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- a two-stage LCA + DEA efficiency case study on 75 Danish wind farms

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Abstract

It is generally known that wind power has an offsetting effect on emissions by crowding out fossil dependent energy sources. What has not been studied to any further extent is the variability in environmental impacts caused by wind turbine erection and manufacturing. Also, it is not known how economic incentives could affect these impacts. The argument made in this thesis was that the Danish price-premium feed-in tariff system provides incentives for WF operators to upscale, as this maximizes profit. Upscaling in turn is hypothesized to reduce the environmental impacts of the Danish wind farm (WF) fleet. The aim was to investigate whether the Danish wind subsidization policies indirectly have a positive effect on environmental efficiency for WFs, and if so, what factors mediate this effect. An environmental and operational two-stage LCA + DEA (SBM-I) efficiency analysis on a sample of 75 onshore and offshore Danish WFs was performed. The second stage analysis showed a strong association between environmental efficiency and feed-in tariffs per MW. There is suggestive evidence that the main driving factors behind this association are upscaling related variables, as well as production type. Such that Danish policy makers explicitly want to target environmental impact reductions of the WF fleet, it is recommended to promote large-scale operations, and preferably offshore.

Sammanfattning

Det är allmänt känt att vindkraft har en utsläppsminskande effekt när denna energikälla ersätter fossila energikällor. Något som är mindre beforskat är variabiliteten i miljöpåverkan inom vindkraften – en variabilitet vars ursprung främst kan härledas till vindkraftverkets tillverknings- och installationsfas samt lokala förhållanden. Det är inte heller känt i vilken utsträckning – eller om – subsidier har någon effekt på vindkraftsbetingade miljöpåverkan. I denna uppsats argumenteras att det danska s.k. relativprisbaserade *feed-in*-tariffsystemet (sv. inmatningstariff) har en positiv inverkan på den miljömässiga effektiviteten. Vidare medlas denna effekt genom de storskalighetsincitament som denna subventionstyp skapar. Syftet bakom uppsatsen var att undersöka de hypotiserade positiva miljömässiga externa effekter som orsakas av detta subventionssystem – och om evidens för denna effekt finns, undersöka vilka exogena faktorer som påverkar den miljömässiga effektiviteten för vindkraftsparker. En miljöinriktad och en verksamhetsinriktad effektivitetsberäkning, kallad *two-stage* LCA + DEA, genomfördes på sjuttiofem land- och havsbaserade danska vindkraftsparker. Den statistiska analysen gav indicier för en stark association mellan *feed-in*-tariffer per MW och miljömässig effektivitet. Ytterligare fanns indikativ för att den medlande effekten är graden av storskalighet, liksom produktionstyp (havsbaserad vindkraft är mer miljömässigt effektiv). Om danska beslutsfattare önskar att specifikt inrikta sig mot att minska vindkraftsflottans miljöpåverkan rekommenderas att premiera havsbaserad vindkraft och storskalighet i både turbin- och parkstorlek.

Abbreviations

By alphabetical order

BCC	Banker-Charnes-Cooper (DEA)
CCR	Charnes-Cooper-Rhodes (DEA)
DEA	Data envelopment analysis
DMU	Decision-making unit
ENS	*Energistyrelsen*, The Danish Energy Board
FIT	Feed-in tariff
KW	Kilowatt
KWh	Kilowatt-hour
LCA	Life cycle assessment/analysis
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
MW	Megawatt
MWh	Megawatt-hour
NPV	Net present value
OLS	Ordinary least squares
RES	Renewable energy source
SBM	Slacks-based measure
WF	Wind farm

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1 Introduction

As environmental concerns grow due to ecological degradation and climatological issues, policy makers around the world try to find feasible and sustainable solutions to energy production. A common haven is renewable energy sources (RES), which have been growing rapidly in past decades. It is generally known that switching from fossil dependent energy sources to RES will effectively decrease the environmental footprint of the economy. Wind power is one of the most popular alternatives when progressing towards a minimized environmental footprint. These generators convert kinetic energy – that is wind – to electrical energy. There are two production types of wind power: onshore and offshore. These essentially build on the same technology, whereas the offshore alternative needs an additional substructure to keep it above the surface and avoiding corrosion. The reason for installing offshore turbines is mainly higher and more stable wind speeds, which results in a higher electricity production. Other reasons are space limitations on land and visual degradation. RES's are generally not as competitive in pricing as conventional energy sources. To support the deployment of RES's, many countries provide these with subsidies. These subsidies come in many shapes and forms, such as investment support and quantity (quota) support, although the most common is the feed-in tariff (FIT) support. Couture & Gagnon (2010) describe two main types of FIT: the premium price and the fixed-price regimes. The most commonly used is the market price independent fixed-price regime, where the operator is guaranteed a certain remuneration per KWh. Denmark, on the other hand, practices a two-part price-premium FIT: the price supplement and the balancing reimbursement. The price supplementation is a traditional price premium, whereas the balancing reimbursement part is a consequence of the energy balancing system of Europe, commonly referred to as the European Network of Transmission System Operators for Electricity (ENTSO-E). The energy balancing system is essentially an electricity import and export scheme intended for the EU electricity market. As the output of RES's is hard to regulate or predict, the EU reasoned it would be beneficial for all countries to export occasional overcapacity and avoid capacity congestion within an economy (ENTSO-E, 2009). The additional balancing tariff is due to transmission losses, stemming from electric potential loss when transmitting the current for longer distances.

A benefit from wind turbines is that they have no associated adverse by-products at the operational stage, such as CO_2 emissions. Furthermore, the median lifecycle CO_2-eq. per KWh for wind power is the lowest for all types of RES's according to the Intergovernmental Panel on Climate Change, IPCC (2018). This combined with upscaling potential makes this energy source an attractive alternative to fossil fuels for many economies. This, on the other hand, does not mean that they are without environmental impacts. As the trend in most Western countries is steering away from fossil dependency, it could become of interest for these economies to investigate environmental cross-sectional fleet optimality of wind power. This since there is further environmental impact reduction potential in operationally optimizing the fleet, as suggested by Iribarren et al. (2013). The natural resources used for a wind turbine could lead to substantial emissions per MWh and varies strongly, based on the background processes involved in the manufacturing and erection phase. Life cycle assessments (LCAs) are used to evaluate the environmental impact over the whole lifecycle of a good. LCAs are done in two stages:

1. life cycle inventory (LCI): the evaluation of actual or estimated materials used for a given unit, and
2. life cycle impact analysis (LCIA), where the materials are attributed environmental impacts, usually with the help of a computer modelling software.

There have been several LCA case studies on WFs, but up to this date just one has been done for a whole fleet of turbines – the Danish wind turbine fleet. Average impacts and average performances were evaluated for the Danish WF fleet by Besseau et al. (2019) and Sacchi et al. (2019), wherein it was found that offshore turbines and high capacity turbines were more efficient than onshore small-scale turbines. However, no research has yet targeted the individual performance of Danish wind turbines. Sometimes it is sufficient to look at averages, but if the variability is high in terms of environmental impacts, it is crucial to investigate the causes behind this variability. One typical way of evaluating individual performance among a set of decision-making units (DMUs), that is WFs, is by employing a data envelopment analysis (DEA). A relatively recent addition to the many variations of DEA is the LCA + DEA method, proposed by Lozano et al. (2009), which combines material inventories, environmental impacts, and the production for a set of DMUs.

The aim behind subsidizing wind power in Denmark, and arguably for any country, is to maintain the profitability of current wind turbines when competing with cheaper alternatives, such as nuclear or coal plants. Also, it is to incentivize the undertaking of new wind turbine projects as described by Jenner et al. (2013). In other words, a subsidy is a way for policy makers to control the direction in which the energy supply mix is heading. However, the way in which a subsidy is designed could potentially alter the incentive structure for the operator from a microeconomic perspective. A price support, of which the FIT is one possible design, incentivizes the operator to minimize the costs per KWh according to Nordensvärd & Urban (2015). In Denmark, this is mainly achieved by upscaling wind turbines and WFs. Larger turbines should also lead to the minimization of environmental footprint, as found by Sacchi et al. (2019). In other words, my argument is that there is a potential positive external effect from this type of subsidy. The objectives of this thesis are the following:

1. By using an LCA + DEA (SBM-I) efficiency estimation model, estimate the environmental and operational performance for a sample of utility scale WFs (>100 kW) in Denmark for the year 2016.
2. Perform a second-stage analysis to evaluate to what extent a larger modelled FIT allotment is related to environmental efficiency among WFs in Denmark and investigate whether upscaling factors are facilitating this contingent effect.

The argument made in this thesis is that the price-premium FIT through economic incentives promotes upscaling of WFs in Denmark, which causes higher environmental efficiency as a positive external effect. By illuminating this possible association, I aim to contribute to the FIT literature by investigating whether this system, as hypothesized, is discriminatory against environmentally inefficient WFs in Denmark. The purpose is to introduce a new perspective for consideration when implementing energy policies for – in particular, but not exclusively – wind power. The success of a policy so far is mainly judged on additional deployment and permanence of wind power, whereas the overarching goal of renewable energy policies is reducing environmental impacts. It should follow that an environment-focused policy evaluation of the economic incentives is of importance. Moreover, by identifying environmental and operational efficiency facilitating factors, I aim to provide a basis for policy makers to design policies or subsidy systems which explicitly target the minimization of environmental impacts of the wind power fleet.

2 Earlier research

The LCA + DEA framework has been put to test in several different contexts and for different types of DMUs. Iribarren et al. (2013) applied the methodology on Spanish WFs, using a one-stage input-oriented slacks-based measure (SBM-I). The authors had LCA accounts and labor data for a sample of 25 Spanish onshore WFs. The efficiency estimation results were given in two consecutive steps: operational efficiency estimation and a conversion of operational savings to environmental savings. The inputs used for the operational estimation was a selection of LCI accounts; concrete, steel, epoxy resin, lubricating oil, iron, paint and fiberglass; and average number of hours worked per WF. It was found that, while the operational efficiency was rather high, the WFs on average had a lower environmental efficiency. Also, the authors found that a high nameplate capacity tends to yield a higher efficiency score, which will be further investigated in this thesis. The authors concluded that the method is feasible for application on WFs. They did not analyze offshore WFs. As this turbine type is becoming increasingly more popular, it would be beneficial for the overall understanding of wind power to include this production type in an LCA + DEA efficiency framework. Other applications where the LCA + DEA method has been used are, among others, Avádi et al. (2014) and Lorenzo-Toja et al. (2015). The former used LCIs on fishery ventures in Peru, where the environmental efficiency of vessels was estimated. The authors followed the methodology as in Iribarren et al. (2013) and analogically concluded the operational efficiency was high, albeit further potential environmental savings could be made without reducing production. Lorenzo-Toja et al. (2015) applied the SBM-I model onto Spanish wastewater treatment plants.

Wu et al. (2016) performed a two-stage Charnes-Cooper-Rhodes (CCR) DEA and Banker-Charnes-Cooper (BCC) DEA on 42 Chinese utility scale onshore WFs. A discussion on efficiency models can be found below. The inputs used for the efficiency estimation was capacity, auxiliary electricity consumption (electricity consumed by the WF itself) and wind density; and the outputs being electricity production and availability. This is, to my knowledge, the first two-stage DEA performed on wind power. Whereas earlier studies, as those mentioned above, analyze patterns in the efficiency scores by studying e.g. scatterplots, none feature an explicit second stage analysis. The authors regress on the efficiency scores using a tobit regression model. The exogenous variables are age, wind curtailment rate and a dummy for WF operators. The authors found that the age has a significant effect on the performance of a WF, as well as the wind curtailment rate. It is also suggested by Green and Staffell (2014) that the age approximately reduces the output of an onshore WF by 16% per decade. Therefore, an age variable, acting as a confounding factor will be added to the second stage analysis of this thesis. Wu et al. (2016) did not find significant differences between any of the WF operators. The operators were located in separate regions of China, which suggests there are no regional differences between the efficiency scores given the inputs used by the authors. There is still reason to suspect differences between regions with respect to environmental and operational efficiency, as there may be differing average local conditions, which may either influence the output or input variables. This is also proposed by Sameie & Arvan (2015). Area and manufacturer variables will be included as control variables to the second stage analysis.

Papiez et al. (2019) conducted a two-stage DEA on the efficiency of European wind power. The authors used five models with differing inputs and outputs. The inputs are installed capacity per country and average wind density per country. The outputs are electricity production per country, economic savings aspects (the price of fossil fuels being replaced by wind), environmental aspects (avoided emissions by producing with wind power) and energy security aspects (decreased imports dependency). A second-stage analysis was conducted, where the efficiency scores per country are regressed on institutional factors, such as FITs per country, investment support, regulatory support, or policy related promotion schemes. Among other things, the authors find that FITs increase the efficiency of wind power in a country. Also, they find indices on that the fraction of offshore wind power is positively related to a higher wind efficiency score. The authors do not necessarily cover why the FITs cause higher efficiency in a country, which is where the objectives of this thesis fit (pun not intended) in the literature, as it will be possible to illuminate how the policy incentives could affect the wind fleet composition with respect to overall sizing. Within the FIT literature field, one common policy effect studied is additional deployment, as has been done by Couture and Gagnon (2010) and Jenner et al. (2013). Couture and Gagnon (2010) provide with a literature review on studies conducted on different types of subsidization schemes and how these have been found affecting, among other factors, the additional capacity deployment for RES's. The review generally suggests a positive association with deployment rate. Jenner et al. (2013) instead argue that earlier studies did not control for country-specific fixed effects, which could have caused spurious correlations. They found no evidence of additional capacity deployment resulting from the FIT. As discussed above, there may still be structural effects resulting from such a policy, without necessarily increasing the total capacity. Moreover, previous FIT research has not to my knowing covered whether there are environmental aspects to these kinds of subsidization systems.

