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Evaluation of cost efficiency in hydropower-related biodiversity restoration projects in Sweden – a stochastic frontier approach

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Various restoration projects intended to mitigate the adverse ecological effects of hydropower plants, e.g. by restoration of fish habitats and spawning grounds, have been implemented in different parts of the world. However, it is unclear whether these projects are in line with least-cost principles. In this study, we estimated the cost efficiency level for different biodiversity mitigation measures in Sweden by using stochastic frontier analysis with data from 245 projects in Sweden that were carried out between 1987 and 2013. The results indicated evidence of cost inefficiency in the projects, which had an average efficiency score of 53%, suggesting a potential to reduce costs by 47%. Project ownership by private entities compared with municipalities showed a statistically significant reduction of the cost inefficiency score. This points out a possibility of reducing the total cost of restoration by targeting relatively efficient project owners.

Keywords: Hydropower; biodiversity restoration; cost efficiency; stochastic frontier analysis

1. Introduction

Hydropower is a vital source of energy supply worldwide and accounted for approximately 16% of the total supply of electricity in 2018 (IEA [International Energy Agency] 2021). The hydropower energy source is well known for its minimal emissions of pollutants and low production costs and is an effective mechanism for controlling the significant fluctuations in energy demand and supply (e.g. IRENA [International Renewable Energy Agency] 2021). For these reasons, hydropower is regarded as an efficient means for mitigating climate change by replacing energy production from fossil fuel, and a global boom in dam construction is anticipated (e.g. Zarfl *et al*. 2015). However, there has been growing criticism of hydropower dams due to their distortion of ecological conditions in the riverine landscape (e.g. Lange *et al*. 2018). For instance, streams can be entirely or partly desiccated, thereby destroying habitats and migration pathways for fish species. Furthermore, fish species such as eel and salmon, which are protected under the EU Habitat Directive (Council Directive 92/43/EEC 1992), are affected by hydropower plants (HaV [Havs- och Vattenmyndigheten] 2020). Therefore, regulations concerning biodiversity requirements

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on existing and planned hydro power plants have been implemented in several countries (Coutu and Olden 2018).

A key issue is then how to design cost efficient biodiversity protection to avoid unnecessary cost impacts on society. Cost calculations require data on both the ecological and economic effects of the restoration measures. Measures aimed at improving biodiversity, such as stabilization of channels and improvement of riparian and in-stream habitats and water quality around hydropower plants, usually require a considerable amount of investment. Before restoration projects are implemented, economic and ecological aspects of these projects need to be evaluated, in order to utilize the limited investment resources most effectively. Several studies have assessed the ecological effects of different biodiversity restoration measures in the aquatic system e.g. (Green and O'Connor 2001; Pejchar and Warner 2001; Renöfält, Jansson, and Nilsson 2010; Carlson, Donadi, and Sandin 2018; Göthe *et al*. 2019; Kupilas *et al*. 2020). A few studies have calculated the cost of environmental constraints for planned hydropower plants, which consider different types of measures such as adjustment passages for fish or instream restoration (e.g. Guisández, Pérez-Diaz, and Wilhelm 2013; Lillesund *et al*. 2017; Oladosu *et al*. 2021), but no study has evaluated the cost efficiency of hydropower restoration projects.

The purpose of this study is twofold; to test for the existence of cost inefficiency in providing biodiversity by hydropower restoration projects in Sweden and, when there is evidence of inefficiency, to assess the impact of different explanatory variables on cost inefficiency. Identifying the determinants of cost inefficiency can be important for effective resource utilization and policy formulation with respect to biodiversity restoration measures. The outputs from the restoration projects are improved biodiversity in terms of preservation of one or several species. The inefficiency determinants include project characteristics such as type of restoration project, project ownership, and time aspect of the project. To this end, we apply stochastic frontier analysis (SFA) using micro level data on hydropower restoration projects in Sweden.

In Sweden, official reports indicate that energy production from approximately 2,100 hydro power sources supplied nearly 61 TWh in 2019, which corresponded to 40% of total electricity production (SEA 2020). In 2019, electricity production by hydropower plants in Sweden was among the 10 largest in Europe (Statista 2021). Almost 1,000 lakes and 4,000 rivers are affected by these power plants (HaV 2021). Only a small fraction of the power plants has been adjusted to the modern environmental requirements set by national laws and EU directives (SWA [Swedish Water Authorities] 2021). Environmental regulations have not been changed for established power plants with operational licenses during the last century, and recent legislation requires investigation and renewal of licenses for about 1,300 power plants (SWA 2021). The analysis of cost efficiency of the implemented hydropower restoration projects can therefore be of relevance for the priority of future restoration measures.

Following the seminal works of Aigner, Lovell, and Schmidt (1977), Battese and Corra (1977), Meeusen and Van Den Broeck (1977), Førsund, Lovell, and Schmidt (1980), and Greene (2008), applications of SFA have become popular in measuring firms' technical efficiency or productivity level. The economic reasoning behind technical efficiency is directly linked to how a firm utilizes an existing limited resource to produce a maximum level of output. The advantage of this method compared with another common method estimating inefficiency, data envelopment analysis (DEA), is that it distinguishes the total error term into inefficiency and random noise components[1]. SFA then allows for simultaneously identifying the variable determining the minimum restoration cost and the main sources of inefficiency variations across the study sample. Both methods have been applied to a variety of sectors including banking, health care, insurance companies, energy production, agriculture, and fishery (see e.g. Lampe and Hilgers (2015) for applications and comparison of the methods). Studies on environmental efficiency generally regard pollution as a negative side effect of the production of outputs (e.g. Reinhard, Lovell, and Thijssen 2002; Tang *et al*. 2014; Huang, Bruemmer, and Huntsinger 2016; Gezahegn *et al*. 2020).

