RESEARCH INSTITUTE OF
INDUSTRIAL ECONOMICS

IFN Working Paper No. 940, 2012

Scrapping a Wind Turbine: Policy Changes, Scrapping Incentives and Why Wind Turbines in Good Locations Get Scrapped First

Johannes Mauritzen

Research Institute of Industrial Economics
P.O. Box 55665
SE-102 15 Stockholm, Sweden
info@ifn.se
www.ifn.se

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Policy changes, scrapping incentives and why wind turbines in good locations get scrapped first

Johannes Mauritzen
Research Institute of Industrial Economics (IFN)
Stockholm, Sweden

johannes.mauritzen@ifn.se

Abstract

The most common reason for scrapping a wind turbine in Denmark is to make room for a newer turbine. The decision to scrap a wind turbine is then highly dependent on an opportunity cost that comes from the interaction of scarce land resources, technological change and changes in subsidy policy. Using a Cox regression model I show that turbines that are located in areas with better wind resources are at a higher risk of being scrapped. Policies put in place in order to encourage the scrapping of older, poorly placed turbines actually have a larger effect on well-placed turbines.

Keywords: Wind power scrapping, Nordic electricity market, Cox regression model
JEL codes: D22, D92, L94, O13, Q42

I would like to thank Jonas Andersson, Jarle Møen, Thomas Tangerås, Leif Sandal, Gunnar Eskeland and Sturla Kvamsdal for their comments and suggestions. Participants at the IAEE North American Conference in Washington DC, the Swedish Association of Energy Economics annual meeting and the NHH Finance and Management Science Geilo seminar provided helpful discussion. This research was financed partly within the IFN research program "The Economics of Electricity Markets." I also received financial support from NHH Norwegian School of Economics.

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I. Introduction

The cost of electricity that comes from wind turbines or other renewable energy sources is to a large degree based on capital costs and associated financing costs. The expected lifetime of the turbine is then an important factor in the investment decision. In turn, the decision to scrap a wind turbine becomes particularly important in analyzing the economics of wind power. Yet few empirical studies of wind power scrapping exist. In this article I use non-parametric and semi-parametric survival models and a data set consisting of all wind turbines built in Denmark to analyze the scrapping decision.

Wind turbines[1] along with other forms of renewable energy production have several properties that make the scrapping decision for these goods different from most other types of productive goods:

- Low marginal operating costs
- Importance of geographic placement and infrastructure
- High rate of technological change
- High level of government involvement in output price-setting and subsidies

Though turbines do incur considerable costs for maintenance and repair, there are of course no fuel costs. Once the turbine is built, the real operating margin – defined loosely as the flow of revenue received less the real operating costs like repair and land rent – is likely to be positive. Compared to coal or gas plants, a negative real operating margin is unlikely to be the direct cause of scrapping.

In a study of Danish wind turbines by Jensen et al. (2002) it was found that of those turbines that were scrapped the largest single reason given for scrapping (40 percent) was to make room for newer turbines – often called repowering in the industry. Only 12 percent were reported to be

[1] The scrapping of a wind turbine in this context means the scrapping of the entire structure and not just the turbine component.

scrapped due to mechanical defect or due to wear. Jensen et al. suggest that repowering is also the grounds for the scrapping of most of the remaining 47 percent where the reason was not reported.

The study by Jensen et al. then strongly suggests that an important reason for scrapping a wind turbine is the opportunity cost that results from a combination of scarce land resources and a high rate of technological change. An older turbine operating on a wind-rich location means that one cannot put in its place a newer, larger and more productive turbine.

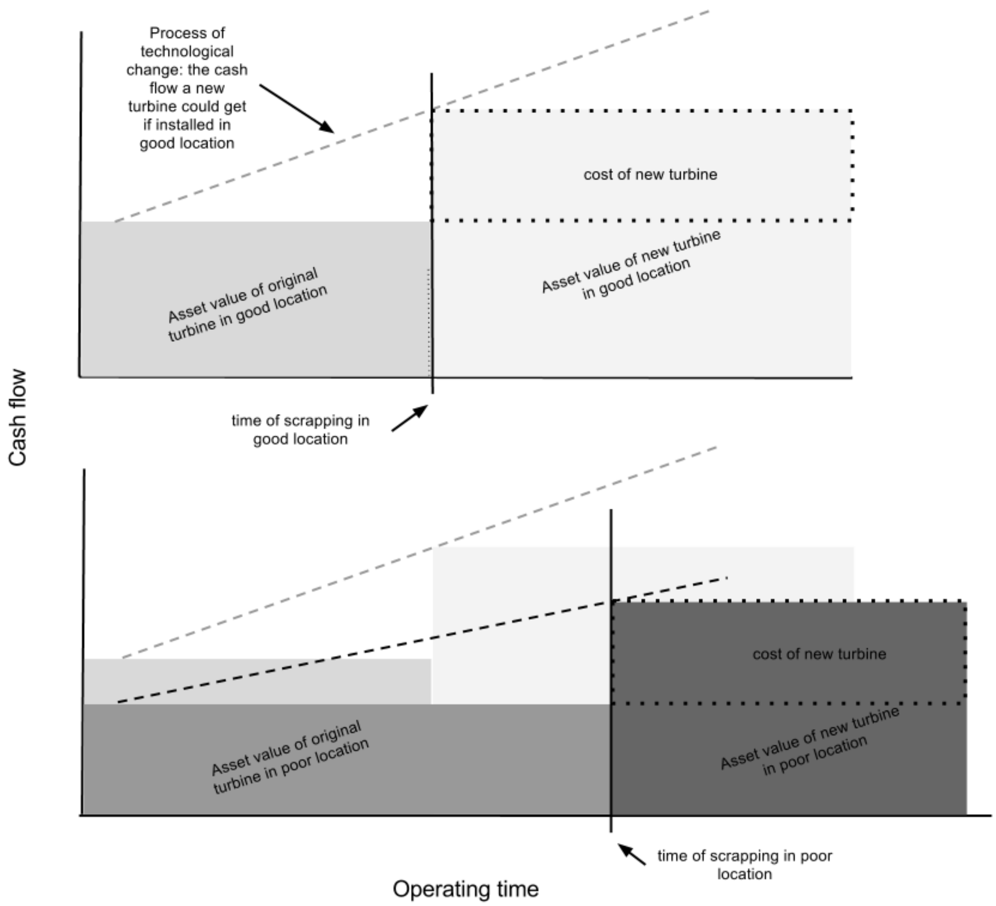
Scarce land resources is an especially important consideration for wind turbines since the total energy yield of wind turbines is highly dependent on average wind speeds. A simplified energy conversion formula[2] for wind power is $E = \frac{1}{2}\Phi \mathrm{A} \mathrm{t} \mathrm{v}^3$ where A is the sweeping area of the blades, Φ is a constant and v is the average wind velocity (MacKay, 2008). Thus energy output from a wind turbine increases approximately cubically with average wind speed.

The scarcity of land resources is not primarily about the amount of geographic land available – though this certainly plays a role. Building out the appropriate grid infrastructure is expensive and the planning process of zoning an area for wind turbines can be both contentious and lengthy. As I will show – policy can create strong incentives to invest quickly, leading to artificially high land scarcity as there simply is not enough time to go through the planning process of zoning and grid infrastructure.

The role of land scarcity and opportunity costs leads to some testable implications about the pattern of wind power scrapping. In particular turbines located in better, windier locations will tend to be at a higher risk of being scrapped and on average have a lower lifetime. The simplified idea is illustrated in figure 1.[3]

[2] A more realistic calculation of the actual power produced by a wind turbine would need to take into consideration the mechanical and engineering properties of a turbine such as minimum and maximum wind speeds it can operate with – called the "power curve" in the engineering literature.
[3] The illustration could be formalized as a simple dynamic programming or optimal control problem. However with the simple set-up, as in the illustration, it would add little insight. A more complex model, taking into account not just uncertainty of price but also of technological change and policy would quickly become unwieldy and, I think, a distraction from the empirical and descriptive scope of this paper.

Figure 1. Wind Resources and the Timing of Scrapping



Consider first the top panel in the figure. The vertical height represents the instantaneous cash flow from a turbine while the horizontal distance represents time. The dotted line represents the instantaneous cash flow that could be obtained by investing in a newer turbine. Since in practice technological change and manufacturing improvements have meant the ability to produce larger turbines with higher rated capacity, I draw the line sloping upwards.