2.1 Efficiency estimation model

An LCA + DEA estimation, as proposed by Lozano et al. (2009), will be performed on a sample of 75 Danish WFs using cross-sectional data for the year 2016. After deliberation, I argue that the most adequate efficiency model is the SBM-I. Lorenzo-Toja et al. (2015), Avádi (2014), Iribarren et al. (2013) recommend using this efficiency model for LCA + DEA applications. SBM accounts for non-radial inefficiencies, meaning that it computes the non-radial (relative) input use (e.g. concrete to metal use) and the radial input use (input to output) simultaneously – not only radial, or proportional, input decreases as in the CCR. A CCR would proportionately decrease the input use (e.g., a 20% overall decrease in input use), whereas the SBM can compute unique input reduction potentials. This is a desirable property in a context where there are loose interconnections between the inputs, as argued by Lorenzo-Toja et al. (2015). For instance, it is not apparent how logistics relates to the concrete use, or the acidification with the eutrophication. One input may easily be reduced, whereas another is hard to dispose of. Low disposability could be reflected in low variability in a specific input use among DMUs. Another desirable property is that SBM is unit invariant as opposed to CCR. For instance, a CCR would yield different scores if one unit of measure were transformed from kg to tons, as the proportions would change. This is not the case for SBM, which makes it more robust in this setting, where many inputs use differing units. The drawback of SBM is that it is instead not translation invariant, according to Tone (2001). This means it is sensitive to negative numbers or zeroes in the dataset. Fortunately, this is not an issue in the dataset used for this thesis. Iribarren et al. (2013) defined the SBM-I minimization problem as

$$\Phi_j = \min(1 - \tfrac{1}{M}\textstyle\sum_{i=1}^{M} s_{i0}^{-} / x_{i0}) \qquad (1)$$

$$subject\ to$$

$$\textstyle\sum_{j=1}^{N} \lambda_{j0} x_{ij} = x_{i0} - s_{i0}^{-} \qquad (2)$$

$$\textstyle\sum_{j=1}^{N} \lambda_{j0} y_j = y_0 \qquad (3)$$

$$\lambda_{j0} \geq 0, s_{i0}^{-} \geq 0. \qquad (4)$$

Φ_j is the efficiency score. M is the number of inputs to be minimized. s_{i0}^{-} is the potential reduction (slack) in input i for DMU 0. x_{i0} is the amount of input i used by DMU 0, and y_0 the production of DMU 0. λ_{j0} is coefficients of linear combination to be solved for DMU 0 against the remainder of DMUs. The lambda values will in the optimal solution outline an efficient frontier (called "best practice") onto which DMUs are projected. What is meant by "linear combination" is that any production point on the efficient frontier is assumed to be feasible. In other words, the best practice frontier is based on interpolation between one or more input usage points. It should be noted that this is not an SBM-specific assumption but a foundational assumption of DEA in general. By constraint (4) is assumed that $\lambda_{j0} \geq 0$, meaning only positive coefficients of evaluation are allowed, thus hindering optimal solutions with negative combinations of resource use. By imposing the restriction at 0, the efficiency estimations are non-weighted (no specific weight given to specific lambdas) and display constant returns to scale, analogously to a CCR-CRS (constant returns to scale) model. Considering the inputs and number of observations, the optimization problems to be solved for DMU 0 in this thesis is the following:

$$\Phi_0^{OP} = \min(1 - \tfrac{1}{10}\left[\frac{s_{m0}^{-}}{x_{m0}} + \frac{s_{p0}^{-}}{x_{p0}} + \frac{s_{c0}^{-}}{x_{c0}} + \frac{s_{wd0}^{-}}{x_{wd0}} + \frac{s_{ff0}^{-}}{x_{ff0}} + \frac{s_{l0}^{-}}{x_{l0}} + \frac{s_{t0}^{-}}{x_{t0}} + \frac{s_{fc0}^{-}}{x_{fc0}} + \frac{s_{ws0}^{-}}{x_{ws0}} + \frac{s_{fit0}^{-}}{x_{fit0}}\right]) \qquad (5)$$

$$subject\ to$$

$$\textstyle\sum_{j=1}^{75} \lambda_{j0} x_{ij} = x_{i0} - s_{i0}^{-} \qquad (6)$$

$$\textstyle\sum_{j=1}^{75} \lambda_{j0} MWh_j = MWh_0 \qquad (7)$$

$$\lambda_{j0} \geq 0, s_{i0}^{-} \geq 0. \qquad (8)$$

Where m=metals in kg, p=plastics in kg, c=concrete in kg, wd=wire drawing in kg-m, ff=fossil fuels in kg, l=logistics in ton-m, t=number of turbines, fc=farm capacity in MW, ws=wind speed in meters per second, and fit=FIT on the WF level in tDKK. MWh_0 is the output in MWh in 2016 for DMU 0. For the operational efficiency estimation M=10, N=75. The environmental efficiency estimation is analogically then

$$\Phi_0^{ENV} = min(1 - \frac{1}{5}\left[\frac{s_{pnof0}^-}{x_{pnof0}} + \frac{s_{gwp0}^-}{x_{gwp0}} + \frac{s_{pdf0}^-}{x_{pdf0}} + \frac{s_{som0}^-}{x_{som0}} + \frac{s_{odp0}^-}{x_{odp0}}\right]) \tag{9}$$

$$subject\ to$$

$$\sum_{j=1}^{75} \lambda_{j0} x_{ij} = x_{i0} - s_{i0}^- \tag{10}$$

$$\sum_{j=1}^{75} \lambda_{j0} MWh_j = MWh_0 \tag{11}$$

$$\lambda_{j0} \geq 0, s_{i0}^- \geq 0. \tag{12}$$

Where pnof=terrestrial and freshwater acidification, measured in H+ equivalents; gwp=global warming potential, measured in kg CO_2-eq.'s; pdf=freshwater eutrophication, measured in phosphorus-eq.'s; som= land use, measured in kg displaced or occupied soil; odp= ozone layer depletion, measured in kg CFC's. For the environmental efficiency estimation, M=5, S=1 and N=75. The Data section below describes these inputs more in-depth.

3 Method

The two types of efficiency score will be analyzed in a second-stage analysis by performing tobit regressions on key technological, spatial, and temporal variables. A tobit regression is a type of censored regression model, where thresholds can be imposed on the dependent variable. As $0 \leq \Phi \leq 1$, this implies an efficiency score can never be larger than one, but one or more observations are by necessity one. As several DMUs are attributed full efficiency, there will be a hoarding of observations at the upper limit (and theoretically, the lower limit). This method has been used by Wu et al. (2016) as described in the Earlier research section. The latent two-limit Tobit (2LT) regression model is specified by McDonald & Moffitt (1980) as

$$y_i^* = \beta x_i + u_i, \tag{13}$$

$$u_i | x_i \sim N(0, \sigma^2) \;\; i.i.d, \tag{14}$$

where x_i is a vector of $1 \times k$ observations, β a vector of $k \times 1$ coefficients. u_i is a true random error term, which by expression (14) asymptotically is identically and independently distributed with a mean of 0, also known as the Gauss-Markov assumption. The right-hand side of the regression specification is analogous to an ordinary least squares (OLS), with a suppressed intercept. y_i^* is an unobservable, or underlying, value of the observed y_i. In the context of the second-stage analysis, this means

If $y_i^* \leq 0$, then $y_i = 0$
If $0 < y_i^* < 1$, then $y_i = y_i^*$
If $y_i^* \geq 1$, then $y_i = 1$.

This implies the true (or underlying) y_i^*s are censored by the observed y_is. Within the uncensored boundaries, the specification is like an OLS. The previous conditions can be rewritten as

$$y_i = \begin{cases} 1 \; if \; y_i^* \geq 1 \\ y_i^* \; if \; 0 < y_i^* < 1, \\ 0 \; if \; y_i^* \leq 0 \end{cases} \tag{15}$$

Given all above conditions, these can be fitted into a likelihood function, which was specified by McDonald (2009). The likelihood function implies that, if an observation is within the uncensored range ($0 < y_i < 1$), the interpretation of the coefficient β is equal to a standard OLS. If interested in values *above* or *below* the threshold ($y_i^* \geq 1, y_i^* \leq 0$), this interpretation is not valid (McDonald & Moffitt, 1980). The coefficient must in this case be multiplied by the probability of an observation being on the threshold, which implies that $\beta \leq \beta_{OLS}$. For the sake of the commencing second-stage analysis, there is no meaningful interpretation of values below or above the threshold. In other words, in the context of this thesis, the interpretation of the results is analogous to an OLS. In this thesis, the empirical models are then

$$\Phi_j^{ENV*} = \hat{\beta}_0 + \hat{\beta}_1 logFMW_j + \hat{\beta}_2 logCap_j + \hat{\beta}_3 logLT_j + \hat{\beta}_4 logWS_j + \hat{\beta}_5 i.Off_j + u_j, \quad (16)$$

where FMW_j is FIT per MW for WF j. Cap_j is the capacity per turbine in MW of WF j. LT_j is the expected lifetime of WF j. WS_j is the average wind speed in 2016, measured at WF j. $i.Off_j$ is a dummy variable indicating if WF j is offshore.

$$\Phi_j^{ENV*} = \hat{\beta}_0 + \hat{\beta}_1 logCap_j + \hat{\beta}_2 logLT_j + \hat{\beta}_3 logRotor_j + \hat{\beta}_4 logHH_j + \hat{\beta}_5 logWS_j + \hat{\beta}_6 i.Age_j + \hat{\beta}_7 i.Off_j + \hat{\beta}_8 c.Man_j + \hat{\beta}_9 c.Area_j + u_j \quad (17)$$

$$\Phi_j^{OP*} = \hat{\beta}_0 + \hat{\beta}_1 logCap_j + \hat{\beta}_2 logLT_j + \hat{\beta}_3 logRotor_j + \hat{\beta}_4 logHH_j + \hat{\beta}_5 logWS_j + \hat{\beta}_6 i.Age_j + \hat{\beta}_7 i.Off_j + \hat{\beta}_8 c.Man_j + \hat{\beta}_9 c.Area_j + u_j \quad (18)$$

$Rotor_j$ is the rotor diameter of WF j in meters. HH_j is the hub height of WF j in meters. $i.Age_j$ is a dummy variable indicating if WF j is above ($i.Age_j$=1) or below ($i.Age_j$=0) 10 years of age as of 2016. $c.Man_j$ is a categorical variable for manufacturer 0-5 (where 0 is the base level) for WF j. $c.Area_j$ is also a categorical variable for area 0-5 (where 0 is the base level) for WF j. The interpretation of the coefficients is $\frac{\hat{\beta}_i}{100}$, as the specifications are level-log; if X_j increases by one unit, it will change Φ_j by $\frac{\hat{\beta}_i}{100}$ units. The age dummy was originally perceived as a continuous variable, however, there was a significant grouping of observations above 12 years and below 8 years of age and none in between. Consequently, a dummy was created to better capture this idiosyncrasy. While arguably being endogenous to the operational efficiency score, I regard the wind speed variable as a confounding variable which likely affects the other exogenous variables. Lastly, to address the mediating effect of size related variables, a specification using FIT per MW as the dependent variable is specified:

$$logFMW_j = \hat{\beta}_0 + \hat{\beta}_1 logCap_j + \hat{\beta}_2 logLT_j + \hat{\beta}_3 logRotor_j + \hat{\beta}_4 logHH_j + \hat{\beta}_5 logWS_j + \hat{\beta}_6 i.Age_j + \hat{\beta}_7 i.Off_j + \hat{\beta}_8 c.Man_j + \hat{\beta}_9 c.Area_j + u_j. \quad (19)$$

This regression specification is log-log and of a multiple OLS regression type. The interpretation is in terms elasticities, i.e. a 1% increase in X_j yields a $\hat{\beta}_i$ percent change in the dependent variable.

3.1 Regression diagnostics

As an assumption of the empirical model is i.i.d., some pre-analysis tests were run to check the validity of the assumption. The validity relies on non-collinearity of predicting variables and homoscedasticity of residuals. Some predicting variables are potentially correlated, which means I must check for collinearity. While collinearity does not necessarily affect the bias of $\hat{\beta}_i$, it could cause an unnecessary rejection of the alternative hypothesis due to large standard errors, commonly referred to as variance inflating factors (VIFs). By running the chosen regressions in STATA and then running the command *estat vif* it is possible to check for collinearity. Generally, a VIF score below 10 is deemed as good-enough for further analysis. This is a condition which optimally should be fulfilled, as an assumption of the empirical model is independently distributed error terms. If there is significant correlation between the predicting variables, there is a risk of the error terms not being independently distributed. High VIF scores could happen due to two main reasons: there is a significant correlation between two predictors, or many uncorrelated variables without explanatory power are added to the model. It was found that all three size related variables – rotor diameter, capacity per turbine and hub height – were collinear. None of these proxies the others well with respect to an efficiency score. I decided to compromise by first regressing on the collinear variables separately, and then in the last specification add all together. Generally, if out for causal inference, collinearity could be naturally caused by some unknown relation between predictors. This is not necessarily a problem for the accuracy of the regression model. To further test the specification of the regression models, a factor analysis is performed in Appendix 2. All size related variables are factored together to an underlying size factor, which solved the collinearity issues. The size factor is not used as a main predictor due to the infeasibility of interpretation.

The condition of homoscedasticity instead affects the bias of the coefficient estimate $\hat{\beta}_i$. Heteroscedasticity happens because the residuals are not evenly distributed along the x axis. This means that there is a significantly higher or lower residual variance as $x \to \infty$. If heteroscedasticity is detected, the slope of $\hat{\beta}_i$ is likely biased. To detect this type of i.i.d. violation, the STATA command *estat hettest* is run. This command executes the Breusch-Pagan test for heteroscedasticity, where a low p value (and high chi-squared value) result implies the point estimate is heteroscedastic. Usually heteroscedasticity does not cause too much trouble, as STATA can run robust standard errors. This type of standard error is the most commonly used, regardless of heteroscedasticity or not as a safety measure, which is the case in this thesis as well. Having a sense of the collinearity and heteroscedasticity in the dataset is nonetheless paramount for the understanding of overall fitness and robustness of the results.

3.2 Misspecification issues of second stage empirical models

Simar and Wilson (2007) point out that all DEA estimations suffer from serial correlation, which would make any specification using normal or robust standard errors to be inadequate. Serial correlation occurs when a temporal variable is correlated with itself, e.g. if the production of a DMU has been decreasing and the decrease is underestimated for ten years, all ten observations have serially correlating error terms. In the context of a DEA, this is a problem if one is researching e.g. firm efficiency and is using panel data for a series of estimations. In this thesis, I am assessing one point of production, and the estimates should thus not suffer from serial correlation. As of today, there is no consensus on which empirical model is the most appropriate to use for this purpose. McDonald (2009) argues that efficiency scores are neither censored nor corner solution types of data, but fractional – meaning are by definition non-parametrical. While agreeing with the sentiment of Simar and Wilson (2007), he argues that a statistical model which yields very different results to an OLS should rise suspicion and argues further that an OLS is not mis-specified due to the reason above. Furthermore, McDonald (2009) means that what is often the case with statistical models is a tradeoff between ease of interpretation and accuracy of the model. While there may or may not be some degree of misspecification for OLS, these still yield results which would likely be close to any other type of regression model, it is argued. I would analogically argue this is the case for a tobit specification in this setting. Super efficiency estimations have gained in popularity, where a DMU may be attributed a higher efficiency score than one. In this sense, the standard SBM or CCR act censoring, as there may be DMUs that are more efficient than other efficient DMUs – which most likely would be evident if running a second efficiency estimation but only using previously efficient DMUs. For the sake of comparison, the sensitivity analysis in Appendix 3 compares the differences in the estimators, where it is found that tobit yields almost identical results to OLS.