The current study does not apply an environmentally adjusted production efficiency approach, but instead treats the environmental effect as the output of a restoration project and examines its cost efficiency. A cost function approach allows for the handling of problems with multiple outputs in efficiency analysis (Kumbhakar and Lovell 2000). In our view, the novel contribution of this study is the application of a SFA model to evaluate the cost efficiency in the production of biodiversity by hydropower restoration projects, hence aiding policy design for cost efficient implementation of biodiversity restoration projects. The remainder of the paper is structured as follows: Section 2 presents the methodological framework, including the theoretical foundations of a stochastic frontier cost function. Section 3 presents the data, while the econometric results are presented in Section 4. Efficiency score and marginal effects of cost inefficiency determinants are calculated in Section 5, the results are discussed in Section 6 and the main conclusions are presented in Section 7.

2. Conceptual approach

The basic approach with the SFA is illustrated in Figure 1, where we have three hypothetical restoration projects, *A, B* and *C* with different costs and environmental effects (*Q*).

The vertical axis shows the cost of a project and the horizontal axis the environmental effect. It can be seen immediately that project *B* has a higher cost and a lower effect than project *C*, and is thus obviously cost inefficient. It is less clear for project *A*, which has a lower cost and a lower effect than the other two projects.

The calculation of the existence and magnitude of inefficiencies requires information on the relationship between minimum cost and *Q*, which is illustrated by the curve *C(Q)* in Figure 1. Each point on the curve shows the minimum cost for a given *Q,* and

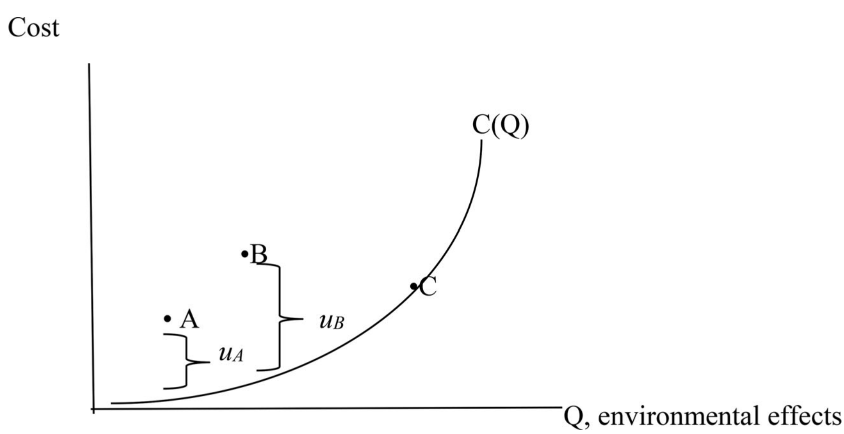

Figure 1. Illustration of calculation of cost inefficiency.

a project can then be at the curve and, hence, be cost efficient, which is the case for project C. The degree of inefficiency of project A and B is then measured by means of the difference in actual cost and the minimum cost for the same level of Q, which is illustrated by u_A and u_B in Figure 1. There can be several explanations for inefficiency, such as the choice of restoration technology, which is discussed in Sections 3 and 4.

The calculation of cost inefficiency and its determinants thus requires a two-step approach; i) estimation of the cost function and calculation of the divergences from the minimum cost for each restoration project, and ii) estimation of the power of different variables in explaining the inefficiency (if it exists). The estimation of the cost function is based on the assumption that a manager of a restoration project *i,* where $i = 1, \ldots, N$ projects, minimizes costs for achieving several environmental outputs under the given prices of inputs and multiple-output production function. The production function includes labor and capital as variable inputs, and climate factors as given inputs for the production of ecological outputs. Following the theoretical representation of the stochastic frontier analysis introduced by Aigner, Lovell, and Schmidt (1977) and Meeusen and Van Den Broeck (1977), the Cobb-Douglas form of cost function is written as:

$$C_i = f(Q_i, w_i, K_i; \beta) \exp\{\varepsilon_i\} \tag{1}$$

where C_i is the cost of biodiversity restoration*,* Q_i represents a vector of ecological output, w_i is a vector or input prices, K_i is a vector of climate conditions, and β is a vector of parameters to be estimated. The term ε_i represents the error term, which is divided into inefficiency, u_i (as illustrated by the distances u_A and u_B in Figure 1) and statistical noise, v_i, *i.e.*

$$\varepsilon_i = u_i + v_i \tag{2}$$

The economic reasoning behind Equation (2) is directly linked to the existence of two distinguishable stochastic random error components in the specified cost function. The first part, u_i, represents cost inefficiency that arises due to several project-specific factors in the restoration process. The second component, v_i, represents stochastic noise that cannot be controlled by a firm, such as climate and any accidental disaster. Consequently, the level of cost efficiency, CE_i, associated with each project is predicted by taking the ratio of the frontier (or possible minimum cost), C_i^*, and the corresponding observed cost level, C_i, calculated as:

$$CE_i = \frac{C_i^*}{C_i} = \frac{f(Q_i, w_i; \beta) \ \exp(v_i)}{f(Q_i, w_i; \beta) \ \exp(u_i + v_i)} = \exp(-u_i) \tag{3}$$

where CE_i is bounded between 0 and 1. Full efficiency occurs when CE_i=1 or $u_i = 0$ and the amount by which Equation (3) is less than one represents the degree of cost inefficiency.

The term u_i denotes a non-negative deviation from the frontier cost function, i.e. minimum cost estimated for a given level of output, input prices and climate conditions, which can follow a half-normal, truncated, exponential, or gamma distributions (Wang and Schmidt 2002, 2). The following are assumptions are made:

a. $u_i \sim N^+(0, \sigma_{u_i}^2), \ u_i \geq 0,$
b. $v_i \sim N(0, \sigma_v^2),$

c. $\sigma^2_{u_i} = \exp(k_i'\phi)$ where k is a $n \times 1$ vector of explanatory variables for the variance of one-sided error term, and ϕ is a $n \times 1$ vector of parameters,
d. u_i and v_i are mutually independent as well as independent of covariates in the frontier cost function (Equation (1)).

