) between 1,000,000 and 5,000,000 m^3/year; and (iii) more than 5,000,000 m^3/year. Table 5 shows that there is a relationship between the size of the plant and its shadow price of CO_2. The largest WWTPs are those with the lowest CO_2 shadow price. Nevertheless, the Kruskal–Wallis test did not lead us to confirm that the differences between the WWTP groups are statistically significant.

[4] The aim in selecting these limits for the volume of wastewater when grouping the WWTPs was to have approximately the same number of WWTPs in each group.

Table 5
Assessment of the factors affecting CO_2 shadow prices of WWTPs. The shadow price is expressed as% of the price of the treated wastewater.

Factor	Mean CO_2 shadow price	p-Value of hypothesis test[1]
Wastewater treatment technology		
Activated sludge (AS)	17.5%	0.938
Extended aeration (EA)	17.3%	
Tertiary treatment (TT)	18.4%	
Sewage sludge treatment technology		
Mechanical dewatering (MD)	18.6%	0.037
Aerobic digestion (AD)	21.0%	
Anaerobic digestion (AnD)	14.1%	
Size (10^3 m^3/year)		
<1000	20.9%	0.733
1000–5000	16.7%	
>5000	15.9%	
Age (years old)		
>18	15.8%	0.438
10–18	20.2%	
<10	16.1%	
Seasonality		
Yes	17.5%	0.912
No	17.7%	

[1] The hypothesis test is Mann–Whitney for two groups and Kruskal–Wallis for three or more groups.

The next explanatory variable we considered was the age of the WWTP, understood as the number of years since it was built or refurbished. To obtain the same number of plants in each group, they were categorised as follows: (i) more than 18 years old; (ii) between 10 and 18 years old; and (iii) less than 10 years old. It was found that there is no relationship between the age of the plant and its shadow price.

Finally, we analysed whether seasonal closures influenced the CO_2 shadow price of the WWTPs. Ten out of the 25 WWTPs in the study were identified as being subject to seasonality, while the remaining 15 plants are not affected by seasonality. We showed that the CO_2 shadow price is very similar for both groups of WWTPs. The p-value of the Mann–Whitney test indicates that the CO_2 shadow price average was not statistically significant.

The environmental and technical assessment of WWTPs has traditionally been focused on water quality, since the main objective of these facilities is to produce an effluent that does not pollute the water bodies into which wastewater is discharged. However, wastewater treatment involves the generation of sewage sludge that must be managed adequately. Hence, from a technical point of view, the processing, reuse, and disposal of sludge present one of the most complex engineering problems in the field of wastewater treatment [61]. An underlying policy implication of the second stage of the analysis we have performed is that the selection of the sewage sludge treatment is important not only from a technical point of view but also from an economic perspective. If a regulatory agency were to introduce a trading system for the water industry, this system should take into account the different abatement costs for WWTPs with different sewage sludge treatment technologies when making its initial permit allocations.

From a policy perspective, whether or not GHG are included in the CBA differs between European countries. Although the European Uniońs Emissions Trading System (EU ETS) is currently running, in 2005 Oddgard et al. [62] provided an overview of the practices in the EU member states. They demonstrated that only 10 out of the 25 states included some economic estimation of GHG emissions in the CBA. The two main approaches followed were the damage cost and the cost of avoiding emissions, and this resulted in values that differed significantly between the countries. While the value per tonne of CO_2 considered by the different countries is not directly comparable with the shadow price of CO_2 estimated in this study, it helps to look at this for a better understanding of the policy implications of our assessment.

The shadow price of CO_2 from our assessment is €88 per tonne, which is consistent with the values applied by European countries. Germany used the highest value of 205 €/tonne of CO_2, while Denmark and Finland applied a value six times lower than this (32 €/tonne of CO_2). Austria, Switzerland and Sweden applied a value of €94.50, €140 and €168 per tonne of CO_2 respectively [62]. In the province of British Columbia (Canada) in 2008 a carbon tax was implemented which used a value of $30 per tonne of CO_2 equivalents in 2012 [2]. The IPCC [1] has suggested that, to attain a global reduction of approximately 20% from the 2005 levels, GHG prices should range from US$15 to $130 per tonne of CO_2 equivalents by 2050.

5. Conclusions

The reduction of CO_2 emissions in the water industry in general and in WWTPs in particular is a necessary step for coping with the challenge of climate change. As the number of WWTPs increases worldwide and effluent quality requirements become more demanding, the issue of energy efficiency has been attracting increasing attention from an environmental and economic point of view. Economic feasibility studies are crucial for supporting the decision making process. This analysis requires the inclusion of both costs and benefits with and without market value. In this context, the economic value of the negative environmental externalities associated with the emission of GHG can be estimated through the estimation of the CO_2 shadow price.

This paper investigates CO_2 shadow prices and their determinants in the wastewater treatment industry. Based on a sample of 25 WWTPs and following the directional distance function approach, the findings show that the average shadow price of CO_2 is 17.7% of the price of treated water. This result is consistent with the different economic values of GHG emissions applied by EU member states in the CBA. A sensitivity analysis for directional vectors was performed to model the points of view of society and WWTP managers. The paper shows that the variability of CO_2 shadow prices as the directional vector changes is quite different among WWTPs. Hence, the shadow prices depend on the setting of the directional vectors. The analysis of the second step provided evidence of the importance of the sewage sludge treatment technology, since this was the only factor significantly affecting the CO_2 shadow price.

While we suggest caution in the interpretation of our results since they are obtained from a sample of WWTPs embracing 25 units, from a policy perspective, some important implications can be drawn from this paper. First, the shadow price of CO_2 emissions from WWTPs can be interpreted as the economic value of the negative environmental externalities associated with energy consumption for treating wastewater. The inclusion of such an externality in the CBA is essential for a true reflection of the economic value of wastewater treatment. Second, as the methodology used to estimate shadow prices was developed in the framework of an efficiency assessment, it can be concluded that our sample utilities have the potential to reduce energy consumption while keeping the quality of the discharged effluent constant. Accordingly, water agencies should provide incentives for WWTP companies to promote energy efficiency improvements, since this will have positive effects not just for WWTP operators but also for society as a whole.

Finally, while the high transaction costs of implementing a trading system or tax for CO_2 emissions in the water industry would reduce the net benefits of such an approach, the variation of CO_2 shadow prices across the WWTPs in the study implies that a market-based approach would involve relatively higher benefits than command-and-control regulations. Moreover, information concerning CO_2 shadow prices can be used by policy makers to identify WWTPs with the greatest/least abatement potential.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2015.02.034.

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