4 Data

4.1 Operational and environmental parameters

The Joint Research Centre (JRC) of the European Commission (2012) describes that common approaches for damage assessment is *midpoint* or *endpoint*, which both are part of the so-called ReCiPe method of damage estimation in LCIA. Midpoint refers to a broad matrix of different specific environmental damages which are caused by a given activity. Each damage has damage pathways, such as increased risks for respiratory diseases, or reduction in the number of animal species. A midpoint damage can give rise to several damage pathways. The endpoint measure is an aggregate of the damage pathways, divided into three broader categories: human health impacts, ecosystem impacts and resource impacts. Blending these impact categories could thus cause double counting of some damages. Therefore, only midpoint damages were chosen for this thesis, as they can be more directly related to a specific type of damage. It should also be noticed that the emission of one type of chemical might cause two or more types of damages.

Table 1. Summary statistics on environmental and operational parameters

Non-material inputs	Mean	St. Dev	Min	Max	Description
Turbines	11.37	20.69	4.00	111.00	I1
Capacity, WF, MW	25.29	58.91	1.25	399.60	I1
Wind speed, 2016, m/s	7.57	0.78	6.53	9.31	I1
FIT, WF, tDKK, year	22 707	63 837	440	437 797	I1
Environmental impacts (per year)					
Acidification, PNOF, mol H+-eq.	6 677	17 216	316	108 953	I2
Global warming potential, GWP, kg CO2-eq	1 066 794	2 683 428	49 376	1 995 064	I2
Eutrophication, PDF, kg P-eq.	660	1 772	27	10 896	I2
Land use, SOM, kg soil	1 914 452	3 918 139	114 331	24 588 443	I2
Ozone layer depletion, ODP, kg CFC-11	0.0658	0.1545	0.0034	0.9561	I2
Material inputs (per year)					
Metals, kg	236 476	616 371	9 316	3 665 671	I1
Plastic components, kg	25 055	69 785	862	490 813	I1
Concrete, kg	23 735 582	87 300 175	9 165	468 272 676	I1
Wire drawing, m-kg	1 525	4 710	68	31 862	I1
Fossil fuels, kg	761	1 283	82	7 332	I1
Logistics, ton-meter	504 607	551 659	4 251	2 857 528	I1
Electricity production					
2016, MWh	82 251	235 199	1 605	1 662 027	O1, O2

I1: Input for the operational efficiency estimation; I2: Input for the environmental efficiency estimation; O1, O2: Output for both efficiency estimations.

Freshwater and terrestrial acidification (PNOF) is mainly caused by the emission of NH_3 (ammonia), NO_2 (nitrogen dioxide) and SO_x (sulfur oxide) (JRC, 2012). Emissions of any of these matters from any activity in the life cycle of a wind turbine will be attributed a certain impact on the acidification category, which is then converted to mole equivalents. Mole is a given count of hydrogen ion (H+) particles needed to react with an acid base. Different chemicals release different amounts of hydrogen ions, enabling a point of comparison between acids. Global warming potential, GWP, is the number of kg CO_2-eq.'s all environmental impacts give rise to, calculated from their climate warming potentials over a timeframe of 100 years. For instance, the above-mentioned mole-eq.'s can be converted to GWP. Freshwater eutrophication (PDF) is mainly caused by NH_3, NO_2 or P (phosphorus) being released into the air or freshwater. Phosphorus is the so-called limiting factor for freshwater eutrophication and is the unit of measure in kg's of phosphorus (P) equivalents. Land use (SOM) is the kg's of soil a given wind turbine is occupying and/or displacing. Ozone layer depletion (ODP) is caused by the emissions of freons to the air – in the case of wind turbine activities it is the CFC-11's (chlorofluorocarbon-11) that are the main source of ozone depletion. This impact is measured in kg's.

For this thesis, the metals category is an aggregate of chromium steel, rolled sheet steel, reinforcing steel and cast iron. These are measured in kg's. The plastic components category is constituted by all components that either are plastics or *related to* plastic constructions, such as the rotor of a wind turbine. The inputs aggregated are glass fiber, polypropylene, polyethylene, polyvinylchloride and epoxy resin. These are measured in kg's. In the raw data set, concrete is measured as cubic meters. For the purposes of this thesis and for ease of interpretation, this unit was converted to kg's. The wire drawing input is the amount of copper used to connect a wind turbine to the main grid. The measurement is kg-m. The kg-m measure is interchangeable, which means it could either be interpreted as one kg or one meter, since it is assumed that one meter of copper wire weighs one kg. For the purposes of this thesis, it is regarded as one meter. The fossil fuels category is an aggregate of diesel consumed by the time of construction and for daily maintenance operations and the amount of lubricating oil consumed over the lifetime of a wind turbine. In the raw dataset, the diesel consumption was described in megajoules, but for the purposes of this thesis and for ease of interpretation this unit was converted to kg's. The logistics input category is an aggregate of transportation by lorry and by barge (ship). The unit of measurement is ton-km, which is the number of km's a lorry or barge has transported the equivalent of one ton. For instance, if a lorry transports a rotor blade which weighs six tons and has travelled one km, it is reported as six ton-km's.

Furthermore, not all material categories are accounted for in this thesis due to a limited number of observations. An efficiency estimation has an upper observations-to-parameters ratio, thus a judgment call had to be made on which inputs to include. Considering the material inputs used by Iribarren et al. (2013), a "material input category" solution was reached, which allows for including a larger number of inputs at the expense of more granularity. This aggregation method may be more sensitive than for the previous application, as I also consider two production types. There is in other words a risk for excluding an input which disproportionately is higher or lower for either production type.

Another input for the operational efficiency estimation is the annual FITs, which I define as the discounted value of the average subsidy per expected lifetime year, per WF. This is a modelled variable. For this input I had to assume that all WFs of the sample consist of utility scale WFs and are owned by utility companies. This is not an unreasonable assumption, as the frequency of privately owned utility scale WFs in Denmark is – if not non-existent – very small. The type of ownership matters, as it is the foundation on which the size of the subsidy is based. Table 2 describes the size and conditions of the subsidies. All WF operators are allowed to individually negotiate the level of price supplementation, thus it should be noted that there may be individual positive deviations to these subsidy regimes, as what is assumed is the very minimum subsidy per KWh.

Table 2. Description of FITs

Type of WF	**Price supplement (DKK per KWh)**	**Condition**	**Balancing reimbursement (DKK per KWh)**	**Condition**
Onshore	0.33	Maximum 10 years.	0.1	Until decommissioning.
Offshore	0.353	Maximum 42000 full-load hours.	0.1	Until decommissioning.

Full-load hours are calculated as follows:

$$FLH_{k \in j} = C_k * 6600. \tag{20}$$

C_k is the median capacity factor for a vector of wind turbines k belonging to WF j. Here, it is the median measured capacity factor that is used instead of the wind speed, as the actual wind speed data only covers 2016 and could become misleading if used as a representative average. The factor of 6600 is referring to the number of hours in a year. Simply put, the full load hour measure is the number of hours per year that a given WF is working at its highest capacity. The total subsidy for a given WF is calculated as

$$FIT_j|onshore = \sum_{k=1}^{K} FLH_k \, KW_k \left(0.1ELT_j + 3.3\right) \; k \in j, \tag{21}$$

and

$$FIT_j|offshore = \sum_{k=1}^{K} FLH_k \, KW_k \left(0.1ELT_j + 0.353\,\frac{42000}{FLH_k}\right) \; k \in j. \tag{22}$$

k is a vector of wind turbines belonging to WF j, and K is the number of turbines belonging to WF j. FLH_k is the median full load hours of wind turbine k. KW_k: is the nameplate capacity in KW of wind turbine k. The discounted average subsidy per lifetime year ($DFIT_{j,s}$) is then calculated as

$$DFIT_{j,s} = \frac{FIT_{j,0_S} + \sum_{t_S=1}^{T_S} \frac{FIT_{j,t_S}}{(1+r)^{t_S}}}{ELT_j \times T_S}, \tag{23}$$

where

$$r = 0.07, \tag{24}$$

$$FIT_{j,0_s} = FIT_{j,t_s} = FIT_{j,T_s}. \quad (25)$$

$FIT_{j,0_s}$ is the total of subsidy s in year 0 for WF j. t_s denotes year t of subsidy s. T_s is the number of years eligible for subsidy s. r is the social discount rate. In other words, a social discount rate of 7% is assumed for this thesis. A lower discount rate would yield a higher FIT for WFs that have a longer expected lifetime. An artefact of calculating the average subsidization by discounting on the expected lifetime is that a longer expected lifetime effectively will decrease the FIT. There are in other words two mechanisms – average annual output (measured as FLH) and expected lifetime – which are expected to have a mutually offsetting effect with respect to environmental efficiency. This parameter goes to the efficiency estimation as the subsidy inputs per WF and will also be used for the second stage analysis but is for this purpose divided by the overall capacity of the WF.

4.2 Exogenous variables

Table 3 describes the exogenous variables used for the second stage analysis. Here, FIT per MW was used instead of FIT per WF, as the subsidy is highly dependent on the farm size and number of turbines. This is easily accounted for by dividing the FIT per WF by the total farm capacity, which generates a FIT per MW measure instead. The effect looked for is the environmental efficiency score depending on average subsidization per MW. Capacity per turbine is one of three size related variables and is the maximum momentaneous output (nameplate capacity) for a given turbine in a WF. The rotor diameter is a reflection of the swept area of a wind turbine and is generally larger, the larger the capacity per turbine. Analogously – as the rotor diameter increases the hub height increases to accommodate for larger blades. The hub height is measured from the foundation up to the rotor hub of the turbine. The expected lifetime is an estimate based on decommissioned turbines and is used as a control variable in this context. The wind speed is the average wind speed of 2016, measured at the center of a given WF at an altitude equaling the hub height. The expected lifetime and wind speeds will be further discussed below.

Table 3. Summary statistics. Exogenous variables

Variable	Obs	Mean	Std. Dev.	Min	Max
FIT per MW, 2019, tDKK	75	632.97	222.63	271.51	1122.41
Capacity per turbine, MW	75	1.8	.99	.23	3.6
Expected lifetime, years	75	20.75	2.49	16.25	25.75
Rotor diameter, m	75	73.55	24.84	29	120
Hub height, m	75	64.34	18.43	31	94
Wind speed, 2016, m/s	75	7.57	.78	6.53	9.31

The categorical variables used for the second stage analysis are age, offshore, manufacturer and area. Age denotes whether the WF is 10 years or newer. Offshore denotes whether the WF is located offshore. Manufacturer is a categorical variable consisting of six manufacturers, where 0=Siemens, 1=NEG Micon, 2=MHI Vestas, 3=Nordex, 4=Bonus and 5=Wind World. There are relatively few observations for 1, 3, 4 and 5, as Siemens and MHI Vestas are disproportionately more common manufacturers. Area is also a categorical variable consisting of six areas, where 0=The Northmost tip of Jylland, 1=Mid-East Jylland, 2= Mid-West Jylland, 3=South Jylland, 4=North-West Jylland, and 5= Lolland & Sjælland.

4.3 Data collection and discussion

The LCA_WIND_DK dataset by Sacchi et al. (2019) and Besseau et al. (2019) consists of 11281 observations of planned, operational and decommissioned wind turbines. 2560 turbines are planned, 3125 are decommissioned and 5596 are operational as of 2019. For this thesis I discarded turbines that are either in the planning stage or decommissioned as of 2016. 2016 output is chosen as the output variable, as that is the latest year of actual outputs in the LCA_WIND_DK dataset. It is utility scale wind farms that are of interest, which in this thesis is defined as a wind turbine with a maximal output of ≥ 0.1 MW. Many observations had to be discarded due to lack of sufficient data on vital supplementary information, such as manufacturer, capacity, tower height or rotor diameter. Another variable which many observations lacked was actual median capacity factors, which is an important variable for estimating the total lifetime subsidy.

Figure 1. Distribution of WFs. Yellow: Northmost tip of Jylland; Blue: Mid-East Jylland, Green: North-West Jylland; Red: Mid-West Jylland; Purple: South Jylland, Orange: Lolland & Sjælland.

As the LCA_WIND_DK dataset consists of single turbines, these had to be aggregated to WFs. I chose to define a WF as a constellation of ≥4 wind turbines that are situated in close proximity. “Proximity” has a loose definition here, as there is a significant difference in distance to the closest turbine between different WFs. Mostly, the grouping of turbines is obvious due to close-matching IDs, turbine types and locations. For some occasions, the proximity criterium showed to be intricate to apply. In such cases I grouped turbines by referring to their longitudinal and latitudinal coordinates and other parameters which matched well. Undoubtedly, the WF grouping process introduced some amount of arbitrariness to the sample selection. All in all, 852 individual turbine observations, totaling 75 (whereof 65 onshore and 10 offshore) WFs, were deemed feasible for further analysis given the criteria above and the exclusion of incomplete observations. Moreover, WFs containing two or more manufacturers of turbines were separated into two or more separate DMUs. A typical case is the Rønland offshore WF, where four turbines are manufactured by Bonus and four by MHI Vestas. As the sample was selected, the coordinates were transferred to Google Maps for a visual inspection of the distribution over the Danish map. The distribution can be seen in Figure 1. As most WFs of the population are located in Western Jylland, there should not be a considerable spatial bias. The WFs were grouped into six areas, covering all of Denmark besides Bornholm.