As indicated by assumptions (*a)* and (*c)*, the two error components u_i and v_i can be heteroscedastic. Ignorance of such heteroscedasticity can lead to inconsistent estimates (Kumbhakar and Lovell 2000; Wang and Schmidt 2002). Neglecting heteroscedasticity assumption in u_i creates a bias in the frontier cost function parameters as well as in cost efficiency score. Disregarding the heteroscedasticity assumption in v_i gives consistent parameter estimates for the frontier cost function, but creates a downward bias in the intercept as well as in the cost efficiency score. Therefore, our study assumed that the two error components are heteroscedastic.

There are several ways of explaining the inefficiency. The dataset in this study includes restoration projects implemented at different time periods and locations in Sweden. As pointed out by Greene (2004), the introduction of variables representing project heterogeneity in the cost function may lead to an over specified cost function, which may result in an underestimation of the inefficiency. This can be counteracted by letting the variables residing in the inefficiency distribution (Greene 2004). Sweden is an elongated country with different climate conditions depending on the location of the project, which is captured by the climate variables in the cost frontier function. Further, we introduce dummies for counties in the cost function to account for heterogeneity related to other given spatial conditions. The data indicated substantial variation in the distribution of biodiversity restoration projects across counties, (see Figure S1 in the Appendix [online supplemental data]). This could have an implication for the estimates, for instance, the concentration of small hydropower plants in a given county could result in higher costs than in other regions.

For each project, we then defined a measure of the deviation from the frontier, u_i, as illustrated in Figure 1 and shown in Equation (3) and estimated a function:

$$u_i = \phi_0 + \sum_{k=1}^{K} \phi_k z_{ik} + \omega_i, \qquad i = 1, 2, ..., N \tag{4}$$

where u_i represents the predicted cost inefficiency and z_{ik} denotes project-specific characteristics that affect cost inefficiency and the terms ϕ_k are parameters to be estimated. The term ω_i is an idiosyncratic error component. In this study, we include project ownership, restoration measure, and project duration as factors affecting the inefficiency distribution. There is a large body of literature in economics on the impact of ownership on firms' economic performance, which offers a variety of explanations such as differences in managers' objectives for the operations, skills, and market conditions (see reviews in Vining and Boardman [1992] and Walter *et al.* [2009]). The results concerning ownership are inconclusive. Choice of restoration measures at a certain site may be another source of inefficiency because of considerable differences in costs and ecological effects (Sandin *et al.* 2017). Long duration of a project may generate cost savings from learning but can also reflect cost increasing delays in project implementation.

In order to proceed with the regression estimation, we need to specify the regression equation to be estimated. To be consistent with the economic theory, the cost function needs to be increasing in input prices and environmental output and should satisfy the concavity assumption in input prices (Greene 2008; Kumbhakar, Wang, and Horncastle 2015). Thus, we imposed a linear homogeneity restriction in the input prices which is ensured by normalizing cost, C_i and input price (wage rate), w_i using one of the input prices (interest rate), r_i. Homogeneity implies that, for a given environmental effect, the cost increases proportionally to a simultaneous increase in the input prices. The data for a longer period of time (1987-2013 as described in Section 3) raises the need to control for eventual monotonic technological change, T. The cost function to be estimated is therefore written as:

$$\log\left(C_i/r_i\right) = \beta_0 + \beta_1 \log\left(w_i/r_i\right) + \sum\nolimits_s \beta_2^s \log\left(Q_i^s\right) + \sum\nolimits_{s<y} \beta_3^{sy} \log\left(Q_i^s\right) \log\left(Q_i^y\right) + \sum\nolimits_1 \beta_4^l \log(\mathrm{K}_i^1) + \beta_5 \mathrm{T} + \mathrm{D}_i + u_i + v_i \tag{5}$$

where w_i is the input price (wage), Q_i^s the ecological outputs $s = y = 1, \ldots, n$, K_i^l the climate variables $l = 1, \ldots, m$, T is a trend variable, and D_i denote dummy variables that control county specific unobserved factors. By introducing the variable $\log\left(Q_i^s\right)\log\left(Q_i^y\right)$ where $s < y$ we allow for interaction in the provision of different ecological outputs since restoration in e.g. a stream can have simultaneous effects on several outputs.

The estimation procedure followed the one-step maximum likelihood estimation (MLE) of the stochastic frontier model including Equations (4) and (5) suggested by Wang and Schmidt (2002) and Schmidt (2011). This approach was chosen since it addresses the potential bias in parameters due to the possible correlation between regressors of the cost frontier function and inefficiency determinants. A parameter, $\gamma = \sigma_u/(\sigma_u + \sigma_v)$ is used for testing the existence of cost inefficiency (Battese and Corra 1977). Rejecting the null hypothesis of $\gamma = 0$ confirms the existence of cost inefficiency when the model fits half-normal distribution. However, in the case of more complicated models (such as truncated normal), a log-likelihood-based test for inefficiency is recommended, as the gamma parameter does not provide essential information on the existence of a one-sided error term (Kumbhakar, Wang, and Horncastle 2015). In general, accepting the null hypothesis implies an absence of cost inefficiency that the variation in the total error term, ε_i in Equation (2), is attributable to the statistical noise component, and thus Equation (5) can be estimated using the ordinary least square regression method.