The turbine owner would choose to scrap the turbine at a point at which turbine technology has advanced so that the total expected revenue from the new turbine less the cost of investing in a new turbine is greater than the revenue lost from scrapping the old turbine. In the figure this point is shown by the insertion of a bold vertical line.

Now consider the effect of lower average wind speed, as illustrated in the lower panel. Assume that lower average wind speed affects the cash-flow of old and new turbines proportionally. When replacing a turbine, the foregone revenue from the scrapped turbine is higher for the turbine located in the windier area. However the benefits of installing the bigger turbine are in absolute terms even greater. Assuming that the cost of investing in the new turbine is fixed then the investment in the new turbine, and corresponding scrapping of the old turbine, will take place later in the poor location.

The figure, of course, represents an extreme simplification of the actual replacement decision. Discounting and the effects of uncertainty are not considered. The role of technological change is in itself complex. I use the term ‘technological change’ as an umbrella term for several factors like improved engineering knowledge that has allowed for larger turbines over time and the advantages of scaled manufacturing that has also developed over time. But when considering the interaction of technological change, scarce land resources and variation in wind resources, the figure shows the essential elements of the replacement decision.

To test the predictions I use a Cox regression model on data of Danish wind turbines. Since I do not have data on the actual wind conditions of each location I create a proxy instead – the average annual full-load hours of a turbine. I take the average yearly electricity produced from each turbine and divide it by the rated power capacity of the turbine. This variable can be interpreted as the number of hours per year a turbine producing at full rated capacity would need to operate to equal the actual energy produced by that turbine. This variable, which can be seen as an indicator for capacity utilization, likely reflects the wind resources of a turbine's placement. The results show that turbines with a higher average annual full-load hours have a *higher* hazard[4] of being scrapped.

I will also show that subsidies and changes in subsidies for wind power play a strong role in the timing of the scrapping decision. The effect of wind resources and associated opportunity costs interact strongly with the implementation and changing of such subsidies. In particular, the announcement of a forthcoming reduction of subsidies creates an incentive to invest quickly. As discussed, planning new wind turbine sites takes time, thus a rush to invest in effect creates its own form of land scarcity. This in turn has a substantial effect on the scrapping decision.

Subsidies were also introduced to directly encourage the scrapping of older, poorly placed turbines. However, I show that these policies actually have a greater effect on turbines in wind-rich locations. A rigorous analysis of the optimality and efficiency of these subsidies is outside the scope of this paper, but I do want to emphasize that even though the observed effects of the scrapping policies seem to go against the stated goals of the policy, this does not necessarily mean that the end result was suboptimal. In fact, it is likely that the scrapping of older turbines in good locations first is economically optimal.

An extensive literature exists on the optimal scrapping of a productive good and the economics literature on renewable energy is growing. The literature on optimal abandonment is vast and goes all the way back to Hotelling (1925). It has long been acknowledged that a capital good or project can be abandoned well before it becomes unprofitable. The role of technological change in early investment and abandonment is taken up by Gaumitz & Emery (1980).

More recently, a large and growing literature exists on the effects of uncertainty in the face of irreversible investment or abandonment - so called real options. Chapter 7 of Dixit & Pindyck (1994) focuses on output and input price uncertainty on the decision to scrap. A related analysis on firm entry and exit with irreversible investments can be found in Dixit (1989). Subsequent work has recognized that technological change is also ex-ante uncertain and can affect the timing

[4] Here I use hazard in the mathematical sense of a time-dependent probability of an event occurring. It is not meant to imply that the scrapping of a wind turbine is an adverse event.

of investment decisions. See for example Murto (2007), Huisman & Kort (2000) and most recently Meyer (2011).

Empirical work on investments in the energy sector under uncertainty have been done by Bøckman et al., (2008) for investments in small hydropower plants and by Kellogg (2010) for oil rigs in Texas. Empirical studies of vehicle scrapping are a particularly popular subject and tend to focus on repair and replacement costs and issues of depreciation. See for example Walker (1968), Parks (1977) or Manski & Goldin (1983).

This article is mainly descriptive in scope. I do not attempt to explicitly estimate or test aspects of optimal abandonment or real options theory. But the results have important implications for studies that do seek to take a real options approach to the investment and scrapping decision of wind turbines, and possibly other renewable energy technologies. Uncertainty around technological advances and government policy should be seen as at least as important a factor as uncertainty around output prices.

A growing literature on wind power investment and wind power subsidies also exists. In particular, analysis of the Danish market includes Morthorst (1999) who looks at the driving forces of wind power capacity development in Denmark. Munksgaard & Morthorst (2008) give a general overview and analysis of Danish wind power policy and try to identify the causes for the "recession" in Danish wind turbine investment between 2002 and 2008. However, despite the growing literature in the area of investment in renewable energy and in particular wind power, to my knowledge this is the first empirical economic analysis of wind turbine scrapping.

While I assert that the scrapping decision of a wind turbine is a special case, it is an important special case. In 2011 40.5 gigawatts of wind power was installed globally (*Global Wind Report Annual market update,* 2011), the equivalent in rated capacity terms of roughly 40 large nuclear power reactors. Solar power plants, which also share some of the same key features of wind turbines, are also becoming a significant source of electricity generation. Moreover, while many wind turbine markets are quite young and will not face a high number of scrappings for many years, understanding the determinants of the scrapping decision is important in estimating expected lifetime, and in turn the investment decision itself.

My main data set consists of all 6754 turbines constructed in Denmark between 1977 and July 2012. 2279 of the turbines were scrapped before July of 2012. The data set includes variables for turbine capacity, height, rotor diameter, coordinates and principality of installation. Date of installation, and if applicable, date of scrapping are also noted, as is the yearly amount of energy produced from each turbine. The full data set is publicly available on the website of the Danish state energy directorate (http://www.ens.dk). A cleaned data set as well as code for the complete analysis is available on my website (sites.google.com/site/johannesmauritzen/home/publications).

II. Wind Power Subsidies in Denmark and Their Effects on Scrapping

Subsidy policy for wind power production has changed over time as wind energy investment has grown in scale. The policies are shown in table 1.

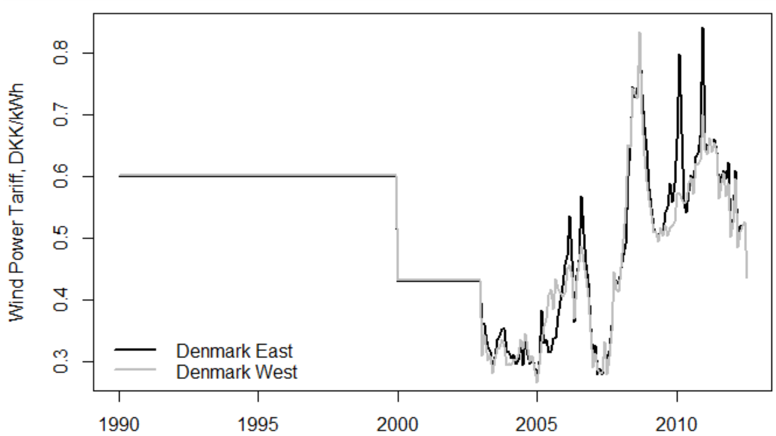
Table 1. Danish Wind Power Tariff Policy

Period	Policy
Up to Jan. 1st, 2000	DKK .60/kWh price guarantee for 10 years. DKK .10/kWh guaranteed price for next 20 years
Jan. 1st, 2000 - Dec. 31st, 2002	DKK .43/kWh guaranteed price for 22,000 full-load hours
Jan. 1st, 2003 - Dec. 31st, 2004	Feed-in tariff of up to DKK .10/kWh above market price Max payment of DKK .36/kWh
Jan. 1st, 2005 - Feb. 20th, 2008	Feed-in tariff of DKK .10/kWh over market price
Feb. 21st, 2008 -	Feed-in tariff of DKK .25/kWh for 22,000 full-load hours

The changes in policies led to sharp shifts in the tariff paid to wind power producers. This is shown in Figure 2. Notable was the change in policy that was put into effect at the start of 2003. In 2003 Denmark fully transitioned over to a market-based power system operated jointly with the other Nordic countries (excluding Iceland). With this came a shift away from fixed tariffs to a feed-in tariff above the going market price – set at a central exchange called Nord Pool.