As the wind turbines are grouped into WFs, the respective input and output parameters had to be aggregated. There are two possible ways of going about the aggregation process, where the first is to simply add all inputs and outputs together for each WF. The second option is to aggregate the total inputs and outputs per expected lifetime year. I argue choosing the first option of aggregating could lead to treating WFs with high expected lifetime unfairly, as this is expected to increase the overall efficiency positively. Thus, the aggregation method chosen is

$$Y_{i,j} = \frac{\sum_{k=1}^{K} y_{i,k}}{ELT_j} \qquad k \in j. \tag{26}$$

$$ELT_j = \sum_{k=1}^{K} ELT_k \,/K \tag{27}$$

Where $Y_{i,j}$ is input i of WF j, k is a vector of wind turbines belonging to WF j, $y_{i,k}$ is input i of wind turbine k, and ELT_j is the expected lifetime of WF j. The expected lifetime of WF j is the average expected lifetime of each wind turbine belonging to WF j. The aggregation process is analogous for both input sets. The output of 2016 is simply aggregated for each WF, as it is already on an annual basis.

The information on subsidy rates was gathered from ENS (2017) and consists of predicted minimum price supplements for utility scale wind turbines of both offshore and onshore types for 2020. The wind speed data from 2016 was collected from Renewables Ninja (2020). Renewables Ninja is a data source which focuses on key RES inputs, such as wind speeds, sun hours and precipitation, as predicted by MERRA-2 simulations.[1] The simulations are based on weather satellite data. By not relying on weather stations, coordinates can be used to locate the

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[1]See Staffell & Pfenninger (2016) and Pfenninger & Staffell (2016) for a more elaborate account on how these data points were predicted. The interactive platform can be accessed via https://www.renewables.ninja/.

onsite wind speed. The raw wind speed data is given hourly, at an altitude equaling the hub height of the wind turbines in each WF. The hourly wind speeds were then averaged to a yearly average wind speed per WF. A drawback in relying on wind speed simulations is that satellites may be granular in the predictions and there is a chance of disregarding highly local factors. However, relying on adjacent weather stations would likely not increase the precision of the data, as these are often not onsite; and if so, not necessarily in the middle of the WF.

Before presenting the results, I will discuss the reliability and accuracy issues of the dataset used for this thesis. LCA studies are in most cases associated with a significant degree of uncertainty – especially the LCIA step. It is depending on a number of assumptions and on imposed restrictions on degrees of separation from the original emissions source. A given DMU could in other words be causing additional impacts to the environment, and this would not be accounted for, as the inventories are based on an *a priori* LCA method. There could be many differences between LCAs performed *a priori* and *a posteriori*, where the latter could account for this type of idiosyncratic impacts. There are on the other hand instances where these event-caused impacts could be less interesting. For instance, maintenance work which is above or under the estimate level is not necessarily interesting unless it is caused by an explanatory variable. Accounting for such events could on the contrary potentially reduce the external validity of the results. Nonetheless, such maintenance work could be reflected in an *a posteriori* LCA through e.g. additional metal use or plastics use. For this thesis, I would argue an *a priori* LCA method is likely more feasible than the prior.

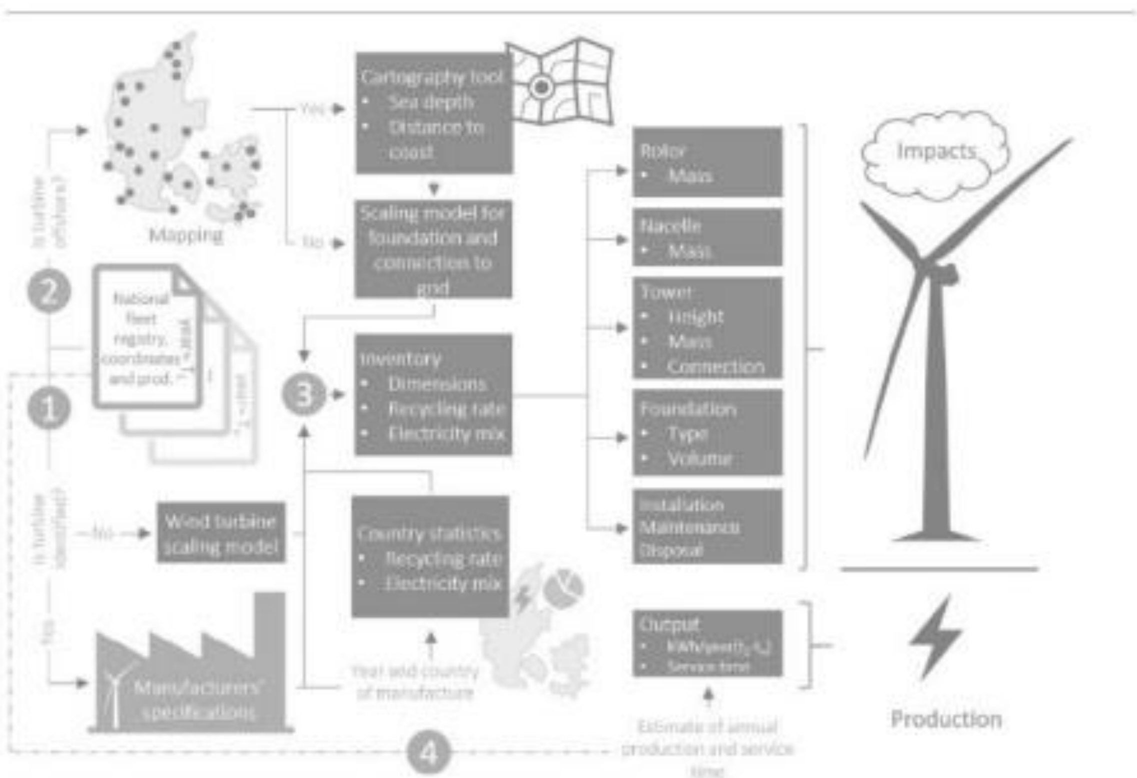


Figure 2. 4-step chart on fleet-wide LCAs in Denmark, as published in Sacchi et al. (2019).

The dataset this thesis is mainly based on is a tailormade fleetwide LCA authored by Sacchi et al. (2019) and Besseau et al. (2019), as mentioned above. The LCI is built on, among other things, manufacturer data, spatial information (such as location, on/offshore, distance to main grid), production type specific information (e.g. additional material for an offshore turbine), ecoinvent directories for background processes, local installation proceedings, year of installation/manufacturing and service time. The synthetization of the dataset is described thoroughly in both authors above. A flow-chart over the process is displayed in Figure 2. An important difference between other LCAs is that this one targets the whole fleet, rather than a subset of turbines, such as 2 MW turbines, or a specific WF. While enabling this type of analysis, it inevitably also introduces some arbitrariness to the dataset. For instance, exceptional maintenance work (e.g. if a turbine fails) cannot be accounted for, as mentioned above. Generally, for the turbines themselves, the inventories are based on the manufacturer's LCI data. If these do not exist, the authors interpolated the inventories based on known upscaling ratios, such as foundation weight to tower height, or rotor diameter to hub height. In the chosen sample, which was described above, these are discarded to enhance the reliability. Spatially dependent inventories, such as wire drawing, are based on known parameters, such as the distance to the main grid. It is also conditioned on the nominal output of the turbine. The logistics, road builds and lubricating inputs are based on ecoinvent inventories on background processes and interpolated, conditional on the capacity of a given wind turbine. This since ecoinvent inventories on wind turbines are categorized by capacity.

As is common practice for LCA analyses, the LCIAs are modelled using an LCA software as the inventories are created. A unique feature of this dataset and which sets it apart from most other LCAs is that it does not assume values on proven crucial factors of lifecycle impacts, such as the expected operational lifetime or capacity factor. Most other LCAs assume a capacity factor as reported by the manufacturer and a lifetime of 20 years. While there were no significant differences in expected lifetime between installation year, manufacturer or capacity, Besseau et al. (2019) and Sacchi et al. (2019) found a normal distribution of decommissioned turbines with respect to their lifetime, and randomly assigned expected lifetimes to operational turbines based on this distribution. Other problems arising from interpolating data, which could affect the results of the efficiency estimation, especially concern spatially dependent variables. Technology-specific upscaling algorithms are used for most LCAs and have proven feasible. There is a higher degree of stochasticity in the spatial variables, however. For instance, the concrete use is probably strongly affected by the soil type, as harder soil would imply less grouting for the foundation. Furthermore, different kinds of vessels may have been used for different transports, which could significantly alter the ton-km's required for transportation. Generally, the authors' LCAs lie within the realm of previous LCA studies in terms of GWP per KWh, based on a sample of 500 KW, 1 MW and 2 MW (offshore/onshore) turbines. This indicates the fleet wide LCA is sufficiently reliable for further studies. Other factors which the authors analyze for their fleetwide LCA is recycling rates and mode of recycling. These factors were not used in this thesis, as they are strongly temporally dependent as noted by the authors. As all turbines of the chosen sample are operational as of 2016, I argue it would introduce additional uncertainty if hypothesizing on the future recycling rate of different materials.

5 Results and discussion

5.1 Efficiency estimation results

In Table 4 and Table 5, summary statistics describe the operational efficiency estimation and the environmental efficiency estimation. Just as in Lozano et al. (2009), there seems to be a discrepancy between the two efficiency scores, where WFs generally score higher in the operational efficiency score. The complete results, where individual efficiency scores are presented for the environmental and operational estimation, can be found in Appendix 1.

Table 4. Summary statistics. Operational efficiency estimation.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Operational efficiency score, Φ^{OP}	75	.7	.2	.37	1
Input slack, turbine count	75	3.54	5.35	0	33.29
Input slack, WF capacity, MW	75	3.24	5.18	0	37.77
Input slack, wind speeds, m/s	75	4.37	2.58	0	7.84
Input slack, FITs, tDKK	75	733.76	2313.34	0	16045.15
Input slack, metal, kg	75	37080.75	108439.6	0	729958.4
Input slack, plastics, kg	75	1935.86	3301.94	0	18390.63
Input slack, fossil fuel, kg	75	201.44	276.11	0	1692.11
Input slack, concrete, kg	75	3080000	1.73e+07	0	1.14e+08
Input slack, wire drawing, m/kg	75	171.46	574.27	0	4915.76
Input slack, logistics, ton-km	75	116115.1	166174.2	0	1130000

Table 5. Summary statistics. Environmental efficiency estimation.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Environmental efficiency score, Φ^{ENV}	75	.54	.17	.25	1
Input slack acidification	75	2005.54	4442.1	0	24135
Input slack GWP, CO2-eq.'s	75	320219.1	680133.6	0	3990000
Input slack eutrophication	75	194.05	494.02	0	2752.69
Input slack land use, kg soil	75	772854.9	1060000	0	6260000
Input slack ozone depletion, CFC-eq.'s	75	.02	.04	0	.24

In the operational efficiency estimations, 16 WFs were fully efficient, of which 10 are sited onshore and 6 offshore. Of all onshore WFs, 15.3% are reported efficient, whereas 60% of the offshore WFs are efficient. On average, it was found that most WFs could use less operational inputs to achieve a given output level. As is evident, most input slack categories displayed large standard deviations, stretching well beyond the mean. This could be explained by the differential in farm sizes, as can be seen in Table 1 in the Data section, as well as offshore farms generally using more concrete per turbine. In the environmental efficiency estimations, two WFs were reported efficient. Among these, one was situated onshore and one offshore; 1.5% of the onshore WFs were efficient, and 10% of the offshore WFs. Summary statistics on efficient DMUs from both estimations can be found in Appendix 1.

A Spearman rank correlation test was carried out to investigate whether the internal ranking of efficiencies differ significantly. The internal ranking correlation was found to be .9365 (*p<.001*), which implies that the efficiency ranking of DMUs between the two estimations highly correlates.

Table 6. Two-sample T test with unequal variances

	Obs., onshore	Obs., offshore	Mean, onshore	Mean, offshore	Dif.	SE	T value	P value
Φ^{ENV}	65	10	.676	.85	-.173	.065	-2.7	.009
Φ^{OP}	65	10	.515	.699	-.183	.056	-3.3	.002

As both offshore and onshore WFs are included in the estimation sample, a Welch's T test was performed to evaluate the hypothesized mean difference between the two production types. The results are displayed in Table 6. The differences in means are significant on the 1% level for both types of efficiency scores, which suggests that an offshore farm on average is more efficient than its' onshore counterpart, which is analogous to the findings of Sacchi et al. (2019). The point estimate in difference is 17-18% higher for offshore WFs for both types of efficiency. This also suggests there is a significant heterogeneity in the sample, which should be addressed by adding an offshore dummy to the second stage analysis.

5.2 Sensitivity analysis

A third efficiency estimation was carried out, where non-material inputs from the operational efficiency estimation were omitted. The average efficiency score was .7, with lower variance than the operational efficiency score. To investigate changes in internal ranking, another Spearman rank correlation test was carried out. The correlation results were .929 (*p<.001*) between the operational and material efficiency estimation, and .8955 (*p<.001*) between the environmental and material efficiency estimation. This suggests the internal rankings are robust to omitting inputs. To further test this contingent association, I tried to replicate the efficiency score association found by Lozano et al. (2009), Avádi et al. (2014) and Vasquez-Rowe et al. (2015). The results were comparable to those found by the authors, with a below-one point estimate for the environmental and operational efficiency score. The associations were further compared with an OLS to examine how close the point estimates are. No significant difference between OLS and the preferred tobit specification was found. By the same token, the material efficiency score was regressed to check further robustness of this association. The results from this sensitivity analysis (including material efficiency estimation results and summary statistics) can be found in Appendix 3. All in all, the sensitivity analysis suggests that the efficiency estimations are robust to input omission and are highly correlated, indicating operational, material and environmental efficiency all depend on similar facilitating factors.

5.3 Second stage results

The following coefficient interpretations are in a 95% confidence interval if nothing else is specified. A central aim of this thesis was to predict the association between environmental efficiency and annual subsidy grants per MW. Column 1-3 of Table 7 describes the results of the FITs, regressed on the environmental efficiency score. Column 1 only regresses Φ^{ENV} on the FIT and controlling for offshore WFs, while column 2 addresses all variables which could affect the FIT. Column 3 additionally controls for differences with respect to age, manufacturer, and area. The results of the FIT seem robust, with statistically insignificant coefficient differences. The point estimate varies from .3748±.08 ($p<.01$) to .3148±.117 ($p<.01$). From the latter, a 1% increase in FIT per MW is on average predicted to increase Φ^{ENV} by .00315 units. An interesting find is that being situated offshore does not have explanatory power in this specification. This does not contradict the results in the previous section, as it means that the differences in efficiency between onshore and offshore WFs can largely be explained by the components of the FIT variable. It be pointed out that the results of these three specifications are not to be interpreted causally. It is unlikely that a higher subsidy would encourage WF operators to become more environmentally efficient. The FIT per MW reflects underlying factors by design, such as increased output, higher capacity factors, and lower expected lifetime. Moreover, it does not seem like there are differences with respect to manufacturer or area when regressing on the residual values of FIT per MW, although adding to the model's overall significance. It seems this predictor provides a very good fit to predicting environmental efficiency, which suggests that the first part of the argument presented in this thesis holds. Further investigation on the factors mediating this effect is feasible.