3. Description of data

A minimum requirement of data for the estimation of the regression equations presented in Section 2 is a sufficient number of projects with observations on costs and ecological effects. Data for these variables were taken from two main sources: the national database for restoration measures (CBJ 2016) and a survey of hydropower plants in Sweden (Sandin *et al.* 2017). The national database includes information on the costs of different types of restoration measures, the timing of the project, project duration, and project owner. The data on costs included the principal's total operating the costs for implementing and managing the measures. Data on costs in terms of impacts on hydropower plants' provision of energy were not available, which implies underestimation of the overall costs. This may be of particular importance for measures restoring connectivity in the landscape. In total, the national database included 487 different hydropower plants. The projects were implemented over 26 years, between 1987 and 2013, but all costs were measured in 2016 prices by using the consumer price index.

Ideally, data on ecological effects of the projects would be based on measurements of ecological status before and after the implementation of the restoration project. Biodiversity recovery of restoration projects may take time, which would necessitate repeated measurements at the sites. Such data is not available. Therefore, we used results from a survey of experts at county boards (Sandin *et al.* 2017). This approach has been applied by other studies on efficiency analysis (e.g. Korhonen and Syrjänen 2003; Ustundag, Uğurlu, and Serdar 2011; Torres-Jiménez *et al.* 2015).

The survey data contained responses for 410 restoration projects on several indices of perceived ecological effect. One is the effect on the primary target of the project, such as improvements in trout, salmon, or eel, while others include five additional ecological effects. For each ecological effect, the responses were scaled from 1 to 20, where 20 is the best achievement. Since both targets and additional ecological effects may impact the decision on project investment, we included both these effects. To reduce the number of variables, we constructed a weighted index of the five other ecological effects by employing principal component analysis (e.g. OECD 2008). Two different ecological effect variables were then constructed: *Targeffect*, which includes only the effect on the target for the restoration, and *Addeffect*, which represents the constructed index on additional effect. Data on ecological effects were not available for all hydropower plants with cost information in the national database, but for 245 of these plants.

The responses to the survey rest on the experts' subjective evaluation. Therefore, there is a risk of comparing the efficiency of measures with different ecological outcomes where, for example, a grading of 4 by one expert may not reflect the same ecological performance as the same grading by another expert. However, Sandin *et al.* (2017) found that the expert evaluation scores were close to measured performance at a small sample (33) of the 410 restoration projects. This finding indicates some consistency in the measurement of target achievement. Another heterogeneity may occur from differences in the formulation of main targets, which can be expressed in terms of viable populations of different species. A viable population of salmon trout is reported as the main target for 83% of all projects (Sandin *et al.* 2017), which indicates a similar target formulation among the experts.

The cost frontier variables (i.e. Equations (1) and (5) in Section 2) included in this study are input prices (wage and interest rate), climate variables (temperature and precipitation), and monotonic technological development represented by a trend variable. Data on average annual salary was obtained from Statistics Sweden (2016a) and the return on a relatively risk-free asset, short-term government bonds, was used as a measure of the interest rate (Statistics Sweden 2016b). The return on short-term government bonds was chosen since the opportunity cost of investing in risky capital is proportional to the potential return on risk-free investment such as government bonds and treasury bills.

The climate variables include temperature (degree centigrade) and precipitation (millimeters). They were obtained from the Copernicus Climate Change Service (C3S) portal, which provides high-quality georeferenced climate data in Europe and worldwide (Muñoz Sabater 2019). These datasets represent 2 meters above the surface of the land with a gridded horizontal resolution of $0.1° \times 0.1°$ spatial coverage. The dataset is given on an hourly basis and thus we computed the annual average per hour for the project site. The expected impact of the climate variables is unclear. If increased temperature or precipitation promotes biodiversity, the cost would decrease for a given ecological output, and vice versa.

With respect to the explanatory variables in the cost inefficiency estimates (i.e. Equation (4) in Section 2), three different categories of inefficiency sources can be identified; *i*) type of restoration project, *ii)* principal manager of the project, and *iii)* duration of the project. With respect to the first category, there are a number of different measures improving biodiversity, which can be divided into two main classes; improvements of the migratory connectivity in the catchment and improvements of habitats (Nieminen, Hyytiäinen, and Lindroos 2017). Fish passage is the earliest system for removing migratory barriers which was introduced at hydro power plants in Europe about 300 years ago. The fishways are divided into two main classes: technical and natural. Removal of the dam is a more drastic measure, which is mainly applied on small dams (<15 m height) (Carlson, Donadi, and Sandin 2018). Construction of road culverts is used in Sweden for improving migratory passages (Sandin *et al.* 2017). Two measures improving habitat conditions are reported in Nieminen, Hyytiäinen, and Lindroos *et al.* (2017) and Sandin *et al.* (2017), instream restoration and improved spawning conditions, which are included in this study.

Regarding the second category, principal manager, all restoration projects included in this study are funded by the Swedish government as complements to the restoration requirements set by the Swedish Environmental Law on hydropower plants. The county boards are responsible for the distribution of the funds and can decide to use part of the budget for its own restoration or to pay other actors to make the restoration. The payments to other actors are based on their applications to the county boards. In order to examine the impact on cost efficiency, we include four classes of actors in addition to the county boards; municipalities, NGOs, private entities, and others. NGOs are local organizations for water and fish management, while private actors can be individuals but also firms such as hydropower producers and forest companies. Others consist of government authorities, such as the Swedish Forest and the Swedish Transport Administration.

With respect to the final group of inefficiency factors, project duration could have a positive or negative effect on the level of cost inefficiency. If a project runs for a long period, this could provide the potential for learning where project owners can reduce cost inefficiency. However, the positive effect of project duration could reflect additional spending by principals in order to maintain the planned amount of operation.

Descriptive statistics for the 245 observations with data on cost and ecological effects are displayed in Table 1.

The average cost per project is 355,755 SEK (9.47 SEK =1 Euro on average 2016), but there is large variation between projects. Each of the two classes of biotope improvement measures (instream and spawning restoration) accounted for approximately half of the total number of measures. Municipalities were responsible for more than half of all projects (Sandin *et al.* 2017).