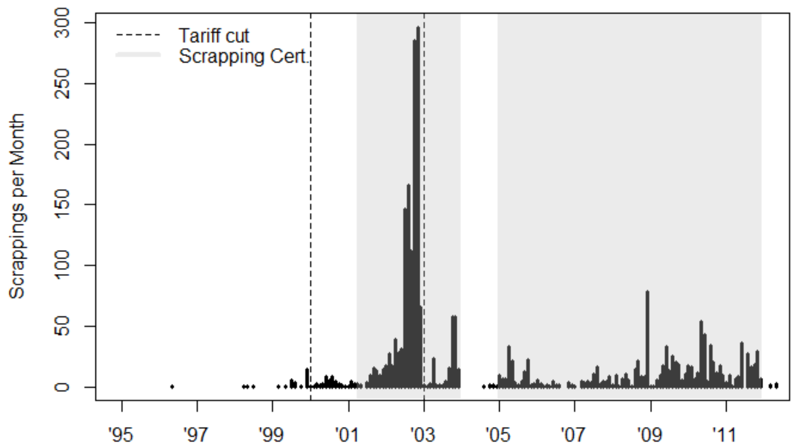
Importantly, the wind power producers received not only a lower average price for the electricity that they produced, but also faced uncertainty about the market price they would receive.

Figure 2. Changes in Wind Power Tariff



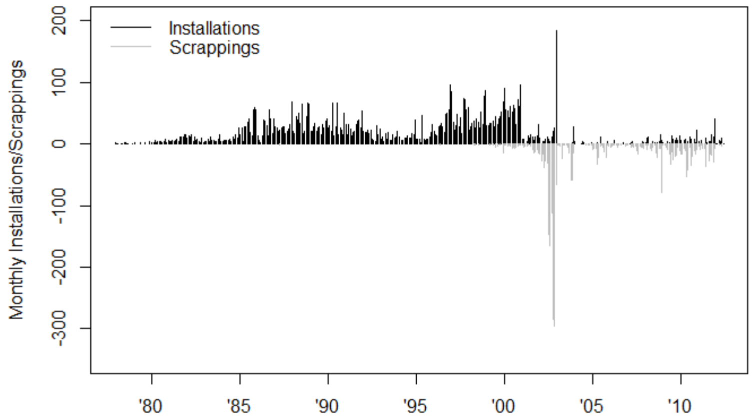
The tariffs are set such that a turbine installed under a certain regime will receive that tariff over a defined lifetime. The change in tariff then creates a sharp discontinuity in the opportunity cost. A decrease in the tariff at a certain date, for instance, means that turbines installed just before and after this date can have sharply different expected lifetime asset values. This in turn creates sharp jumps in the opportunity cost of operating an older wind turbine. The dramatic effect on scrapping rates can be seen in figure 3.

Figure 3. Wind Turbine Scrappings per Month



The dotted lines in the figure show the two times where the tariff was lowered. A small jump in scrappings happened directly before tariffs were lowered at the beginning of 2000. But the large jump came before the shift to market prices and a feed-in tariff in 2003. As mentioned, land scarcity and reductions in wind power subsidies likely interact in their effect on scrapping. Given time, a wind power investor could go through the process of obtaining permits and building the infrastructure for a new wind turbine site. However when wind turbine investors know that subsidies will drop near in the future and rush to invest, they will be more land constrained and must, to a greater extent, resort to scrapping older turbines. Figure 4 shows the relationship between scrappings and new installations – especially directly before the beginning of 2003.

Figure 4. Wind Turbine Installations and Scrappings per Month



Two factors likely explain the magnitude of the jump in scrappings before the beginning of 2003. The first was the effect of added price uncertainty that the turbine owners would face on top of a lower average price for electricity. By scrapping and installing newer and larger turbines in place of the old turbines, operators were able to lock in the fixed tariff of the pre-2003 policy for several more years. As figure 3 also shows the second reduction in wind power tariffs took place while a scrapping subsidy was in place – indicated by the shaded regions in the figure – this likely compounded the effect.

The Danish government introduced several such scrapping schemes in order to expand wind power and "[decommission] older and less appropriately sited wind turbines" (*Energy Policy Agreement - 21. February, 2008*). The first scheme was introduced in April of 2001 and lasted through January 1st, 2004. It was also made retroactive to cover turbines that had been scrapped after 1999.

Under this scheme, wind power producers that scrapped a turbine with a rated power capacity of less than 150 kW would receive a certificate. This certificate entitled the producer to a subsidy of DKK .17 per kWh in addition to the regular tariff and subsidy for a newly built turbine, though the new turbine did not necessarily need to be built in the same location. For scrapped turbines rated less than 100 kW the extra subsidy was provided for up to three times the scrapped capacity. For turbines between 100 and 150 kW the subsidy could be applied to twice the scrapped capacity. For example a producer who scrapped a 150 kW turbine would receive DKK .17 extra subsidy per kWh for up to 300kW of a new turbine.

A new, expanded scrapping scheme was put into place beginning December 15th, 2004. This scheme applied to turbines rated less than 450 kW. A scrapped turbine entitled the owner to a price supplement of DKK .12 per kWh for twice the scrapped capacity. This subsidy was limited to 12,000 full load hours and the total tariff with all subsidies included could not exceed DKK .48 per kWh. The 2005 scrapping policy was amended from February 21, 2008. An extra supplement of DKK .08/kWh was provided in scrap incentives for up to twice the scrapped certificate.

An analysis of the scrapping policy, which is the subject of the next section, indicates that the scrapping policies had a large and statistically significant effect on scrapping.

III. The Effect of Scrapping Policy

To see the effects of the scrapping policies I compare Kaplan-Meier estimates of the survivor functions of turbines that are rated just above and below the policies turbine capacity cut-off point. The identifying assumption is that the relatively small differences in capacities will not in themselves have a significant effect on scrapping and significant differences observed in the survival function will be due to the policy.

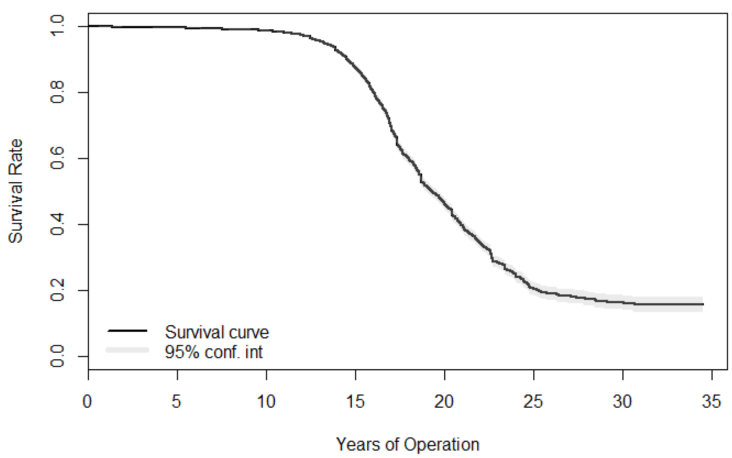
A Kaplan-Meier estimate is a completely non-parametric approach to estimating a survivor function. A survival function can be estimated by calculating the fraction of survivors at each failure time as in equation 1.

$$\hat{S}(t) = \prod_{(j|t_j \leq t)} \left(\frac{n_j - d_j}{n_j}\right) \qquad (1)$$

Here $\hat{S}(t)$ represents the estimated survival function over time, t. d_j represents the number of scrappings or "deaths" at each scrapping time, j. n_j is the total number of turbines still operating up until time j.

A plot of a Kaplan-Meier estimate of the survivor function of the full set of Danish wind turbines is presented in figure 5.

Figure 5. Kaplan-Meier Estimate of the Turbine Survivor Function



From this estimate we get a survivor shape that appears reasonable. The risk of scrapping is low early in the turbines life, gradually increasing up to the 10-year mark with acceleration thereafter.