Table 7. Second stage analysis. Environmental efficiency score

	(1) Tobit	(2) Tobit	(3) Tobit	(4) Tobit	(5) Tobit	(6) Tobit	(7) Tobit
FIT per MW, tDKK, log	0.3748***	0.3653***	0.3189***				
	(0.0408)	(0.0384)	(0.0597)				
Offshore	0.0327	-0.0030	0.0485	0.1474**	0.1464**	0.1732***	0.1787***
	(0.0467)	(0.0396)	(0.0513)	(0.0589)	(0.0603)	(0.0561)	(0.0577)
Expected lifetime, years, log		0.6562***	0.5058**	0.3834*	0.3298*	0.4255*	0.3637
		(0.1397)	(0.2101)	(0.2209)	(0.1822)	(0.2199)	(0.2255)
Capacity per turbine, MW, log		0.1084***	0.1538***	0.1689***			0.2613**
		(0.0212)	(0.0437)	(0.0524)			(0.1079)
Wind speed 2016, m/s, log		0.1482	-0.0276	0.2176	0.2725	0.3077	0.2651
		(0.1430)	(0.2082)	(0.2479)	(0.2599)	(0.2363)	(0.2258)
New WF (<10 years)			-0.0830	-0.0065		0.0502	0.0486
			(0.0887)	(0.0948)		(0.0790)	(0.0903)
Rotor diameter, m, log					0.2951***		-0.5756**
					(0.0775)		(0.2364)
Hub height, m, log						0.3483***	0.3841*
						(0.0912)	(0.2052)
Manufacturer (Siemens=0)							
1. NEG Micon			-0.0522	-0.1031	-0.0719	-0.0456	-0.1167
			(0.0695)	(0.0713)	(0.0482)	(0.0654)	(0.0728)
2. MHI Vestas			-0.0227	-0.0738	-0.0525	-0.0485	-0.0973**
			(0.0518)	(0.0488)	(0.0484)	(0.0467)	(0.0478)
3. Nordex			-0.1216	-0.3250***	-0.2664***	-0.1844**	-0.2819***
			(0.0979)	(0.0847)	(0.0605)	(0.0746)	(0.1047)
4. Bonus			-0.0867	-0.0957	-0.0634	-0.0477	-0.1049
			(0.0783)	(0.0913)	(0.0694)	(0.0837)	(0.0896)
5. Wind world			-0.0434	-0.0895	-0.0718	-0.0676	-0.1395*
			(0.0585)	(0.0747)	(0.0808)	(0.0774)	(0.0764)
Area (Jylland, Northmost tip=0)							
1. Jylland, Mid-East			-0.0709	-0.0908*	-0.0795*	-0.0693	-0.0803
			(0.0533)	(0.0537)	(0.0455)	(0.0503)	(0.0541)
2. Jylland, Mid-West			-0.0282	-0.0135	-0.0194	-0.0160	-0.0032
			(0.0478)	(0.0552)	(0.0516)	(0.0502)	(0.0521)
3. Jylland, South			-0.0654	-0.0635	-0.0595	-0.0581	-0.0570
			(0.0433)	(0.0512)	(0.0513)	(0.0464)	(0.0469)
4. Jylland, North-West			0.0005	0.0346	0.0252	0.0314	0.0439
			(0.0582)	(0.0639)	(0.0669)	(0.0642)	(0.0593)
5. Lolland & Sjælland			-0.1050	-0.1596**	-0.1508**	-0.1534**	-0.1684**
			(0.0642)	(0.0688)	(0.0676)	(0.0721)	(0.0704)
Obs.	75	75	75	75	75	75	75
Pseudo R^2	-1.8012	-2.1689	-2.3979	-1.9618	-1.8137	-1.9844	-2.1308
F	53.1903	38.0268	49.2334	17.8389	16.6102	18.1630	16.6311

Standard errors are in parenthesis
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Column 4-7 are specifications which analyze the mediating factors of environmental efficiency. As discussed in the Method section, capacity per turbine, rotor diameter, and hub height are strongly collinear in Table 7. These were first regressed in three separate specifications (column 4-6 of Table 7). The age dummy also showed signs of collinearity in column 5 and was omitted. This way of addressing the collinearity was chosen throughout the remainder of the results and is mainly intended for comparative purposes to the full specification. Put differently, the first three columns are to be interpreted as predictive findings, whereas the full specification is closer to a causal interpretation. The full specification in column 7 has a mean VIF of 10.86 and individual predictors up to 62. This does not necessarily bias the coefficients but inflates the coefficient standard error and causes lower significance levels for collinear variables. This likely also explains the overall significance of column 7, as it is lower than for the previous models, despite having relatively many significant results. A quite robust find is that capacity per turbine has a positive effect on Φ^{ENV}. The coefficient almost doubled in column 7 ($\beta_1 = .261 \pm .212$), which is an interesting find. This is likely due to the strong confoundedness with the rotor diameter; the rotor diameter was predicted to affect Φ^{ENV} positively ($\beta_3 = .295 \pm .152$) in column 5, while in column 7 it is predicted to strongly decrease Φ^{ENV} by $-.00576 \pm .00463$ units. The finding suggests, despite high collinearity that including collinear variables is preferable as it is not always obvious in which way they affect other predictors. The results from this specification would further indicate that a single size variable is not sufficient to analyze the overall size effect. Instead, it is the compound of these which are of most interest for a causal interpretation. For the remainder of the results discussion, I will mainly focus on the specifications which account for all size factors.

It seems the hub height has an overall positive effect on Φ^{ENV}, and which seems relatively robust in column 6 and 7. A possible explanation is that higher or more stable wind speeds at a higher altitude offset the additional material needed for construction, or is simply proxying an underlying quality of environmental economies of upscaling. Also, offshore WFs are consistently and significantly differing from the baseline intercept. They are predicted to on average be .17±.113 units more efficient than being onshore. As the FIT per MW predictor caused the offshore WF intercept to become insignificantly different to onshore WFs, the explanation is likely found in the components of this variable. It is likely due to an on average higher capacity factor, meaning a higher output per MW, everything else being equal. A high capacity factor can be reached either through high wind speeds or stable wind speeds (commonly referred to as wind curtailment rate) – or a combination of both. Wu et al. (2016) found wind curtailment rates to be of high explanatory value in their second stage analysis, and it is likely an omitted factor in these specifications. A more general discussion on omitted variables and heterogeneities with respect to manufacturer and area will be held below.

Table 8 displays the results of the second stage analysis of the operational efficiency score. It can be noticed that the point estimates on average are higher for this efficiency score. This is due to a generally higher operational efficiency score among WFs, as noted in the Efficiency estimation results section above. Also, coefficients above one occur in this table. This does not imply a larger effect size than the allowed range, as a level-log specification is interpreted as $\frac{\widehat{\beta}_i}{100}$, as described in the Method section.

Table 8. Second stage analysis. Operational efficiency score

	(1) Tobit	(2) Tobit	(3) Tobit	(4) Tobit
Capacity per turbine, MW, log	0.1041			0.1659
	(0.0878)			(0.1700)
Expected lifetime, years, log	0.9527**	0.6221*	1.0700***	0.9332**
	(0.3699)	(0.3339)	(0.3681)	(0.3839)
Wind speed 2016, m/s, log	0.7435	0.7796	0.7672	0.8824**
	(0.5038)	(0.5128)	(0.4717)	(0.4393)
New WF (<10 years)	0.2278		0.2096	0.3469**
	(0.1649)		(0.1412)	(0.1468)
Offshore	0.2427**	0.1999*	0.2581**	0.3237***
	(0.1153)	(0.1123)	(0.1028)	(0.0917)
Rotor diameter, m, log		0.3134**		-1.0881**
		(0.1546)		(0.4719)
Hub height, m, log			0.3566*	0.9905**
			(0.1868)	(0.3875)
Manufacturer (Siemens=0)				
1. NEG Micon	0.0576	-0.0293	0.0941	0.0660
	(0.1103)	(0.0836)	(0.1029)	(0.1123)
2. MHI Vestas	0.0146	-0.0052	0.0366	-0.0123
	(0.0818)	(0.0837)	(0.0765)	(0.0798)
3. Nordex	-0.1961	-0.2930***	-0.1038	-0.0228
	(0.1372)	(0.1041)	(0.1178)	(0.1751)
4. Bonus	-0.0509	-0.1668	-0.0460	-0.0425
	(0.1465)	(0.1375)	(0.1399)	(0.1415)
5. Wind world	0.0954	0.0493	0.1327	0.0112
	(0.1648)	(0.1854)	(0.1626)	(0.1760)
Area (Jylland, Northmost tip=0)				
1. Jylland, Mid-East	-0.0453	-0.0746	-0.0452	-0.0205
	(0.0702)	(0.0662)	(0.0654)	(0.0652)
2. Jylland, Mid-West	0.0421	0.0144	0.0322	0.0538
	(0.0925)	(0.0884)	(0.0859)	(0.0773)
3. Jylland, South	-0.0609	-0.0628	-0.0637	-0.0408
	(0.0818)	(0.0821)	(0.0748)	(0.0637)
4. Jylland, North-West	0.0407	-0.0024	0.0344	0.0533
	(0.1182)	(0.1208)	(0.1156)	(0.1104)
5. Lolland & Sjælland	-0.1257	-0.1454	-0.1294	-0.1408
	(0.0850)	(0.0906)	(0.0875)	(0.0876)
Obs.	75	75	75	75
Pseudo R^2	1.3951	1.2404	1.5015	1.7426
F	17.4308	12.5872	11.8897	6.9673

Standard errors are in parenthesis
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

A surprising find is that capacity per turbine is not driving Φ^{OP} in column 1 or 4, albeit with a positive point estimate. Possibly it could be explained by that the operational efficiency estimation has a broader spectrum of inputs than the environmental estimation, and of which not all inputs become relatively smaller per MW with higher turbine capacity (e.g. wind speed, number of turbines). Also, the same effect on the rotor diameter variable is evident for Φ^{OP} in column 4, but with a larger coefficient ($\beta_3 = -1.088 \pm .925$), which is to be expected. A 1% increase in rotor diameter is expected to reduce Φ^{OP} by more than .01 units. That is, if the rotor diameter is 100 meters, a 1-meter increase is expected to reduce Φ^{OP} by more than .01, everything else being equal. This is a relatively large effect size. By the same token, the hub height is just weakly significant and positive in column 3, whereas in column 4 the coefficient is larger, which again indicates negative confounding likely caused by the size variables. The effect size in column 4 is smaller than for the rotor diameter variable ($\beta_3 = -.991 \pm .76$). As above, the offshore WFs are significantly more efficient than onshore WFs, where the point estimate in column 4 is .324±.18 efficiency units higher than onshore and are in line with the findings of Sacchi et al. (2019). Other factors held constant, this is relatively large effect size. The point estimate varies notably when adding and omitting size related variables and the offshore dummy border-to being insignificant in column 2. This is likely due to that a component of the offshore quality is an on average larger size.

Table 9. Second stage analysis. FIT per MW

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Capacity per turbine,	0.046			-0.607***
MW, log	(0.073)			(0.179)
Wind speed 2016, m/s,	0.773*	0.685	0.767*	0.902**
log	(0.415)	(0.415)	(0.406)	(0.413)
Expected lifetime,	-0.374	-0.429	-0.269	-0.140
years, log	(0.425)	(0.391)	(0.408)	(0.343)
New WF (<10 years)	0.245**		0.213**	0.255**
	(0.102)		(0.090)	(0.104)
Offshore	0.310***	0.251***	0.311***	0.313***
	(0.078)	(0.075)	(0.075)	(0.086)
Rotor diameter, m, log		0.377***		1.155***
		(0.135)		(0.325)
Hub height, m, log			0.233*	0.302
			(0.119)	(0.230)
Manufacturer (Siemens=0)				
1. NEG Micon	-0.156*	-0.211**	-0.136	0.035
	(0.088)	(0.083)	(0.090)	(0.098)
2. MHI Vestas	-0.159**	-0.158**	-0.145**	-0.036
	(0.067)	(0.065)	(0.066)	(0.069)
3. Nordex	-0.634***	-0.729***	-0.587***	-0.324*
	(0.130)	(0.120)	(0.132)	(0.163)
4. Bonus	-0.025	-0.135	-0.033	0.110
	(0.140)	(0.115)	(0.137)	(0.140)
5. Wind World	-0.142	-0.113	-0.109	0.042
	(0.152)	(0.156)	(0.148)	(0.173)
Area (Jylland, Northmost tip=0)				
1. Jylland, Mid-East	-0.059	-0.105*	-0.065	-0.030
	(0.056)	(0.057)	(0.054)	(0.055)
2. Jylland, Mid-West	0.049	0.015	0.039	0.015
	(0.077)	(0.076)	(0.074)	(0.066)
3. Jylland, South	0.008	-0.011	0.001	0.004
	(0.083)	(0.081)	(0.078)	(0.066)
4. Jylland, North-West	0.108	0.074	0.102	0.077
	(0.093)	(0.087)	(0.091)	(0.094)
5. Lolland & Sjælland	-0.168*	-0.182*	-0.172*	-0.136
	(0.088)	(0.097)	(0.090)	(0.093)
Obs.	75	75	75	75
R-squared	0.823	0.827	0.830	0.860
F	35.226	46.262	43.407	42.521

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Contrary to the previous results on capacity per turbine, the FIT per MW is predicted to decrease ($\beta_1 = .607 \pm .351$) from a higher turbine capacity in Table 9. Furthermore, regressing on this variable it is instead the rotor diameter which is expected to positively affect the FIT per MW ($\beta_3 = 1.155 \pm .637$), whereas the hub height has an insignificant effect on the FIT per MW. These results are conflicting to the previous two findings. As the two previous results also had somewhat contradictory results, there seems to be some degree of randomness with respect to which size variable predicts in which way. If averaging out the effect sizes from the size related variables, there is suggestively a positive total size effect on both efficiencies and FIT per MW. Due to the stochasticity in the size results, a factor analysis was carried out as a supplementary analysis and can be found in Appendix 2. These results do indeed suggest a positive size effect, alas the coefficients cannot be interpreted in any meaningful way. All indices taken together, there does seem to be a positive turbine-specific upscaling effect on both efficiencies and the FIT per MW. This partly confirms Nordensvärd & Urban's (2015) contention that upscaling indeed maximizes profit, as the FIT is a significant part of the overall revenue per KWh. This suggests these variables are indeed mediating the effect on the efficiencies from the subsidization. However, this does not seem to be the whole story, as there also are other variables which to varying degree seem to influence all three dependent variables, such as wind speeds, average expected lifetime, and age. These are on the other hand truly exogenous, meaning they cannot in any realistic way be altered and are from a policy perspective uninteresting. Moreover, as the R-squared numbers are below 1 in the FIT per MW specifications, there are also one or more omitted variables, of which one has been discussed above. The pseudo R-squared results do unfortunately not say to what extent there is unexplained residual variation, as the STATA software does not reveal which type of pseudo R-squared is computed.