4. Regression results

Prior to maximum likelihood estimation, it is essential to test the OLS residuals skewness in order to endorse whether the specification of stochastic cost frontier function is

Table 1. Summary of descriptive statistics ($N = 245$).

Variable	Mean	Std. Dev.	Min	Max
Cost function				
Total cost (SEK[a])	355,755	785,451	2,060	5,994,082
Wage rate (SEK[a]/year)	460,735	46,042	330,509	531,164
Interest rate (%)	2.772	3.005	0.133	9.000
Targeffect	16.204	3.437	1	20
Addeffect	1.084	1.081	2.09	4.24
Average temperature/year (°C)	8.816	1.300	6.189	12.312
Average precipitation (mm/hour)	0.0013	0.0005	0.0006	0.0023
Time trend	22.28	5.57	1	30
Inefficiency determinants				
Project duration (Years)	1.110	1.982	0.0	24.065
Managing principal;				
NGO	0.192		0	1
Private	0.106		0	1
County board	0.216		0	1
Municipality	0.555		0	1
Others	0.041		0	1
Restoration projects;				
Instream restoration	0.229		0	1
Natural fishway	0.139		0	1
Road culvert	0.086		0	1
Spawning	0.318		0	1
Technical fishway	0.114		0	1
Dam removal	0.114		0	1

[a]9.47 SEK = 1 Euro in average 2016.

valid (see Olson, Schmidt, and Waldman 1980; Schmidt and Lin 1984; Kumbhakar, Wang, and Horncastle 2015). The maximum likelihood estimates are consistent if the distribution of OLS residuals is skewed to the right, i.e. positive skewness. The corresponding skewness test statistics showed a positive sign (*skewness* = *0.112*), as was expected and this confirmed maximum likelihood estimation was in line with a stochastic cost frontier specification. We also tested whether the functional form presented in eq (5) in Section 2 by implementing a log-likelihood ratio (LR)-based test with translog specification as an alternative. The corresponding test statistics failed to reject the null hypothesis favoring the unrestricted or Cobb-Doulas specification ($p > 0.1264$). Therefore, we preferred the Cobb-Douglas functional form over the translog specification.

Results based on the specification in Equation (5) showed that *Addeffect* and the interaction between the two ecological effect variables had no statistically significant effects (Table S1). This suggests the absence of economies of scope despite multiple ecological outputs in the specified cost function. Therefore, we estimated the explanatory power of different variables on cost inefficiency using only *Targeffect* as ecological output. Three outliers were identified and removed from the dataset.

It can be argued that different project owners chose specific restoration measures based on e.g. knowledge and skill. Regressions are therefore made for separate and combined inclusion of project owners and restoration measures (Table 2). The reference variables for management and measure type variables are municipalities and dam removal, respectively.

Table 2. One-step maximum likelihood estimates of cost frontier function cost frontier and inefficiency functions ($N = 242$).

Variables	The dependent variable is log(Cost)		
	Model 1	Model 2	Model 3
Cost frontier variables			
Log(wage)	0.492*** (0.142)	0.242 (0.213)	0.363* (0.213)
Log(Targeffect)	0.440*** (0.165)	0.722*** (0.165)	0.612*** (0.199)
Log(Temperature)	−2.551*** (0.498)	−2.628*** (0.057)	−3.352*** (0.469)
Log(Precipitation)	129.044** (55.925)	188.621 (155.012)	245.027*** (53.738)
Time trend	−0.026 (0.039)	−0.010 (0.033)	−0.016 (0.054)
County fixed effects	YES	YES	YES
Inefficiency determinant variables			
Log(Project duration)	0.880*** (0.223)	0.766*** (0.024)	0.761*** (0.054)
Management:			
NGO	−2.413 (1.653)		−2.161 (1.472)
Others	−0.386 (0.265)		−0.446 (0.274)
Private	−1.290** (0.557)		−1.162*** (0.391)
County board	−0.221 (0.231)		−0.148 (0.548)
Measure type:			
Instream restoration		−0.269 (0.751)	−0.347 (0.906)
Natural fishway		0.995*** (0.207)	0.535 (0.683)
Road culvert		0.523 (0.540)	0.130 (0.116)
Spawning		−2.012* (1.070)	−1.253 (0.904)
Technical fishway		−0.176 (0.430)	−0.743 (1.144)
Constant	0.234 (0.228)	−0.306*** (0.117)	0.710 (0.658)
Vsigma	0.166 (0.441)	0.044*** (0.010)	−0.458 (0.403)
Mean efficiency	0.52	0.56	0.53
LR ratio test	167.31***	167.87***	172.73***
Log likelihood	−414.459	−414.178	−411.752
AIC	832.919	832.356	827.505
BIC	839.888	839.326	834.474

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Municipality level clustered standard errors in the parentheses. The inefficiency component follows the assumption of truncated normal distribution.

We compared the distributional assumptions associated with the inefficiency component, u_i in Equation (4). The implemented log-likelihood ratio test for model selection favored the truncated normal assumption instead of half-normal and exponential assumptions. Hence, the estimates in Table 2 are based on the assumption of truncated normal distribution on the one-sided idiosyncratic term. Checking the existence of cost inefficiency following the estimation of stochastic frontier models is essential. Thus, we implemented a generalized log-likelihood ratio (LR) test to check whether there is cost inefficiency in all specifications. This procedure is preferred in the case of a truncated normal assumption, as the LR test statistics follow a mixture of χ^2 distribution (Coelli 1995; Kumbhakar, Wang, and Horncastle 2015). The test has two degrees of freedom since the null hypothesis has two restrictions: $\sigma_u^2 = 0$ and $\mu = 0$, where μ denotes a mean of the one-sided error term. The critical values for the corresponding test hypothesis testing are illustrated in Kodde and Palm (1986).