For the first scrapping policy, the incentives differed depending on whether turbines were rated lower than or equal to 100 kW, or lower than or equal to 150 kW. Figure 6 shows the Kaplan-Meier survivor functions for turbines with rated capacity between 125 and 175 kW, split into subgroups of turbines rated less than or equal to and higher than 150 kW. While both sub-groups experience a fairly substantial rate of scrapping, the survival rate appears to become steeper for the under-150 turbines at around the 12-year mark. A substantial percentage of turbines between 150 and 175 kW are also scrapped, and it is important to note that they come under the later scrapping scheme for under-450 turbines. Consistent with this, the survival function stays flatter longer, dropping off steeply only after a several year delay.

Figure 6. Survivor Function for Turbines Close to 150 kW

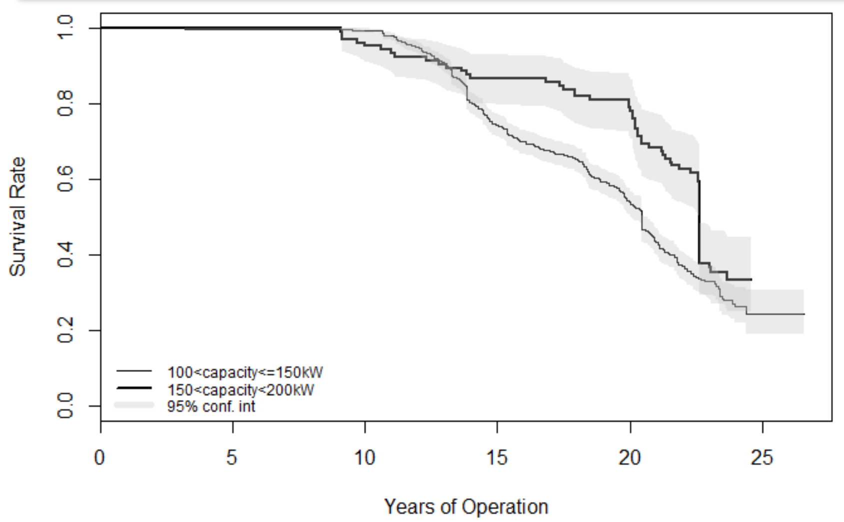
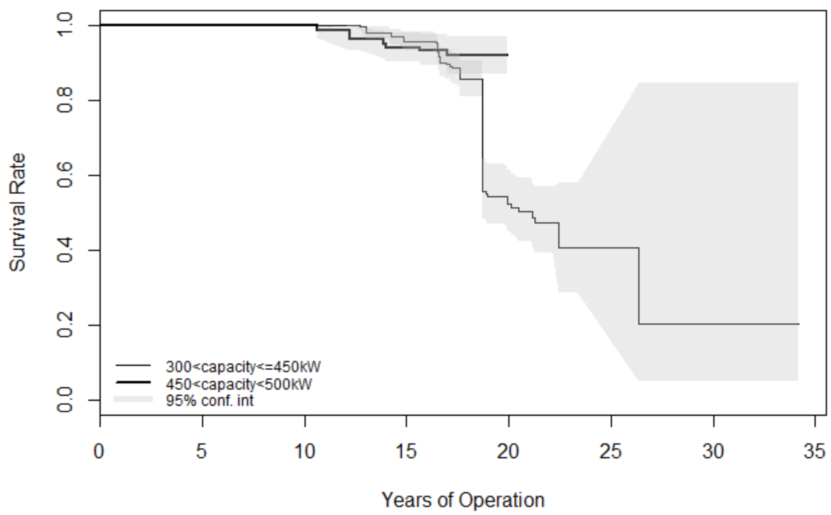


Figure 7 shows survivor curves for turbines rated just over and under 100 kW. Both these groups of turbines came under the same scrapping scheme, but the turbines that were rated at or lower than 100kW received a higher scrapping subsidy (see the description of the scrapping schemes in the previous section). Here it appears that turbines just above 100 kW begin to be scrapped earlier in their lives but eventually the rate of scrapping becomes much steeper for the turbines just under 100kW. The reason for this pattern is likely that the turbines rated just under 100 kW were more likely to be installed earlier and thus were older at the time of the introduction of the scrapping scheme. On average the turbines rated just under 100 kW were installed four years before those rated just above 100kW.

Figure 7. Survivor Function for Turbines Rated Close to 100 kW

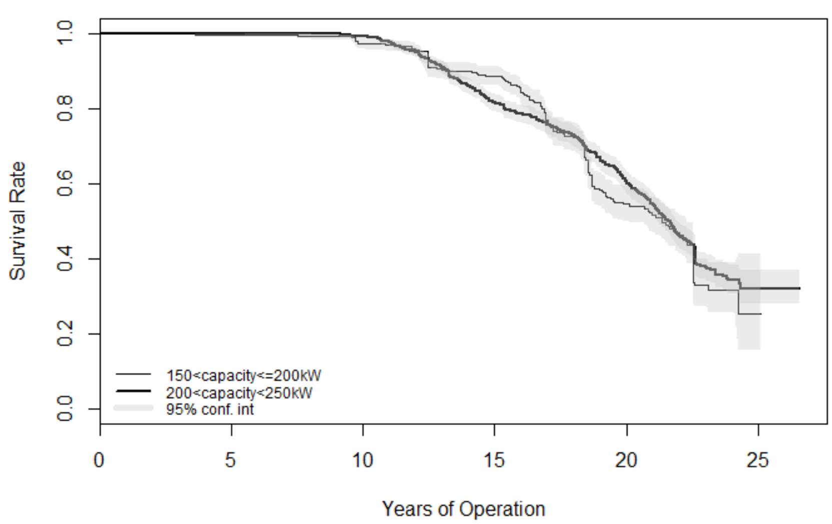
Figure 8 shows the Kaplan-Meier survival functions for turbines rated between 300 and 500 kW, with the split at the policy cut-off of 450 kW. The wider capacity band was necessary in order to gain a large enough sample for inference. Here we see the survivor rate for turbines rated under 450kW dropping off sharply after approximately 17 years. Meanwhile, more than 90 percent of the turbines rated just over 450kW were still operating at the time of data collection (July, 2012).

Figure 8. Survivor Function for Turbines Close to 450 kW



As a robustness check, I compare turbines with rated power between 200 and 300 kW - split into subgroups of under and over 250. All these turbines come under the same scrapping policy and should therefore display a similar survival function given that my assumption that the difference in capacities does not play a significant role is correct. The survival curves appear similar throughout their lifetimes.

Figure 9. Survivor Function for Turbines Rated Close to 200 kW



For all of the survival curves presented above, I also formally test the null-hypothesis of equal survival curves using a log-rank test (Cleves et al., 2008, p 123). The results are displayed in table 2 along with the number of observations from each subgroup. The equality of turbines rated just over and under 100 kW and 150kW is strongly rejected with low p-values. The low number of observations of scrapped turbines over 450 kW made for a low-powered test of survival equality, but the null of equal survival functions was still rejected at the 10% level. On the other hand, the survival curves of turbines rated just over and under 200kW – which came under the same policy – could not reject the null hypothesis of equal survival curves.

Table 3. Log-Rank Test of the Equality of Survival Curves

	100kW	150kW	450kW	200kW
# observations, over	901	105	140	1080
# scrappings, over	568	66	10	587
# observations, under	1287	834	270	606
# scrapping, under	1198	509	83	261
Log-Rank, Chisq	148	28.6	3	0.7
P-value	0.00	0.00	0.08	0.42

IV. The Cox Regression Model

I choose to use a semi-parametric Cox regression model to analyze the scrapping event. See Singer & Willett (2003) for an accessible overview or Kalbfleisch & Prentice (2002) for a more thorough treatment. I prefer this type of model over more commonly used linear probability, logit or probit models due to two main considerations. First I want to control for the age of the turbine. The effect that age has on the hazard of scrapping is highly non-linear and not well approximated by a linear or quadratic form.

The other main factor is censoring. As of July 2012 approximately two-thirds of all the turbines in my data set were still operating. In the terminology of survival analysis these turbines are right-censored, meaning that we do not observe when they are scrapped. A severe selection bias would result if I were simply to ignore the turbines that are still operating – it would be like only considering the patients that died in a drug-effectiveness study. Yet including the operating turbines in a logit or probit regression model is also not possible since it is impossible to know how long they will survive, or equivalently when they will be scrapped.