More broadly, there is quite robust evidence of heterogeneity with respect to production type, as this dummy significantly and positively modifies the intercept in most specifications. This would imply there is an internal quality to being situated offshore which is not explained by the other predicting variables. It was originally anticipated that this dummy would become insignificant when controlling for other confounding factors, which evidently is not case. A factor which is not controlled for in this thesis is wind curtailment rate, as mentioned above. It is reasonable to assume the wind curtailment rate is lower at sea than on land, as there are more obstacles for the wind to overcome on land. A low curtailment rate would not necessarily be absorbed by the average wind speed. More likely it would be reflected in the total production per year, which would be higher, which positively affects all three dependent variables, everything else being constant. For future studies, this would likely be a relevant variable to include for the analysis.

There is weaker evidence with respect to manufacturer and area heterogeneity. Nordex is quite consistently significantly less efficient than Siemens in many specifications. As there are quite few observations of this manufacturer, as well as for the other smaller manufacturers (Bonus, NEG Micon and Wind World), it cannot be ruled out that it mainly is due to local confoundedness that this manufacturer becomes less efficient. MHI Vestas is an equally popular alternative as Siemens, and there is suggestive evidence in the Φ^{ENV} specifications that it is a less efficient manufacturer than Siemens. This is also apparent in most specifications of Table

9. The reason behind inefficiency could have many possible explanations, as these manufacturers likely have differing production processes and choices of material. As this is not a consistent find, the robustness of this association could be questioned. As for area heterogeneity, there is evidence that Lolland & Sjælland is an environmentally less efficient area to place a WF than the Northmost tip of Jylland. The effect is relatively intact for all Φ^{ENV} specifications. This was reflected in Table 9 as well, although the effect disappeared when adding all size variables. As these two regions are not exposed to the open sea as the other areas, it could likely be explained by the same factor as for the offshore WFs, i.e., higher wind curtailment rate than other areas. This factor is likely influential in most specifications and does in other words weaken the causal interpretation in this context and should arguably have been included. If the effect would still be evident when controlling for curtailment rates, there are more aspects to spatial planning of WFs than maximizing efficiency. For instance, to reduce electric potential loss and place them where the demand is highest. The electricity demand is likely the highest in the Sjælland region, as this area harbors the capital Copenhagen, and could be an explanation for the desire to still accommodate relatively inefficient WFs in this area.

Overall, the results suggest the profit maximization incentives, here measured as FIT per MW, indeed has environmental impact reducing effects. This does on the other hand not necessarily imply that an increased FIT per KWh yields lower environmental impacts. What has been studied here is the incentive structure caused by the FIT. Thus, it is not obvious an increased FIT per KWh would further incentivize upscaling of WFs. From an environmental efficiency perspective, it could instead be further investigated how low the FIT can be to still yield such results found above.

6 Conclusion

The argument of this thesis was that higher FIT (i.e., profitability) per MW also tends to yield higher environmental efficiency, which was hypothesized to be an effect mediated by upscaling factors. As noted in the introductory section, in a premium-based subsidy scheme an operator would maximize profit by minimizing the cost per KWh, while maximizing the FIT per MW. The overall finding is that size factors on average seem to cause a higher profitability per MW. Size factors are suggested to positively affect both environmental and operational efficiency. Taken together, the results support the hypothesis presented in this thesis. The effect from the size variables were on the other hand unreliable, and I would not recommend taking this approach for further studies. Instead, a factor analysis as presented in Appendix 2 could be a feasible approach if interested in a more aggregated size effect. A consistent finding is that offshore WFs on average are more efficient than their onshore counterparts. This result was also found to be robust for adding other explanatory factors. The "offshore effect" is likely due to lower wind curtailment rates, which, everything else being equal, yields higher annual output. For further studies, this variable should arguably be included.

If policy makers explicitly want to minimize the environmental footprint of the electricity grid by targeting wind power efficiency, I would tentatively recommend promoting a general turbine upscaling. There also seems to be environmental economies of scale in offshore projects. As mentioned, however, it could once again be due to lower wind curtailment rates – which also could explain the relative spatial inefficiency of Lolland & Sjælland. There are on the other hand more spatial aspects to WF planning than those considered in this thesis and could be a reflection higher demand for electricity in these regions.

The contribution of this thesis was to add to the FIT literature by highlighting a contingent positive environmental externality of this subsidization system. The contribution also lies in combining onshore and offshore WFs in an efficiency estimation, and analyzing which factors facilitate both onshore and offshore WF efficiency. While finding the combining of offshore and onshore WFs a feasible and novel approach, I would for further studies recommend finding a more robust proxy for general sizing. Moreover, only one type of subsidy was studied here. For future studies, I would recommend performing a similar analysis on the fixed-price FIT.

References

Avadí, Á., Vázquez-Rowe, I., Fréona, P.2014. Eco-efficiency assessment of the Peruvian anchoveta steel and wooden fleets using the LCA+DEA framework. Journal of Cleaner Production, Vol 70, pp. 118-131. Doi: https://doi.org/10.1016/j.jclepro.2014.01.047.

Besseau, R., Sacchi, R., Blanc, I., Pérez-López, P., 2019. Past, present and future environmental footprint of the Danish wind turbine fleet with LCA_WIND_DK, an online interactive platform. *Renewable and Sustainable Energy Reviews*, Vol. 108, p. 274-288. DOI: https://doi.org/10.1016/j.rser.2019.03.030.

Couture, T., Gagnon, Y., 2010. An analysis of feed-in tariff remuneration models: Implications for renewable energy investment. *Energy Policy*, Vol. 38:2, p. 955-965. DOI: https://doi.org/10.1016/j.enpol.2009.10.047.

Danish Energy Agency (Energistyrelsen, ENS), 2017. Memo on the Danish support scheme for electricity generation based on renewables and other environmentally benign electricity production. ENS, 2017-03. Available at: https://ens.dk/sites/ens.dk/files/contents/service/file/memo_on_the_danish_support_scheme_for_electricity_generation_based_on_re.pdf. Accessed 2020-02-20.

European Commission, Joint Research Centre, Institute for Environment and Sustainability. Characterisation factors of the ILCD Recommended Life Cycle Impact Assessment methods. Database and Supporting Information. First edition. February 2012. EUR 25167. Luxembourg. Publications Office of the European Union; 2012. Available at: https://eplca.jrc.ec.europa.eu/uploads/LCIA-characterization-factors-of-the-ILCD.pdf. Accessed 2020-04-10.

European Network of Transmission System Operators for Electricity (ENTSO-E), 2009. European Electricity Transmission System Operators Reach Agreement on an Interim Solution for Inter-TSO Compensation. ENTSOE-E, 2009-12-18. Available at: https://www.entsoe.eu/2009/12/18/compensation/. Accessed 2020-04-30.

Iribarren, D. Martín-Gamboa, M., Dufoura, J., 2013. Environmental benchmarking of wind farms according to their operational performance. *Energy*, Vol. 61, p. 589-597. DOI: https://doi.org/10.1016/j.energy.2013.09.005.

Jenner, S., Groba, F., Indvik, J., 2013. Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries. Energy Policy, Vol. 52, pp. 385-401. Doi: https://doi.org/10.1016/j.enpol.2012.09.046.

Lorenzo-Toja, Y., Vázquez-Rowe, I., Chenel, S., Marín-Navarro, D., Moreira, M.T., Feijoo, G., 2015. Eco-efficiency analysis of Spanish WWTPs using the LCA + DEA method. *Water Research*, Vol. 68, pp. 651-66. Doi: https://doi.org/10.1016/j.watres.2014.10.040.

Lozano, S., Iribarren, D., Teresa Moreira, M., Feijoo, G., 2009. The link between operational efficiency and environmental impacts: A joint application of Life Cycle Assessment and Data Envelopment Analysis. *Science of The Total Environment*, Vol. 407:5, p. 1744-1754. DOI: https://doi.org/10.1016/j.scitotenv.2008.10.062.

McDonald, J.F., 2009. Using least squares and tobit in second stage DEA efficiency analyses. European Journal of Operational Research, Vol. 197:2, pp. 792.798. doi: https://doi.org/10.1016/j.ejor.2008.07.039

McDonald, J.F., Moffitt, R.A., 1980. The Uses of Tobit Analysis. The Review of Economics and Statistics, Vol. 62:2, pp. 318-321. Doi: 10.2307/1924766.

Nordensvärd, J., Urban, F., 2015. The stuttering energy transition in Germany: Wind energy policy and feed-in tariff lock-in. Energy Policy, Vol. 82, pp. 156-165. Doi: https://doi.org/10.1016/j.enpol.2015.03.009.

Papież, M, Śmiech, S., Frodyma, K., 2019. Factors affecting the efficiency of wind power in the European Union countries. Energy Policy, Vol. 132, pp. 965-977. Doi: https://doi.org/10.1016/j.enpol.2019.06.036.

Pfenninger, S., Staffell, Iain (2016). Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy, Vol. 114, pp. 1251-1265. Doi: 10.1016/j.energy.2016.08.060.

Sacchi, R., Besseau, R., Pérez-López, P., Blanc, I., 2019. Exploring technologically, temporally and geographically-sensitive life cycle inventories for wind turbines: A parameterized model for Denmark. Renewable Energy, Vol. 132, pp. 1238-1250. Doi: https://doi.org/10.1016/j.renene.2018.09.020.

Sameie, H., Arvan, M., 2015. A simulation-based Data Envelopment Analysis (DEA) model to evaluate wind plants locations. Decision Science Letters, Vol. 4:2, pp. 165-180. Doi: 10.5267/j.dsl.2015.1.001.

Schlömer S., T. Bruckner, L. Fulton, E. Hertwich, A. McKinnon, D. Perczyk, J. Roy, R. Schaeffer, R. Sims, P. Smith, and R. Wiser, 2014: Annex III: Technology-specific cost and performance parameters. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. Available at: https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_annex-iii.pdf#page=7. Accessed 2020-03-20.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics, Vol. 136:1, p. 31-64. Doi: https://doi.org/10.1016/j.jeconom.2005.07.009

Staffell, I., Green, R., 2014. How does wind farm performance decline with age? Renewable Energy, Vol 66, pp. 775-786. Doi: https://doi.org/10.1016/j.renene.2013.10.041.

Staffell, I., Pfenninger, S., 2016. Using Bias-Corrected Reanalysis to Simulate Current and Future Wind Power Output. Energy, Vol 114, pp. 1224-1239. Doi: 10.1016/j.energy.2016.08.068.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, Vol 130:3, pp. 498-509. Doi: https://doi.org/10.1016/S0377-2217(99)00407-5.

Wu, Y., Hu, Y., Xiao, X., Mao, C. Efficiency assessment of wind farms in China using two-stage data envelopment analysis. Energy Conversion and Management, Vol. 123, pp. 46-55. Doi: https://doi.org/10.1016/j.enconman.2016.06.014.