The results in Table 2 show that the null hypothesis of no cost inefficiency was rejected (at $p < 0.01$) in all specifications, suggesting the presence of cost inefficiency across all the biodiversity restoration projects studied. Other common results are the sign of the estimated coefficients of all variables in the cost frontier function and the inefficiency model. A robust result is the significant and positive effect of *Targeeffect,* which is expected from the theoretical analysis in Section 2. When comparing the three different models with respect to the reported log-likelihood, information criteria, AIC and BIC in Table 2, the model including both management and restoration measures is preferable. Model 3 will therefore be used in the subsequent calculations of cost frontier and interpretation of the results concerning inefficiency and its determination.

5. Calculation of cost frontiers and cost efficiency scores

The estimated regression equation in Model 3 in Table 2 is used to assess the properties of the cost frontier function, i.e. the minimum cost at different levels of ecological effects, and to calculate the magnitude and implications of cost inefficiency.

5.1. Cost frontier

The regression results in Model 3 for the cost frontier are used to calculate the relation between cost per project and ecological outputs, similar to the illustration of the cost function in Figure 1. The coefficient estimates for all variables except *Time trend* show the percentage change in cost from a change by 1% in the respective independent variable. For example, the estimate of 0.612 for *Targeffect* implies that 1% increase in the ecological effect increases the average cost per project by 0.612%. The interpretations are similar for *Wage rate*, *Temperature* and *Precipitation*. The positive sign of *Wage rate* is expected from theory since an increase in labor cost, *ceteris paribus*, raises the cost of a restoration project. The negative sign of *Temperature* implies that the cost decreases when the temperature increases. This can be due to a higher ecological effect when temperature gradient increases the productivity of several aquatic species (e.g. O'Gorman, Olafsson, and Gislason 2018). The positive sign of *Precipitation* has the opposite interpretation, Precipitation affects hydrological conditions in the catchment and contributes to loads of nutrients and other pollutants to fresh water systems in Sweden (e.g. Tornevi, Bergstedt, and Forsberg 2014). This can alter the food web system and hamper fish population growth.

To derive a cost function that shows the relationship between cost and ecological effects, we calibrated the cost function at the average values of the significant independent variables in the cost frontier, and the cost as presented in Table 1. The minimum cost is then assumed to correspond to 0.53 of the actual cost per project because of the estimated inefficiency. However, as shown by the regression results in Table 2, changes in wage rate, temperature, and precipitation will shift the cost curve. Therefore, cost curves are calculated for the reference case at the mean values, and at 10% increases in the wage rate, the temperature and the precipitation (Figure 2)

All curves in Figure 2 show the minimum cost per project at different levels of ecological effects. For example, in the reference case the minimum cost for an ecological effect of 16, which is the average level in the dataset, would be approximately 189 thousand SEK. It can also be noticed that an increase in the temperature by 10% from the average level of 8.81 °C would reduce this cost to 137 thousand SEK. The corresponding increase in the wage rate and precipitation has a smaller impact on the cost by raising it to 211 and 194 thousand SEK, respectively.

A feature common to all cost functions is that they exhibit economies of scale, i.e. that the average cost per ecological output decreases as the output increases. For

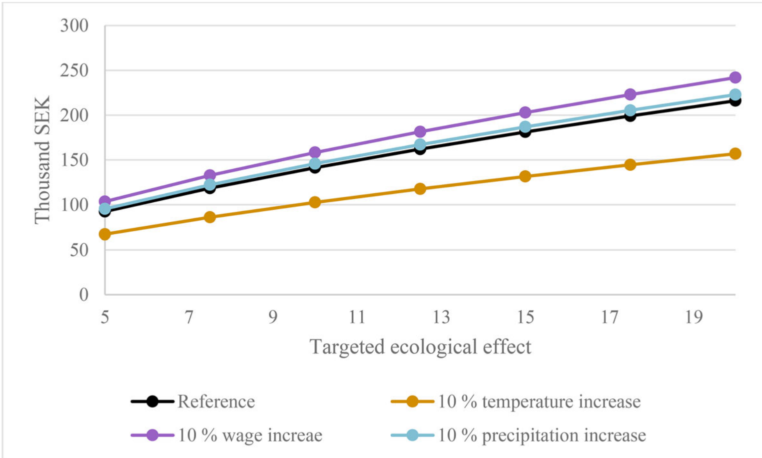

Figure 2. Minimum cost per project at different ecological effects in the reference case and 10 % increases in the wage rate, temperature and precipitation.

example, in the reference case, the average cost at 10 ecological effect is 14.1 thousand SEK, which is reduced to 11.8 thousand SEK at the ecological effect of 16.

5.2. Cost efficiency score

Based on the evidence for the presence of cost inefficiency, we predicted the magnitude of efficiency score associated with different management categories and restoration measures.

The results indicate a range in cost efficiency between 0.44 and 0.75 for the project owners (Figure 3). Projects owned by Municipalities, County Boards and Others show

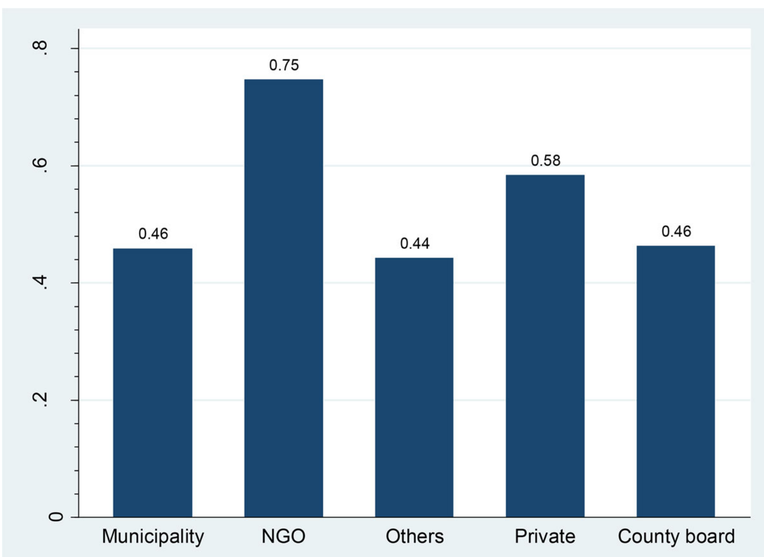

Figure 3. Cost efficiency score for different project management types.