A Cox regression model effectively deals with both of these issues. The model can be written as in equation 1.

$$H(t|X) = H_0(t)e^{\beta X+\epsilon} \qquad (1)$$

$H(t|X)$ represents the hazard function for turbine scrappings. This is a function of turbine lifetime, t, conditional on X, which represents the vector of variables, discussed below, that shift the baseline hazard up or down proportionally. H_0 represents a baseline hazard over turbine lifetime. β represents a vector of parameters on X. These are estimated by a semi-maximum likelihood method that is detailed in Kalbfleisch & Prentice (2002, p. 95).

Though much of the economics literature has tended to use purely parametric survival models where the general shape of the baseline hazard is assumed, there does not appear to be a good justification for this. Parametric models give estimates that are only slightly more efficient than estimates from a Cox model when the baseline hazard is correctly specified but much less efficient estimates when it is not (Singer & Willett, 2003).

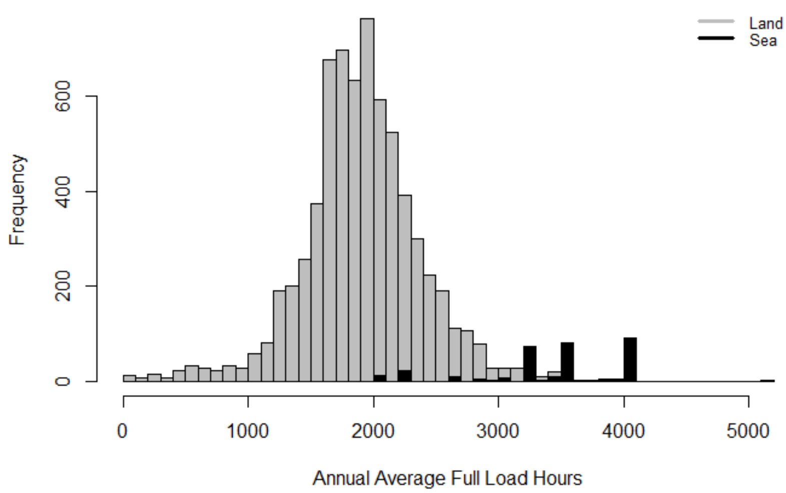
My main variable of interest is a turbine's average annual full-load hours which I claim can be used as a proxy for the wind resources of a turbine's location. I create the variable as in equation 2.

$$fullLoad_i = \frac{\sum_{t=2}^{T-1} Y_{it}^e}{(T-2)*K_i} \qquad (2)$$

I take the average yearly energy yield, Y_{it}^{e} , for every full year of operation, $T-2$, from each turbine and divide by its rated power capacity, K_i. In other words, the variable says how many hours the turbine would need to operate in a year if it was producing at 100 % of its rated capacity to match the actual average annual production of that turbine. In this way, the variable full-load hours is a measure of the capacity utilization of a given turbine.

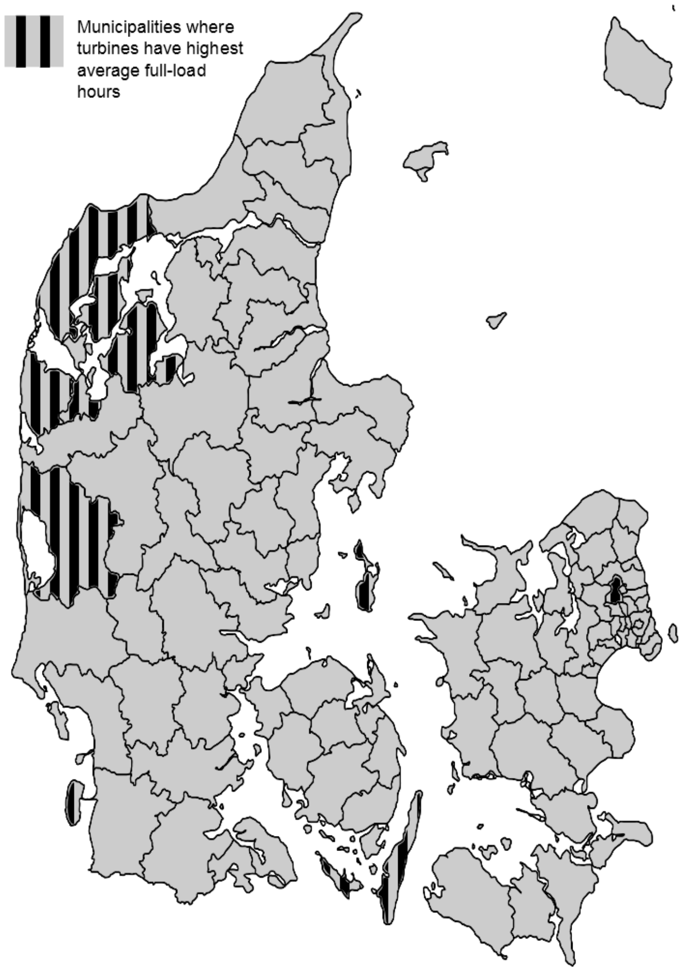
Several factors likely play a role in determining the average annual full-load hours of a given turbine such as manufacturer and build quality. Yet it is the wind resources of a turbine's location that likely plays the dominant role. Some evidence of this can be shown by looking at a histogram of both onshore and offshore turbines' full-load hours as in figure 10. Offshore turbines are known to benefit from steadier and on average higher wind speeds. This is reflected in above average annual full-load hours.

Figure 10. Annual Average Full-load Hours of Land and Sea Turbines



Looking at some of the geographic information in the data also provides evidence for the connection between good wind resources and high average annual full-load hours. In figure 11 the ten counties where turbines obtain the highest average annual full-load hours are filled in with stripes. Comparing this map to the wind resource map created by Risø National Lab and the consultancy EMD (http://emd.dk/files/windres/images/RES_DK99_50pct.jpg) shows a clear relationship.

Figure 11. Municipalities with Highest Average Annual Full-load Hour Turbines



In addition to a turbines average annual full-load hours, I include several other turbine-specific variables in the regression. I include the rated power capacity of the turbine as well as a squared term to capture any potential quadratic relationship. To capture potential geographic differences I include either a dummy variable indicating whether the turbine is located in western Denmark or the municipality the turbine was located in.

As shown earlier, changes in wind power subsidies have had a large effect on scrapping and I attempt to control for this in the regression. I do not control for the changes in tariff policy directly through indicator dummies because such a variable would be time-varying in the context of the Cox regression. Turbines are affected by the policy at different points in their lifetime depending on when they were installed. The inclusion of such time-varying variables in the regression can lead to identification problems and spurious inference (Singer & Willett, 2003, p. 577).

Instead I attempt to partially control for changes in the wind power tariff by including year-of-installation dummies representing years 1977 through 1999. The inclusion of these dummy variable should *not* be taken to represent the age of the turbine. The age of the turbine is already controlled for in the model by way of the baseline hazard. Instead it can be read as a latent variable for turbine-specific factors that changed over calendar time and are not otherwise accounted for, such as the effect of tariff policy.

To control for the effects of the scrapping policies I include a dummy variable representing turbines that have a capacity under both 100kW and 150 kW and were in operation at the time of the scrapping policy. These then will capture jumps in the hazard that are not accounted for by the inclusion of the rated capacity variable and which can then be explained by the effect of the policy. I also run regressions where I include interaction terms of the scrapping policy dummy with the full-load hours variable to show how the effects of this policy varied with the wind resources of a turbines location. Unfortunately, because nearly no turbines rated more than 450kW were scrapped, including a dummy for turbines rated less than 450 kW leads to severe numerical problems in the estimation.

V. Results From the Cox Regression Model

In table 3 I report the results of the Cox regression model in terms of hazard ratios – the exponent of the estimated β 's. $fullload.1000$ represents the main variable of interest – average annual full load hours of a turbine in 1000-hour units that likely captures the wind resources of a turbines location. $under100$ and $under150$ represent the dummy variables for turbines with rated power capacity less than 100kW and 150 kW and that were operational at the start of the first scrapping policy. $capacity.100KW$ represents the rated power capacity of a turbine in 100 kW units and

$capacity.100KW\_sq$ represents the squared term. *East/West* is a dummy with the value of one if the turbine is located in the western Denmark price area.