Appendix 1: Efficiency estimation results

Operational efficiency estimation

DMU	Name	Rank	Φ	Turb.	Cap.	Wind	FIT	Metal	Plastics	Fossils	Conc.	Wire	Logistics	O
	Average	**-**	**0.70**	**3.54**	**3.24**	**4.37**	**734**	**37081**	**1936**	**201**	**3081009**	**171**	**116115**	**0.00**
1	Lyngdrup by WF	42	0.64	3.3	4.84	5.18	327	45238	6280	303	111864	259	297887	0
2	Nørrekær Enge WF	24	0.79	2.1	1.84	5.04	412	14607	2681	167	0	110	82358	0
3	Nyrup by WF	34	0.68	2.7	1.44	5.11	6	2811	422	116	0	23	0	0
4	Oppelstrup by WF	61	0.52	7.9	3.76	5.87	165	26070	784	341	0	85	175201	0
5	Vrå Hovedgård WF	69	0.45	11.9	6.26	6.35	548	40179	1564	503	9069	147	267137	0
6	Hørup by WF	53	0.55	3.4	1.33	5.63	77	9522	0	122	4247	28	64153	0
7	Filskov by	75	0.37	5.2	5.36	6.50	234	39307	2987	344	2662	205	222688	0
8	Urup by WF	70	0.44	4.3	4.43	6.49	161	22883	2145	271	0	151	106657	0
9	Horns rev 2 offshore WF	27	0.77	33.3	3.23	4.81	9385	729958	0	1692	114499784	4916	48123	0
10	Lammefjorden WF extension	67	0.47	3.6	6.57	6.94	335	72730	9234	392	229698	380	498560	0
11	Øslev by WF	23	0.80	1.7	1.75	5.09	566	9468	1866	107	0	67	55172	0
12	Munkebo WF	32	0.69	1.7	2.19	5.88	26	19175	2839	148	37169	118	122232	0
13	Rødsand WF	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
14	Katrineholm Hovedgård WF	52	0.56	1.9	2.80	6.11	1361	38398	5080	230	109411	209	258542	0
15	Overgaard WF extension	35	0.67	2.3	3.06	5.44	131	27736	3972	199	61547	164	179866	0
16	Sødring by WF	41	0.64	2.2	2.86	5.40	380	34855	4836	233	86370	200	229589	0
17	Svoldrup by WF	39	0.65	2.5	3.08	5.26	1209	41422	5783	281	100531	239	272012	0
18	Tolstrup by WF	19	0.88	0.8	0.71	4.35	62	2916	927	30	0	8	21903	0
19	Flemming by WF	63	0.50	4.5	2.61	6.26	78	14267	134	190	16571	44	107339	0
20	Harre by WF	40	0.65	2.6	1.19	6.63	0	8778	0	122	12507	18	70320	0
21	Eggebæk WF	68	0.47	5.4	7.76	5.40	1963	78721	5518	453	8765	422	527128	0
22	Horns rev 1 offshore WF	15	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
23	Grønhede WF	50	0.59	2.5	3.42	7.78	457	19458	2291	230	0	188	93316	0
24	Rønland offshore WF 1	14	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
25	Ramme WF	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
26	Gundtoft by WF	20	0.85	1.1	1.14	2.47	899	13658	1628	164	0	134	64753	0
27	Brejning WF	33	0.68	1.8	0.30	6.18	1098	18589	1286	217	85928	121	134622	0
28	Rens Burkal WF	29	0.75	2.0	5.79	4.54	568	14795	0	179	11883	141	84075	0
29	Gilbjerg by WF	49	0.60	2.0	5.54	5.92	725	39728	215	191	0	177	294735	0
30	Døstrup by WF	31	0.69	2.4	6.89	5.33	820	18853	0	228	15142	179	107131	0
31	Ødum kirkeby WF	21	0.82	2.9	9.44	1.52	0	19401	0	230	17742	189	109740	0
32	Bandbøl by WF	13	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
33	Søgård WF	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
34	Slagelse offshore WF	1	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
35	Restrup hovedgård WF	26	0.78	1.5	4.33	4.10	306	10303	0	125	8275	98	58547	0
36	Anholt offshore WF	3	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
37	Lyderslev WF	60	0.53	3.4	1.41	5.96	80	10493	0	128	7623	32	71630	0
38	Skærbæk WF	44	0.62	4.8	1.66	5.21	0	12063	0	169	0	35	79770	0
39	Dyrebjerg WF	57	0.54	3.5	1.48	6.04	64	8965	0	113	5004	27	60716	0
40	Bindslev by WF	55	0.54	3.5	1.31	6.58	52	8452	54	108	3670	27	51855	0
41	Bur by WF	48	0.61	3.3	1.14	7.19	39	6702	0	94	0	20	39958	0
42	Hollandsbjerg by WF	43	0.64	7.1	7.77	3.66	0	27973	2540	416	0	157	148092	0
43	Ravnhøj WF	74	0.41	4.5	2.98	6.29	74	19726	1259	220	20422	66	136725	0
44	Balle by WF	64	0.49	3.5	1.97	6.77	81	15011	846	186	7930	47	103275	0
45	Næsbjerg by WF	65	0.48	3.6	2.25	6.59	114	12159	678	152	5978	38	83607	0
46	Foldby by WF	71	0.44	3.7	1.93	6.34	177	12856	519	158	3925	47	85632	0
47	Hjortnæs WF	37	0.66	3.0	1.07	5.92	0	8182	0	103	3569	4	62647	0
48	Falsig by WF	66	0.47	4.5	2.23	7.83	169	16165	591	207	1512	59	107148	0
49	Alstrup by WF	46	0.62	4.1	1.69	6.14	44	11153	101	149	0	19	80160	0
50	Over søen WF	56	0.54	9.6	4.63	5.84	60	29928	844	392	0	94	202389	0
51	Bonnet WF	18	0.88	0.5	0.00	4.75	1	2764	0	44	0	0	22900	0
52	Vodder WF	54	0.55	3.4	1.58	6.13	134	9988	219	132	0	27	68946	0
53	Thorup by WF	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
54	Copenhagen's offshore WF	58	0.53	5.8	7.95	7.84	131	73292	2269	263	16895812	56	5554	0
55	Lerchenborg hovedgård WF	17	0.89	0.7	3.37	2.81	2585	2201	1078	33	0	21	0	0
56	Barde by WF	30	0.73	1.4	3.53	5.64	654	24289	2195	122	0	112	160993	0
57	Østergård hovedgård	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
58	Tingsted (Guldborgsund) WF	36	0.67	30.7	37.77	6.30	8228	603554	13259	1522	97497944	386	13796	0
59	Rønland offshore WF 2	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
60	Lammefjorden WF	62	0.51	2.9	4.65	7.60	153	21498	3089	218	0	208	90221	0
61	Overgaard WF	45	0.62	9.3	14.80	3.25	242	53469	10092	725	0	674	140837	0
62	Købelev WF	47	0.62	6.6	3.81	4.68	111	22797	7576	299	0	86	57651	0
63	Dejbjerg WF	25	0.78	4.4	0.11	1.95	40	1916	1011	15	0	45	0	0
64	Arrild WF	73	0.42	3.5	1.40	5.95	139	14925	564	136	10014	48	93662	0
65	Hanstholm WF	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
66	Vrejlev WF	72	0.42	4.6	0.74	6.63	32	7254	592	57	0	47	45124	0
67	Bejstrup by WF	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
68	Kastrup WF	59	0.53	3.5	1.17	6.06	71	10181	430	114	0	31	57094	0
69	Degneboligen WF	2	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
70	Klim by WF	15	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
71	Bur by WF	51	0.56	4.3	17.87	4.20	16045	167066	18391	559	634869	834	1126704	0
72	Lem WF	22	0.81	0.3	0.91	4.31	1051	35873	3941	126	148767	161	259877	0
73	Nørre Vium WF	38	0.65	1.5	4.75	4.84	1272	68945	7574	242	285920	309	499467	0
74	Velling WF	4	1.00	0.0	0.00	0.00	0	0	0	0	0	0	0	0
75	Vejrum WF	28	0.76	0.4	1.22	6.48	889	27389	3009	96	113585	123	198419	0

Environmental efficiency estimation

DMU	Name	Φ	Rank	AP	GWP	EP	LDU	ODP	O
	Average	**0.54**	**-**	**2005.5**	**320219.1**	**194.1**	**772854.9**	**0.02179**	**0**
1	Lyngdrup by WF	0.51	39	1873.6	344778	136.4	1105278	0.02572	0
2	Nørrekær Enge WF	0.65	17	982.3	194873	55.6	780854	0.01598	0
3	Nyrup by WF	0.53	34	211.4	28243	18.7	110836	0.00272	0
4	Oppelstrup by WF	0.38	62	827.4	132587	69.0	471318	0.01175	0
5	Vrå Hovedgård WF	0.33	69	1255.6	200278	106.6	675918	0.01729	0
6	Hørup by WF	0.40	56	289.0	44258	24.9	173384	0.00420	0
7	Filskov by	0.25	75	1163.1	177301	103.0	498761	0.01353	0
8	Urup by WF	0.31	71	844.7	127132	75.7	362016	0.00986	0
9	Horns rev 2 offshore WF	0.69	15	22187.5	3204115	2752.7	4845807	0.18585	0
10	Lammefjorden WF extension	0.34	67	2464.4	434000	201.4	1225237	0.03110	0
11	Øslev by WF	0.67	16	699.2	141775	36.7	605889	0.01203	0
12	Munkebo WF	0.56	31	884.7	167098	60.0	588731	0.01301	0
13	Rødsand WF	0.62	24	24135.0	3986073	2489.6	6259638	0.24052	0
14	Katrineholm Hovedgård WF	0.44	52	1446.0	260757	111.3	776767	0.01891	0
15	Overgaard WF extension	0.54	33	1210.5	225360	85.7	752955	0.01717	0
16	Sødring by WF	0.51	38	1432.7	263566	104.9	846054	0.01975	0
17	Svoldrup by WF	0.51	36	1714.8	317108	123.9	1043062	0.02399	0
18	Tolstrup by WF	0.72	13	428.5	91976	16.4	440033	0.00820	0
19	Flemming by WF	0.38	61	448.9	73504	38.7	270466	0.00675	0
20	Harre by WF	0.48	45	314.9	51998	25.9	220187	0.00520	0
21	Eggebæk WF	0.37	63	1998.4	329198	164.5	1181453	0.02688	0
22	Horns rev 1 offshore WF	0.75	12	10781.0	1550444	1336.4	2231068	0.09224	0
23	Grønhede WF	0.48	43	890.6	133483	92.1	404995	0.01092	0
24	Rønland offshore WF 1	1.00	1	0.0	0	0.0	0	0.00000	0
25	Ramme WF	0.76	10	382.1	69769	9.6	635041	0.00986	0
26	Gundtoft by WF	0.64	20	843.9	145369	52.2	794203	0.01475	0
27	Brejning WF	0.56	32	858.6	161016	60.6	627644	0.01365	0
28	Rens Burkal WF	0.61	26	740.8	127503	58.8	673724	0.01345	0
29	Gilbjerg by WF	0.50	41	880.3	144976	77.4	626626	0.01382	0
30	Døstrup by WF	0.58	29	834.5	140896	69.4	701973	0.01443	0
31	Ødum kirkeby WF	0.63	22	1042.1	180480	80.8	1006050	0.01968	0
32	Bandbøl by WF	0.76	8	368.7	69765	18.8	660569	0.01095	0
33	Søgård WF	0.76	9	553.3	97576	30.4	1006699	0.01676	0
34	Slagelse offshore WF	0.76	11	836.2	101381	124.1	197302	0.00760	0
35	Restrup hovedgård WF	0.64	19	530.9	90931	41.8	526539	0.01023	0
36	Anholt offshore WF	0.89	4	13997.9	1722266	1295.2	2507932	0.07288	0
37	Lyderslev WF	0.37	64	311.3	47604	27.0	182546	0.00448	0
38	Skærbæk WF	0.44	51	397.8	60997	33.5	249941	0.00590	0
39	Dyrebjerg WF	0.39	60	268.1	40949	23.1	160138	0.00390	0
40	Bindslev by WF	0.39	57	261.8	40150	21.5	149814	0.00363	0
41	Bur by WF	0.44	50	232.2	36017	18.6	138221	0.00320	0
42	Hollandsbjerg by WF	0.48	44	1338.9	198657	129.3	614172	0.01695	0
43	Ravnhøj WF	0.30	72	623.2	102403	52.1	326407	0.00846	0
44	Balle by WF	0.37	66	488.9	80956	39.8	275155	0.00689	0
45	Næsbjerg by WF	0.37	65	397.0	65753	32.3	224420	0.00561	0
46	Foldby by WF	0.32	70	401.9	64131	34.2	213623	0.00549	0
47	Hjortnæs WF	0.50	40	275.2	44177	21.2	183695	0.00427	0
48	Falsig by WF	0.34	68	505.8	81229	42.8	278536	0.00702	0
49	Alstrup by WF	0.47	46	361.5	57703	28.7	231222	0.00552	0
50	Over søen WF	0.39	59	952.7	151954	79.0	547840	0.01364	0
51	Bonnet WF	0.60	27	214.8	34810	14.9	181464	0.00389	0
52	Vodder WF	0.41	54	334.5	54079	27.4	192584	0.00469	0
53	Thorup by WF	0.64	18	277.3	44747	17.5	255167	0.00531	0
54	Copenhagen's offshore WF	0.51	37	1852.4	292779	197.4	420753	0.01748	0
55	Lerchenborg hovedgård WF	0.85	5	409.1	60359	48.9	158098	0.00497	0
56	Barde by WF	0.72	14	704.6	114304	69.3	282106	0.00809	0
57	Østergård hovedgård	0.90	3	193.2	25968	27.4	70515	0.00244	0
58	Tingsted (Guldborgsund) WF	0.57	30	16154.5	2610476	1708.5	3802064	0.14945	0
59	Rønland offshore WF 2	0.82	6	419.1	74237	37.6	110316	0.00427	0
60	Lammefjorden WF	0.40	55	921.2	137384	81.7	382643	0.01035	0
61	Overgaard WF	0.46	49	2987.6	441051	269.3	1250961	0.03359	0
62	Købelev WF	0.46	48	1156.3	185948	81.7	394766	0.01142	0
63	Dejbjerg WF	0.46	47	200.0	31665	14.2	92346	0.00208	0
64	Arrild WF	0.27	73	436.1	68360	37.2	203724	0.00543	0
65	Hanstholm WF	0.61	25	252.0	39250	16.9	185093	0.00400	0
66	Vrejlev WF	0.26	74	234.1	37375	21.6	93006	0.00255	0
67	Bejstrup by WF	0.52	35	138.6	21242	9.1	91927	0.00179	0
68	Kastrup WF	0.39	58	332.2	53945	25.7	165812	0.00419	0
69	Degneboligen WF	0.63	21	3519.2	695129	228.4	2364848	0.05200	0
70	Klim by WF	1.00	1	0.0	0	0.0	0	0.00000	0
71	Bur by WF	0.43	53	5653.3	998097	458.4	2722998	0.07086	0
72	Lem WF	0.62	23	1693.8	337970	111.7	1133744	0.02559	0
73	Nørre Vium WF	0.49	42	2485.2	458834	193.9	1323549	0.03329	0
74	Velling WF	0.77	7	1486.4	362827	40.6	1708249	0.03193	0
75	Vejrum WF	0.60	28	1190.1	231087	82.7	766647	0.01775	0

Summary statistics. Operatively efficient DMUs by production type

Offshore

	N	Mean	Std. Dev	Min	Max
Turbine capacity, MW	10	21.133	18.318	2	49.5
Wind speed, 2016, m/s	10	7.948	.762	6.9	9.045
FIT, WF, year, tDKK	10	16751.53	14581.48	773.085	37607.73
Turbines	10	8.4	4.274	4	15
Metals, kg	10	142000	136000	9315.878	402000
Plastic components, kg	10	17037.97	17378.6	1173.963	44190.64
Concrete, kg	10	638000	697000	12026.81	1790000
Wire drawing, m-kg	10	773.702	676.033	72.096	1859.208
Fossil fuels, kg	10	707.422	503.494	125.304	1520.919
Logistics, ton-meters	10	962000	975000	45017.17	2860000
Output 2016, MWh	10	65132.97	59443.03	3097.598	149000

Onshore

	N	Mean	Std. Dev	Min	Max
Turbine capacity, MW	6	133.633	155.855	8	399.6
Wind speed, 2016, m/s	6	8.665	.766	7.264	9.285
FIT, WF, year, tDKK	6	141000	171000	7966.021	438000
Turbines	6	49.167	49.769	4	111
Metals, kg	6	1350000	1520000	70089.6	3670000
Plastic components, kg	6	148000	192000	6175.038	491000
Concrete, kg	6	1.95e+08	2.03e+08	1.34e+07	4.68e+08
Wire drawing, m-kg	6	9419.087	12224.43	337.525	31861.97
Fossil fuels, kg	6	3031.353	3162.312	213.941	7331.985
Logistics, ton-meters	6	132000	160000	4250.529	406000
Output 2016, MWh	6	511000	639000	32321.83	1660000

Summary statistics. Environmentally efficient DMUs by production type

Onshore

	N	mean	sd	min	max
acidification	1	7761.334	.	7761.334	7761.334
gwp	1	1340000	.	1340000	1340000
ozone dep	1	.087	.	.087	.087
eutrophication	1	600.729	.	600.729	600.729
land use	1	3320000	.	3320000	3320000

Offshore

	N	mean	sd	min	max
acidification	1	1846.608	.	1846.608	1846.608
gwp	1	294000	.	294000	294000
ozone dep	1	.017	.	.017	.017
eutrophication	1	186.708	.	186.708	186.708
land use	1	429000	.	429000	429000

Appendix 2: Supplementary second stage analysis

The factoring procedure yielded similar loading for all three factors, meaning that the factors explain the underlying size construct to a similar degree.