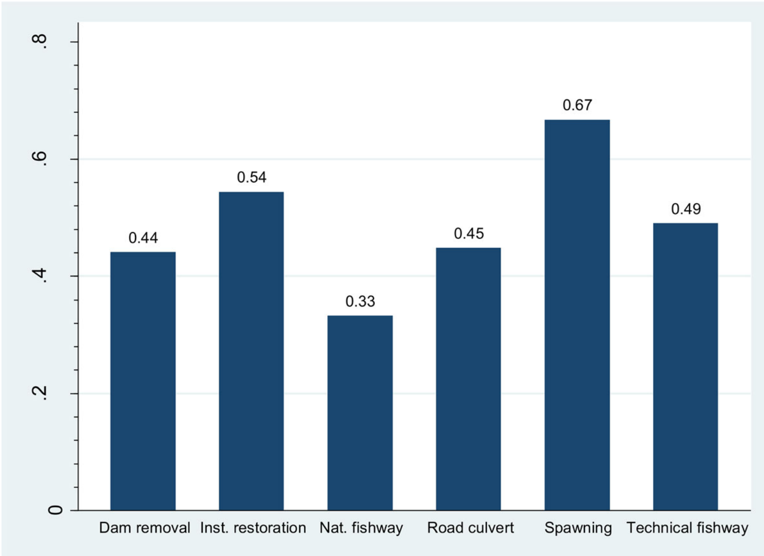

Figure 4. Cost efficiency score for different restoration measure types.

relatively low cost efficiency, and Private and, in particular, NGO project owners display a higher average cost efficiency. The difference in efficiency distribution between project owners could be attributable to a number of factors. For instance, better performance by private owners might be an indication of efficient utilization of resources due to e.g. objectives of maximum profits for these principals.

The relative difference in cost efficiency scores is larger for the restoration measures (Figure 4). The cost efficiency score varies between 0.33 (natural fishways) and 0.67 (improved spawning). The average cost per project is approximately 8 times higher than for improved spawning (Sandin *et al.* 2017), and the results in Figure 4 indicate that part of this cost difference can be explained by differences in efficiency level.

However, despite the differences in efficiency scores among project owners and restoration measures, the regression results in Table 2 show that only two variables, *Project duration* and *Private*, have significant effects on the overall efficiency score. Following the parametrization in Kumbhakar, Wang, and Horncastle (2015), we have computed the marginal effects of these variables on the mean cost inefficiency score (Table 3).

The results in Table 3 show that a marginal increase in project duration by one year reduces cost efficiency by 0.093. On the other hand, a change in project management from municipalities to private management increases the cost efficiency by 0.108.

Table 3. Marginal effects on mean cost efficiency (computed based on model 3 in Table 2).

Variables	Marginal effect	*P*-value
Project duration	−0.093***	0.000
Private project management	0.108***	0.003

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6. Discussion

Given the chosen variables, data and regression model, the results showed that the minimum cost for a given ecological effect is highly affected by temperature; the cost for a given ecological effect can decrease by approximately 3% when the temperature increases by 1%. Similarly, the calculated efficiency score varies considerably for different project managers and restoration measures. Therefore, it would be of interest to compare the results with other studies. However, this cannot be made since similar estimates have not been made for the restoration of biodiversity degradation caused by hydropower plants or from other degrading land use changes. Instead, only partial comparisons can be made with studies estimating restoration costs for some of the same measures as in our study (Lillesund *et al.* 2017; Nieminen, Hyytiäinen, and Lindroos 2017; Venus *et al.* 2020), and with studies estimating project ownership as a cause of cost or technical inefficiency (Tang *et al.* 2014; Sudrajat, Rahaya, and Kusandar 2018; Gezahegn *et al.* 2020).

Lillesund *et al.* (2017) calculated restoration costs of hydropower plants in Norway in an offset setting where degradation of biodiversity from hydropower plants could be compensated for by improved biodiversity from the construction of wetlands, restored alpine and forest ecosystems. The restoration costs ranged between 274 and 813 thousand USD (2016 value) for the four large scale dams used as case studies. This is considerably higher than the average cost of habitat improvements in the present study, the average cost of which amounts to approximately 35 thousand USD (in 2016 USD). The range in cost is large where the highest cost amounts to approximately 506 thousand USD (Table S2), which is within the range of the estimates by Lillesund *et al.* (2017).

Nieminen, Hyytiäinen, and Lindroos (2017) and Venus *et al.* (2020) calculated the costs of natural and technical fish passages and related the cost to the electricity production of the plants. Therefore, we can not compare our estimates with their cost levels but only the relative costs between measures. Nieminen, Hyytiäinen, and Lindroos (2017) found that the cost of technical fishway is approximately 25% lower than for natural fishways. Venus *et al.* (2020) obtained the opposite result where the cost of technical fishways is on average two times higher than for natural fish passages at hydropower plants in Sweden, France, Germany, Switzerland, and Austria. When comparing these results with our estimates it is found that the average cost of a technical fishway is approximately 10% higher than the cost of the natural fishway (Table S2).