Table 3. Cox Model, Hazard of Turbine Scrapping

	1	2	3	4	5
fullload.1000	1.346	1.052	1.097	0.504	1.495
	(0.000)	(0.208)	(0.056)	(0.000)	(0.000)
under100	2.367	3.625	3.851	0.716	1.028[a]
	(0.000)	(0.000)	(0.000)	(0.174)	(0.000)
under150	1.459	1.320	1.296	0.280	1.010[a]
	(0.000)	(0.000)	(0.001)	(0.000)	(0.132)
capacity.100KW	0.847	0.828	0.829	0.808	0.860
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
capacity.100KW_sq	1.008	1.009	1.008	1.009	N/A
	(0.000)	(0.000)	(0.000)	(0.000)	
East/West	1.386	1.424	N/A	N/A	N/A
	(0.000)	(0.000)			
fullLoad.1000 X under100	N/A	N/A	N/A	2.483	N/A
				(0.000)	
fullLoad.1000 X under150	N/A	N/A	N/A	2.315	N/A
				(0.000)	
AIC	36367	35888	35582	35525	36350

Results are displayed in the form of hazard ratios
P-values are shown in parenthesis below the hazard-ratio estimates
6810 turbines
2433 scrapping events
[a] Indicates estimated hazard ratio of variable interacted with time in year-units

The estimated hazard ratios can be interpreted as the effect that a one-unit change in the variable has on the baseline hazard function. The null-hypothesis for the estimated hazard ratios is that they are equal to one. An estimated hazard ratio of 2 for example would indicate that a one-unit increase in the variable would double the hazard of scrapping.

The columns of the tables represent variations of the Cox regression model, explained as follows. In the first column, both install-year dummy variables as well as municipality are left out. The second column shows results from where the install-year dummy variables are included while the third through fifth columns include both the install-year dummies as well as the municipality dummies. The estimated coefficients on the install-year dummies and on the municipalities can be found in the appendix. Since the data of which municipality each turbine is located in implicitly also indicates whether a turbine is in east or west Denmark, I drop the *East/West* dummy from these regressions. In the fourth column I show results from the regression that includes interaction effects between the full-load hours variable and the policy dummy for turbines rated under 100kW and 150kW. In the fifth column, I loosen the proportional hazards constraint by interacting the policy dummies with time.

In the first column, where install-year dummies are left out, the coefficient on full-load hours indicates that a 1000-hour increase in the average annual full-load hours of a turbine leads to a 34% increase in the hazard of scrapping (hazard ratio of 1.34). However controlling for install-years as in column two reduces the magnitude of the estimated effect of full-load hours. A 1000-hour increase is now estimated to lead to a roughly 5% increase in the hazard of scrapping, though this is no longer statistically significant.

That the estimated coefficient on full-load hours is sensitive to the inclusion of the install-year dummies indicates that the two variables are correlated. The install-year dummies partially capture the effects of changes in the wind power tariff that created jumps in the opportunity cost of operating an old wind turbine. We can then interpret their interaction as follows: investors rushed to replace older turbines with newer ones before the wind power tariff was lowered in 2000 and 2003. At these times, they chose to replace turbines situated in locations with better wind resources over more marginally situated turbines. This explains the larger coefficient on full-load hours when the install-year dummies are not included.

A plausible alternative explanation for the positive coefficient on full-load hours exists. Turbines with higher average annual full-load hours may wear-out sooner and therefore be at a higher hazard of scrapping. Yet this explanation is less convincing. In the previous section, I presented evidence that the average annual full-load hours of a turbine at least in part reflects wind resources. In addition, as Jensen et al. showed, most turbines are scrapped well before the end of their physical lifetimes. Finally, the correlation between full-load hours and the effects of policy further suggests that wind resources are the major determinant of this variable.

The use of average annual full-load hours as a proxy for wind resources may also introduce a bias in the estimation if there are differences in technology between turbines that have the same rated capacity. For example two turbines rated at 100kW but from different producers may have different efficiencies. This however would, if anything, bias the hazard ratios towards one, as all other things equal, a turbine owner would be less likely to scrap a more efficient turbine.

The estimated hazard ratios for the other included variables are also fairly intuitive. Looking at the second and third columns, the estimated coefficient on rated capacity indicates that each 100 kW increase in capacity leads to a 20% ($\left(\frac{1}{.83}\right) * 100 \approx 20\%$) reduction in the hazard of scrapping. A larger capacity turbine produces more energy and therefore the cost of scrapping in the form of forgone revenues is then higher. Another likely reason for this result is that larger turbines are more likely to be state-of-the-art. In turn the potential benefit from replacing the turbine is smaller. The positive and significant coefficient on the squared capacity term indicates that the effect of rated capacity on scrapping hazard is decreasing with scale. The difference in the hazard of scrapping between 500 and 600 kW turbines is less than the difference between 100 and 200 kW turbines.

The estimated hazard ratios on the dummy variables that represent turbines rated less than 100kW and 150 kW are, as expected, large and significant. Turbines rated less than 100 kW and which were operating at the start of the first scrapping incentive policy had an increased hazard of scrapping of between 260 and 280% compared to turbines over 100 kW. Turbines rated less than 150 kW (but more than 100 kW) had an increased hazard of scrapping of approximately 30%.

Finally the regression indicates that a turbine built in the western part of the country runs an approximately 40% higher chance of being scrapped than a turbine built in the eastern part of the country. This could reflect several factors including better wind resources and land more suitable for wind power generation – western Denmark is geographically larger with much lower population density.

The table of hazard ratios for the municipalities found in the appendix also shows significant and sometimes large-in-magnitude estimated hazard ratios. As discussed earlier, this could partially reflect the wind resources of a municipality. However, other factors can also be at play. For example, Copenhagen municipality, which is almost entirely urban, has only 11 small turbines which have not been scrapped. We can speculate that there would likely be strong local opposition to the replacement of these with larger turbines, potentially explaining why none of them have been scrapped. Less extreme examples might include municipal-level regulations or incentives. A detailed analysis of municipal policy, though interesting, is outside the scope of this paper.

The estimated hazard ratios for the interaction variables are both large in magnitude and statistically significant. The main point to be taken from the estimates from the fourth column is that there is a strong and positive interaction effect between average annual full-load hours and the scrapping incentives. The story that is most consistent with these results is that the introduction of the turbine policy led many producers to replace their old turbines and that this had a disproportionally large effect on producers who had old turbines located in prime, wind rich areas.

In the regressions with interaction effects, it is difficult to give much economic interpretation to the main effects of the full-load hours variable and the scrapping incentive dummy variables (*under100 and under150)*. The reason is that almost all of the scrapping of turbines rated under 150 kW were done while the scrapping policy was in effect. Since the semi-maximum likelihood procedure that is used to calculate parameter estimates is based on individual scrapping events and not the overall number of turbines, if we control for turbines scrapped under the policy, there is very little information left in the data to make estimates of the main effects.

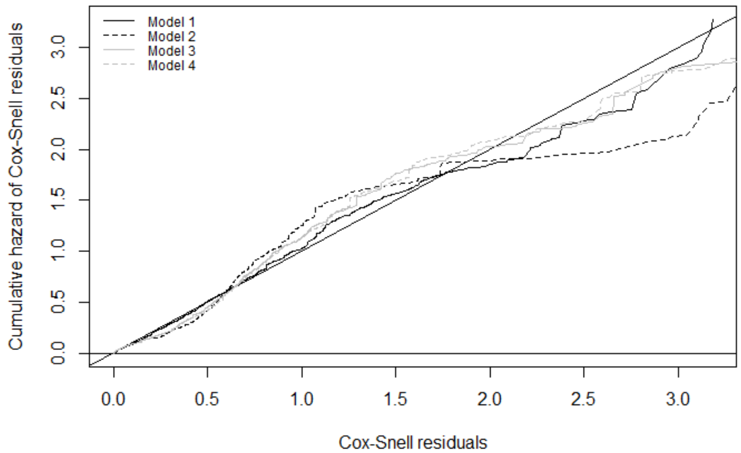
To evaluate the goodness-of-fit of the models I compare both Akaiki Information Criterian (AIC) as well as Cox-Snell residuals (Cox & Snell, 1968). The AIC provides information on the tradeoff of adding additional variables – between the added fit and reduced residual variance they provide and the potential bias introduced by over-fitting a model. In table 3, below the estimated hazard ratios, I show each model's AIC value, where a lower value indicates a better relative fit. Even though adding install-year dummies and municipality dummies adds 24 and 83 extra variables to the data respectively, the inclusion of these variables is still shown to provide a better overall fit.