Environmental efficiency with size factor

	(1) Tobit	(2) Tobit	(3) Tobit	(4) Tobit
Size factor	0.13238***	0.11499***	0.14240***	0.11328***
	(0.04194)	(0.03784)	(0.02268)	(0.01650)
Expected lifetime,	0.39219*	0.62586***	0.58547***	
years, log	(0.20614)	(0.17283)	(0.18882)	
Wind speed 2016, m/s,	0.28356	0.62145***	0.70559***	
log	(0.24233)	(0.16810)	(0.16445)	
New WF (<10 years)	-0.02294	0.06910		
	(0.09760)	(0.06564)		
Offshore	0.14413**	0.08184		
	(0.05867)	(0.04994)		
Manufacturer (Siemens=0)				
1. NEG Micon	-0.06401			
	(0.06425)			
2. MHI Vestas	-0.05352			
	(0.04652)			
3. Nordex	-0.23060***			
	(0.07272)			
4. Bonus	-0.07242			
	(0.08685)			
5. Wind World	-0.09171			
	(0.08359)			
Area (Jylland, Northmost tip=0)				
1. Jylland, Mid-East	-0.07579			
	(0.04890)			
2. Jylland, Mid-West	-0.02722			
	(0.05084)			
3. Jylland, South	-0.04948			
	(0.04519)			
4. Jylland, North-West	0.02995			
	(0.06436)			
5. Lolland & Sjælland	-0.14329**			
	(0.06557)			
Obs.	75	75	75	75
Pseudo R^2	-2.00611	-1.61963	-1.53646	-0.97725
F	20.77111	24.21169	23.91453	47.14803

Standard errors are in parenthesis

**** p<0.01, ** p<0.05, * p<0.1*

Operational efficiency with size factor

	(1) Tobit	(2) Tobit	(3) Tobit	(4) Tobit
Size factor	0.12049*	0.08713	0.15689***	0.11177***
	(0.06975)	(0.06172)	(0.03477)	(0.02708)
Expected lifetime,	1.02239***	1.08021***	0.91662***	
years, log	(0.35548)	(0.34520)	(0.33990)	
Wind speed 2016, m/s,	0.75706	1.03269***	1.11735***	
log	(0.48292)	(0.29902)	(0.26152)	
New WF (<10 years)	0.16118	0.18753		
	(0.16570)	(0.11785)		
Offshore	0.23338**	0.12681		
	(0.11289)	(0.09959)		
Manufacturer (Siemens=0)				
1. NEG Micon	0.07715			
	(0.10169)			
2. MHI Vestas	0.02887			
	(0.07760)			
3. Nordex	-0.14689			
	(0.11497)			
4. Bonus	-0.06152			
	(0.14219)			
5. Wind World	0.10325			
	(0.16939)			
Area (Jylland, Northmost tip=0)				
1. Jylland, Mid-East	-0.04451			
	(0.06599)			
2. Jylland, Mid-West	0.02488			
	(0.08829)			
3. Jylland, South	-0.05443			
	(0.07691)			
4. Jylland, North-West	0.03324			
	(0.11579)			
5. Lolland & Sjælland	-0.12007			
	(0.08472)			
Obs.	75	75	75	75
Pseudo R^2	1.47413	1.20004	1.07214	0.47462
F	17.08764	11.68709	15.47534	17.02987

Standard errors are in parenthesis
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

FIT per MW with size factor

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Size factor	0.08465*	0.06870	0.18659***	0.26849***
	(0.04898)	(0.05176)	(0.04163)	(0.02203)
Expected lifetime, years, log	-0.29683	0.09136	-0.18657	
	(0.42645)	(0.41716)	(0.42860)	
Wind speed 2016, m/s, log	0.75381*	1.31830***	1.49266***	
	(0.40258)	(0.26239)	(0.24263)	
New WF (<10 years)	0.16989*	0.31782***		
	(0.10097)	(0.09645)		
Offshore	0.29353***	0.24356***		
	(0.07825)	(0.06327)		
Manufacturer (Siemens=0)				
1. NEG Micon	-0.14802*			
	(0.08827)			
2. MHI Vestas	-0.14835**			
	(0.06568)			
3. Nordex	-0.61668***			
	(0.12496)			
4. Bonus	-0.04762			
	(0.13954)			
5. Wind World	-0.12626			
	(0.15066)			
Area (Jylland, Northmost tip=0)				
1. Jylland, Mid-East	-0.06800			
	(0.05442)			
2. Jylland, Mid-West	0.03298			
	(0.07406)			
3. Jylland, South	0.00753			
	(0.07883)			
4. Jylland, North-West	0.10205			
	(0.09167)			
5. Lolland & Sjælland	-0.16458*			
	(0.08986)			
Obs.	75	75	75	75
R-squared	0.82931	0.76380	0.70821	0.55900
F	39.72819	66.62778	78.58118	148.59030

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Appendix 3: Sensitivity analysis

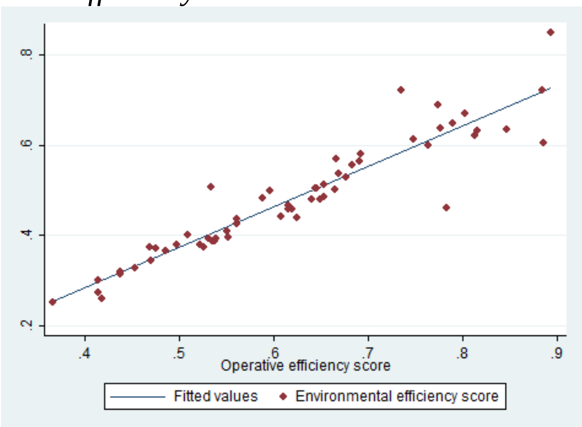
Material efficiency estimation results

DMU	Name	Rank	Φ	Metal	Plastics	Fossils	Concrete	Wire	Logistics	O
	Average	**-**	**0.70**	**67042**	**5207**	**2491110**	**436**	**159**	**219389**	**0**
1	Lyngdrup by WF	45	0.63	85114	4963	8955	228	215	668448	0
2	Nørrekær Enge WF	20	0.81	42080	1660	0	65	49	360186	0
3	Nyrup by WF	25	0.78	2811	422	0	23	116	0	0
4	Oppelstrup by WF	58	0.56	26552	1480	15044	67	306	183948	0
5	Vrå Hovedgård WF	66	0.49	41065	2415	35685	117	447	284271	0
6	Hørup by WF	47	0.63	9366	159	307	31	126	60373	0
7	Filskov by	75	0.36	33060	3279	47618	186	317	176243	0
8	Urup by WF	70	0.45	22925	2228	28548	127	231	118589	0
9	Horns rev 2 offshore WF	31	0.71	764115	80781	9459749	11709	0	136280	0
10	Lammefjorden WF extension	74	0.42	98348	8388	163585	360	336	736625	0
11	Øslev by WF	16	0.84	29910	1106	0	33	19	261891	0
12	Munkebo WF	33	0.70	40441	2110	0	95	87	325505	0
13	Rødsand WF	40	0.66	949331	99530	58332048	4668	788	101804	0
14	Katrineholm Hovedgård WF	60	0.54	61078	4331	50879	192	180	469306	0
15	Overgaard WF extension	39	0.67	55562	3037	0	139	130	441724	0
16	Sødring by WF	46	0.63	65440	3826	7439	176	166	513809	0
17	Svoldrup by WF	44	0.63	79398	4529	2525	209	197	624921	0
18	Tolstrup by WF	13	0.94	7835	744	0	0	9	71640	0
19	Flemming by WF	59	0.55	14683	534	29079	30	164	115391	0
20	Harre by WF	37	0.69	9804	206	15054	8	127	80144	0
21	Eggebæk WF	68	0.48	70336	5731	72240	415	437	462564	0
22	Horns rev 1 offshore WF	35	0.70	419828	29194	56549900	4780	759	94525	0
23	Grønhede WF	50	0.62	29884	1904	914	171	184	199082	0
24	Rønland offshore WF 1	1	1.00	0	0	0	0	0	0	0
25	Ramme WF	1	1.00	0	0	0	0	0	0	0
26	Gundtoft by WF	17	0.84	21277	1344	0	122	131	141802	0
27	Brejning WF	38	0.67	43012	480	22901	102	163	361575	0
28	Rens Burkal WF	21	0.80	28002	0	0	115	120	212668	0
29	Gilbjerg by WF	43	0.64	42029	129	0	173	181	318008	0
30	Døstrup by WF	27	0.75	35259	0	0	145	152	267787	0
31	Ødum kirkeby WF	19	0.83	36886	0	0	152	158	280144	0
32	Bandbøl by WF	11	1.00	0	0	0	0	0	0	0
33	Søgård WF	12	0.99	2790	0	0	11	12	21193	0
34	Slagelse offshore WF	29	0.75	30597	615	3404151	551	45	3999	0
35	Restrup hovedgård WF	18	0.83	19207	0	0	79	83	145875	0
36	Anholt offshore WF	1	1.00	0	0	0	0	0	0	0
37	Lyderslev WF	55	0.59	10282	215	2313	35	133	66536	0
38	Skærbæk WF	34	0.70	11396	111	0	37	162	74607	0
39	Dyrebjerg WF	52	0.61	8804	163	964	29	117	56841	0
40	Bindslev by WF	48	0.62	7927	265	0	30	108	45399	0
41	Bur by WF	32	0.71	5714	165	0	23	84	32307	0
42	Hollandsbjerg by WF	41	0.66	38235	2269	0	149	382	247697	0
43	Ravnhøj WF	73	0.43	20111	1629	31985	53	196	144168	0
44	Balle by WF	64	0.52	15423	1242	20325	33	160	111255	0
45	Næsbjerg by WF	63	0.52	12500	1006	16228	26	130	90205	0
46	Foldby by WF	69	0.47	13126	778	12038	38	141	90855	0
47	Hjortnæs WF	28	0.75	8158	125	0	5	108	60376	0
48	Falsig by WF	65	0.51	16549	960	13063	46	183	114584	0
49	Alstrup by WF	36	0.69	11122	444	0	17	143	78664	0
50	Over søen WF	57	0.57	30403	1675	15192	74	355	210664	0
51	Bonnet WF	15	0.92	2456	132	0	0	41	20401	0
52	Vodder WF	49	0.62	10060	531	2766	22	122	69750	0
53	Thorup by WF	1	1.00	0	0	0	0	0	0	0
54	Copenhagen's offshore WF	67	0.49	74532	5758	12304078	348	190	9326	0
55	Lerchenborg hovedgård WF	14	0.94	7942	659	0	34	36	54246	0
56	Barde by WF	26	0.78	25781	2140	0	109	115	176089	0
57	Østergård hovedgård	1	1.00	0	0	0	0	0	0	0
58	Tingsted (Guldborgsund) WF	51	0.62	617583	52735	45548956	3690	686	56467	0
59	Rønland offshore WF 2	1	1.00	0	0	0	0	0	0	0
60	Lammefjorden WF	62	0.53	25652	2922	8606	198	193	134999	0
61	Overgaard WF	54	0.60	79213	9134	0	632	614	401175	0
62	Købelev WF	42	0.65	22875	7540	0	89	303	57832	0
63	Dejbjerg WF	23	0.80	1916	1011	0	45	15	0	0
64	Arrild WF	72	0.44	14925	564	10014	48	136	93662	0
65	Hanstholm WF	1	1.00	0	0	0	0	0	0	0
66	Vrejlev WF	71	0.44	6231	672	2673	48	43	38944	0
67	Bejstrup by WF	1	1.00	0	0	0	0	0	0	0
68	Kastrup WF	56	0.58	10261	703	2875	26	105	58157	0
69	Degneboligen WF	22	0.80	173618	4457	0	293	0	1414642	0
70	Klim by WF	1	1.00	0	0	0	0	0	0	0
71	Bur by WF	61	0.53	250415	15638	419767	769	375	1901255	0
72	Lem WF	24	0.78	92848	2059	1728	116	0	789343	0
73	Nørre Vium WF	53	0.61	117462	5972	160711	271	135	950329	0
74	Velling WF	1	1.00	0	0	0	0	0	0	0
75	Vejrum WF	30	0.75	66631	1713	12313	92	9	563085	0

Summary statistics on inputs slacks from material efficiency estimation

Variable	Obs	Mean	Std.Dev.	Min	Max
Material efficiency score	75	.7	.18	.36	1
Input slack in metal usage	75	67042.4	160300.8	0	949331.2
Input slack in plastics usage	75	5206.85	15928	0	99529.97
Input slack in concrete usage	75	2490000	1.07e+07	0	5.83e+07
Input slack in wire drawing dist	75	436.12	1574.83	0	11709.15
Input slack in fossil fuel usage	75	159.41	173.14	0	788.12
Input slack in logistics usage	75	219389.1	320370.1	0	1900000

Inter-efficiency association



Inter efficiency association (y=Environmental efficiency score)

	(1) Tobit	(2) OLS	(3) Tobit	(4) OLS
Operative efficiency	0.773***	0.798***		
	(0.015)	(0.060)		
Material efficiency			0.771***	0.845***
			(0.016)	(0.067)
Obs.	75	75	75	75
R-squared	n/a	0.814	n/a	0.757
F	2562.772	179.072	2302.661	156.993

Standard errors are in parenthesis

**** p<0.01, ** p<0.05, * p<0.1*