Regarding the comparison of the calculated efficiency score and its determinants, it is of interest to compare with SFA studies applied to agriculture, since the output is also subject to stochastic weather conditions. There are only a few studies considering project managers as a source of efficiency and all of them calculate technical efficiency (Tang *et al.* 2014; Sudrajat, Rahaya, and Kusandar 2018; Gezahegn *et al.* 2020). The estimated mean efficiency varies between 0.42 and 0.83 in these studies. Our result of a mean cost efficiency of 0.69 is thus within the range of the estimates from these studies. The studies also found significant impacts of project managers on efficiency but in different ways. Management by farm cooperatives were examined in all studies. Tang *et al.* (2014) and Sudrajat, Rahaya, and Kusandar (2018) found a positive effect of cooperatives on efficiency while Gezahegn *et al.* (2020) obtained the opposite result. Only one study included private management as an efficiency determinant and found that it improves efficiency compared with community management of water use in China (Tang *et al.* 2014).

The partial comparison thus indicates that our results are in line with other studies. The average cost efficiency of 0.53 implies that the same average ecological effect could be obtained at a lower cost. In the reference case, the total cost of all projects amounts to approximately 87 million SEK, which then could be reduced by approximately 41 million SEK and still obtain the same ecological effects. However, this estimate is uncertain and the calculated cost efficiency scores and associated cost savings per project and totally within a 95% confidence interval can be considerable (Table S3). A 95% confidence interval implies a range in the cost efficiency score between 0.39 and 0.66. This generates a range in the excess cost, i.e. actual cost minus minimum cost, between approximately 30 and 53 million SEK

However, the calculations are affected, not only by the level of included variables but also by excluded factors because of lack of data. One such factor is the exclusion of costs of reductions in electricity production, which implies an underestimation of the restoration cost. A potential source of cost inefficiency not considered in this study is the law regulating hydropower restoration projects. In Sweden, regulators issue perpetual licenses to hydropower plants and the plant operators have to comply with the national laws, such as the Environmental Code, and European Union directives including the Water Framework Directive and the Habitats Directive. Several licenses are issued to regulate different aspects of a plant, and the regulator requires the use of the best available technology and decides about conditions and measures for biodiversity restoration, such as the requirement of dam removals (Rudberg *et al*. 2014).

It is well-known in economics that such so-called command and control policies give higher costs for a given environmental target than performance based instruments, such as payments for biodiversity improvements (e.g. Baumol and Oates 1988). The reason is that project owners, in general, operate at cost levels below the payment in order to avoid net losses. The cost of restoration measures required by a regulator can be higher because of e.g. less information on project specific costs and effects. If so, considerable cost savings can be made by considering a change in the current command and control regulation in Sweden to a performance based system in the future investigation of about 1300 power plants (SWA 2021).

7. Conclusions

This study evaluated cost efficiency in biodiversity restoration projects at hydropower plants in Sweden using stochastic frontier analysis. To this end, we used data on costs and ecological effects of 245 different restoration measures obtained from official statistics and a survey of hydropower plants. Two measures of ecological effects were constructed, an index of targeted effects and an index of additional effects. Econometric analysis of all restoration measures indicated that only the targeted ecological effect had a significant and positive impact on the cost frontier. Expected results were obtained for the costs of inputs where total costs increase when the wage rate increases. Other findings were that climate factors, measured as temperature, had a significant effect on the cost frontier and that the restoration exhibited economies of scale where the average cost per ecological effect decreases as the effect increases.

A major finding was that the null hypothesis of no cost inefficiency was rejected in all regression models. The estimated average cost efficiency score for individual biodiversity restoration projects was 53%, suggesting substantial potential in cost savings. The results also pointed out a considerable range in the average cost efficiency score; between 0.39 and 0.66 within a 95% confidence interval. Estimates of the determinants of cost inefficiency showed that project ownership and project duration significantly contributed to variation in inefficiency level. Biodiversity restoration projects owned and managed by private entities had a higher likelihood of being cost efficient than projects operated by municipalities.

The role of cost efficient restoration may be more important in many countries in the future because of the promotion of small scale hydropower plants because of the relatively low environmental damage and capital cost (Oladosu *et al*. 2021). On the other hand, the cost of mitigating environmental damage is relatively higher than for large scale dams (Oladosu *et al*. 2021). The willingness to pay for environmental restoration of damage caused by hydropower plants was estimated by Mattman, Logar, and Brouwer (2016). They found in a meta-analysis of studies on willingness to pay for environmental restoration at hydropower plants that, although respondents are positive to restoration, there is weak evidence of willingness to pay.

A potential policy conclusion based on the results in this study is that the total cost of biodiversity restoration at hydropower plants in Sweden could be reduced by a reallocation of projects between owners. The total expenses of 87 million SEK for the restoration projects included in this study could then have generated more ecological outputs in terms of the targeted output or, equivalently, the output could have been obtained at a lower total cost. This could have been achieved by reallocating projects to private owners from the municipality. It was also noted that project managers might be constrained by the current national laws and EU directives, the implementation of which is much focused on the requirements of specific restoration measures. The results in this study indicate potential social gains in terms of cost savings of a move from such technology-based regulation to performance-based regulations for hydropower restoration. In Sweden, the expenses for the projects were paid by governmental funding and the consideration of cost efficiency would imply a wiser use of the revenues from the Swedish tax payers.

However, our data on ecological effects rest on experts' subjective evaluation. It is therefore unclear if and how differences in spatial and dynamic scales of the ecological effects between restoration measures are considered. On the other hand, a small sample of projects comparing the experts' evaluations with actual performance at the sites indicated consistency in the evaluations. This points to the need for more assessments of expert evaluations and data based on measurements and assessments of ecological status at the sites before and after implementation of the restoration projects.

Note

1. Unlike SFA, the DEA based estimate is sensitive to measurement errors or other noise in the data given the model is deterministic and attributes all deviations from the frontier to inefficiencies (Kuosmanen and Kortelainen 2012).

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Supplemental data

Supplemental data for this article can be accessed online at https://doi.org/10.1080/09640568.2021.1987865.

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