Cox-Snell residuals provide a visual method of checking for goodness-of-fit. The Cox-Snell residuals are defined as in equation 3.

$$CS_j = \widehat{H}_0(t_j)e^{X\hat{\beta}} \qquad (3)$$

CS_j represents the residual on the jth observation. $\widehat{H}_0(t_j)$ represents the semi-maximum likelihood estimate of the baseline cumulative hazard function and $\hat{\beta}$ represents the vector of estimated coefficients on the explanatory variables. Figure 12 shows the estimated cumulative hazard (Nelson-Aalen estimator) of the Cox-Snell residuals for the first four regression models plotted against the values of the residuals for the regression. If the estimated Cox model has a good fit, then the Cox-Snell residuals should have an exponential distribution with a hazard function of approximately 1 (Cleves et al., 2008). This in turn implies that the cumulative hazard function of the Cox-Snell residuals in figure 12 should roughly follow a 45 degree line.

Figure 12. Wind Turbine Installations and Scrappings per Month



Comparing the Cox-Snell residuals from the different models indicates that the inclusion of the install-year dummies in model 2 leads to a worse overall fit. However the inclusion of municipality dummies in models three and four tended to significantly improve fit. I nonetheless choose to include the install-year dummies since it is important to control for the effect of changes in tariff policy which strongly affects the pattern of scrappings. The Cox-Snell residuals suggest, however, that using a model that includes installation-year dummies to predict out-of-sample scrapping times or hazard rates may lead to a bias.

It is likely that the proportional hazards assumption is not fully satisfied for all the covariates. A simple way to check the proportional hazards assumption for each explanatory variable is to run the Cox regression with an added interaction term of the variable of interest and time, as in equation 4.

$$H(t_i) = H_0(t)e^{\beta X+\beta_1 x_1+\phi x_i * t+\epsilon_i} \qquad (4)$$

If the proportional hazards model is satisfied, then the effect of the covariates should not vary with time in ways that are not already parameterized (Cleves et al., 2008).

Running such regressions for the various covariates shows that the proportional hazards assumption is likely satisfied for the full-load hours variable as well as the west dummy variable. Not surprisingly, the terms involving rated capacity do not fully satisfy the assumption. This is likely because turbines were at different ages at the start of the scrapping policy for smaller turbines.

As a robustness check I can slacken the proportional hazards requirement by interacting the *under100* and *under150* variables with a function of analysis time, allowing their effect to increase (decrease) proportionally through the lifetime of the turbines. The function I choose is the age of the turbine at the time of the introduction of the scrapping subsidy. Turbines installed after the start of the turbine subsidy are restricted to a value of zero, restricting the estimation to turbines built before the subsidy. The results are shown in the fifth column of table 3.

The coefficients for the time-interacted *under100* and *under150* dummy variables now represent effects proportional to both the baseline hazard and the age in years of the turbines. The estimated hazard ratio of 1.028 on the *under100* dummy variable can be interpreted as meaning that turbines rated under 100kW having approximately a 30 % higher hazard of being scrapped if it were 10 years old at the time of scrapping policy ($1.028^{10} \approx 1.30$) and 70% higher if it were 20 years old ($1.028^{20} \approx 1.70$). Similarly the hazard ratio on the *under150* dummy variable can be interpreted as meaning turbines rated under 150 kW but over 100 kW as having 10% higher hazard of being scrapped if the turbine was 10 years old and approximately 20% increased chance of being scrapped if it were 20 years old at the time of the scrapping policy.

As discussed earlier, a linear probability model or logit-type model is not appropriate because of the censored data and the non-linear effect of time. However, as a check on the main results of the Cox regression model, I can reframe the question in terms of the probability of scrapping at a *particular point in calendar time*. While this still leaves the issue of a non-linear effect of turbine lifetime, the censoring problem is no longer an issue, and a linear probability or logit model could be expected to give reasonable results. I choose to use a linear probability model as the results are easier to interpret while the functional and distributional assumptions of a logit model can often be difficult to justify in practice (Angrist & Pischke, 2008).

A natural point in time to analyze is the period immediately preceding the change in subsidies on January 1st, 2003. A large number of turbines – nearly16% of the total – were scrapped in the last six months of 2002, and the event itself is of interest since it involved both a change in the wind power tariff as well as the effect of the scrapping subsidy.

Table 4 below shows the results of the linear probability model regression. Most of the variables are the same as were used in the Cox regression model with the exception of *years* and *years_sq*. These variables represent the lifetime of a turbine and its square. Recall that the baseline hazard controlled for the effects of turbine lifetime in the Cox regression model. The second column shows results of the model where the municipality dummies are included, though in practice there is little difference in the estimates.

The coefficient on the main variable of interest – the average annual full load hours of a turbine – indicates that a 1000-hour increase in the full load hours lead to an approximately 5% increase in the probability of a turbine being scrapped. Though it is difficult to directly compare the magnitudes of the estimated coefficients from the linear probability model with the estimated hazard ratios from the Cox model, the estimates for the effect of full-load hours are roughly in line with each other. This is further evidence to support the idea that as turbine owners rushed to repower before the shift to market prices and lower subsidies in 2003, they tended to scrap turbines in good locations.

The linear probability model also shows large and significant effects of the scrapping subsidies with turbines rated less than 100 kW having a 60% higher probability of being scrapped while turbines rated between 100 and 150 kW had between 12% and 15% increased probability of being scrapped in the six months before 2003.

The estimated coefficient on the rated capacity variable, *capacity.100KW,* does however diverge from the results of the Cox regression model. It indicates that turbines with a higher rated capacity have a higher probability of being scrapped. In the Cox model, higher rated capacity was estimated to reduce the hazard of being scrapped. This result likely comes from the inadequacy of the linear representation to control for turbine lifetime in this model. The rated capacities of turbines grew over time and thus are correlated with the age of a turbine at the beginning of 2003. The inability to sufficiently control for the effects of turbine age then biases the coefficient on the rated capacity term.

Table 4. Linear Probability Model,
Probability of Scrapping, July-Dec 2002

	1	2
(Intercept)	-0.481	-0.458
	(0.000)	(0.000)
fullLoad.1000	0.055	0.051
	(0.000)	(0.000)
capacity.100KW	0.043	0.039
	(0.000)	(0.000)
capacity.100KW_sq	-0.001	-0.001
	(0.000)	(0.000)
under100	0.600	0.577
	(0.000)	(0.000)
under150	0.158	0.124
	(0.000)	(0.000)
years	0.039	0.043
	(0.000)	(0.000)
years_sq	-0.001	-0.001
	(0.000)	(0.000)
AIC	-16425	-16741

P-values in parenthesis
6612 Observations

VI. The Decision to Scrap a Wind Turbine

This article shows that the decision to scrap a wind turbine is complex. Economists have generally focused on factors such as operating costs and the uncertainty of output prices when modeling the shut-down or scrapping decision for a plant or productive good. For wind turbines and presumably other forms of renewable energy generation, these issues appear to be second-order compared to the effect of the interaction of technological change, scarce land resources and changes in subsidy policy. These factors can be considerably more difficult to model formally.

This also has implications for the investment decision. The expected lifetime of a wind turbine or other renewable energy investment is an important factor in the investment decision. This article shows that expected lifetime is dependent on the location of a wind turbine as well as on changes in policy and technological change which must both be considered ex-ante uncertain.

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VII. Appendix

Table 5. Estimated Hazard Ratios on Install Year Dummy Variables

	2	3	4	5
1978	0.933	1.234	1.513	1.905
	(0.931)	(0.797)	(0.612)	(0.431)
1979	0.590	0.628	0.729	1.109
	(0.528)	(0.581)	(0.708)	(0.902)
1980	0.858	1.059	1.224	1.578
	(0.835)	(0.939)	(0.786)	(0.543)
1981	1.160	1.366	1.514	1.205
	(0.837)	(0.669)	(0.570)	(0.798)
1982	1.296	1.546	1.766	2.051
	(0.718)	(0.549)	(0.434)	(0.324)
1983	1.533	1.846	1.988	2.455
	(0.553)	(0.402)	(0.348)	(0.220)
1984	2.273	2.906	3.084	2.903
	(0.252)	(0.142)	(0.121)	(0.143)
1985	3.510	4.927	5.139	5.851
	(0.077)	(0.027)	(0.023)	(0.014)
1986	4.299	6.590	6.921	10.534
	(0.040)	(0.009)	(0.007)	(0.001)
1987	7.141	11.173	11.397	13.280
	(0.006)	(0.001)	(0.001)	(0.000)
1988	6.659	9.143	9.444	7.285
	(0.008)	(0.002)	(0.002)	(0.006)
1989	4.519	6.467	6.689	4.619
	(0.035)	(0.010)	(0.009)	(0.035)
1990	5.711	7.834	8.562	8.707
	(0.015)	(0.004)	(0.003)	(0.003)
1991	4.371	6.187	6.854	4.650
	(0.039)	(0.012)	(0.008)	(0.035)
1992	6.293	8.000	9.240	5.626
	(0.010)	(0.004)	(0.002)	(0.018)
1993	4.050	6.582	7.570	4.305
	(0.056)	(0.011)	(0.006)	(0.050)
1994	2.947	4.441	5.142	3.623
	(0.148)	(0.049)	(0.031)	(0.091)
1995	2.850	5.601	7.240	4.870
	(0.171)	(0.026)	(0.011)	(0.040)
1996	2.806	4.310	5.309	3.657

	(0.167)	(0.053)	(0.027)	(0.085)
1997	3.133	4.653	5.752	3.202
	(0.129)	(0.043)	(0.021)	(0.125)
1998	4.213	6.848	8.598	4.328
	(0.064)	(0.014)	(0.006)	(0.061)
1999	7.237	12.591	15.230	5.129
	(0.010)	(0.001)	(0.000)	(0.035)

Table 6. Estimated Hazard Ratios on Municipality Dummy Variables

	3	4	5
Ærø	1.175	1.132	0.971
	(0.610)	(0.695)	(0.927)
Allerød	0.909	0.873	1.518
	(0.880)	(0.830)	(0.507)
Assens	1.002	1.015	1.645
	(0.996)	(0.966)	(0.148)
Billund	1.519	1.458	2.022
	(0.274)	(0.326)	(0.066)
Bornholm	1.949	1.984	2.089
	(0.014)	(0.012)	(0.007)
Brønderslev	1.182	1.194	1.388
	(0.538)	(0.513)	(0.227)
Dragør	3.823	4.135	5.740
	(0.002)	(0.001)	(0.000)
Egedal	0.394	0.419	1.557
	(0.093)	(0.117)	(0.425)
Esbjerg	1.268	1.288	1.343
	(0.393)	(0.364)	(0.291)
Faaborg-Midtfyn	0.707	0.745	0.748
	(0.362)	(0.440)	(0.448)
Fanø	1.883	1.857	1.113
	(0.086)	(0.094)	(0.770)
Favrskov	1.210	1.215	1.415
	(0.530)	(0.521)	(0.256)
Faxe	1.180	1.215	1.523
	(0.641)	(0.583)	(0.238)
Fredericia	1.396	1.247	1.196
	(0.512)	(0.665)	(0.737)
Frederikshavn	0.725	0.720	1.010

	(0.261)	(0.249)	(0.972)
Frederikssund	0.835	0.653	0.537
	(0.555)	(0.165)	(0.041)
Furesø	1.612	1.498	1.555
	(0.645)	(0.696)	(0.670)
Greve	0.540	0.454	0.412
	(0.409)	(0.290)	(0.235)
Gribskov	1.735	1.669	1.082
	(0.378)	(0.413)	(0.899)
Guldborgsund	0.423	0.427	0.852
	(0.004)	(0.004)	(0.590)
Haderslev	0.680	0.664	0.689
	(0.298)	(0.268)	(0.318)
Hedensted	0.604	0.623	0.998
	(0.187)	(0.214)	(0.995)
Helsingør	0.562	0.617	1.416
	(0.575)	(0.639)	(0.735)
Herning	1.716	1.520	1.272
	(0.071)	(0.164)	(0.426)
Hillerød	1.181	1.233	2.088
	(0.743)	(0.680)	(0.146)
Hjørring	0.562	0.569	0.748
	(0.049)	(0.053)	(0.321)
Holbæk	0.635	0.579	0.772
	(0.191)	(0.116)	(0.456)
Holstebro	0.745	0.770	1.226
	(0.276)	(0.333)	(0.453)
Horsens	0.518	0.522	0.926
	(0.054)	(0.057)	(0.823)
Hvidovre	7.221	7.850	27.266
	(0.000)	(0.000)	(0.000)
Høje-Taastrup	6.295	3.933	5.264
	(0.003)	(0.029)	(0.008)
Ikast-Brande	1.171	1.175	1.377
	(0.606)	(0.599)	(0.298)
Ishøj	NA	NA	0.000
	(NA)	(NA)	(0.999)
Jammerbugt	1.063	1.018	1.134
	(0.825)	(0.948)	(0.649)
Kalundborg	0.478	0.469	0.727
	(0.024)	(0.020)	(0.330)
Kerteminde	2.414	1.914	2.532
	(0.010)	(0.061)	(0.008)

Kolding	0.743	0.731	1.208
	(0.451)	(0.426)	(0.632)
København	0.000	0.000	0.000
	(0.975)	(0.976)	(0.981)
Køge	2.353	2.382	2.608
	(0.038)	(0.035)	(0.020)
Læsø	0.477	0.455	0.329
	(0.471)	(0.443)	(0.279)
Langeland	1.761	1.738	2.177
	(0.040)	(0.047)	(0.005)
Lejre	0.549	0.545	1.505
	(0.142)	(0.137)	(0.318)
Lemvig	2.152	2.620	2.062
	(0.003)	(0.000)	(0.005)
Lolland	0.430	0.480	1.116
	(0.004)	(0.013)	(0.712)
Mariagerfjord	0.697	0.613	0.988
	(0.317)	(0.177)	(0.974)
Middelfart	0.373	0.381	1.037
	(0.074)	(0.081)	(0.948)
Morsø	0.966	1.009	1.132
	(0.897)	(0.972)	(0.642)
Næstved	0.620	0.614	0.727
	(0.110)	(0.103)	(0.288)
Norddjurs	2.696	2.785	2.145
	(0.000)	(0.000)	(0.004)
Nordfyns	0.545	0.542	0.390
	(0.273)	(0.269)	(0.088)
Nyborg	1.422	1.487	1.901
	(0.357)	(0.300)	(0.094)
Odder	2.058	2.113	2.477
	(0.013)	(0.010)	(0.002)
Odense	0.574	0.625	0.568
	(0.377)	(0.453)	(0.368)
Odsherred	0.394	0.417	0.600
	(0.018)	(0.027)	(0.195)
Randers	2.031	1.961	1.361
	(0.020)	(0.027)	(0.312)
Rebild	1.408	1.321	1.148
	(0.231)	(0.330)	(0.630)
Ringkøbing-Skjern	0.742	0.732	1.274
	(0.216)	(0.197)	(0.315)
Ringsted	0.924	0.801	0.842

	(0.851)	(0.601)	(0.686)
Roskilde	1.045	1.024	1.841
	(0.896)	(0.943)	(0.069)
Samsø	0.430	0.408	0.508
	(0.176)	(0.151)	(0.279)
Silkeborg	1.614	1.700	1.767
	(0.107)	(0.074)	(0.057)
Skanderborg	1.570	1.649	2.001
	(0.123)	(0.087)	(0.018)
Skive	1.209	1.253	1.306
	(0.448)	(0.367)	(0.287)
Slagelse	0.196	0.189	0.240
	(0.000)	(0.000)	(0.000)
Solrød	1.018	1.015	0.697
	(0.986)	(0.988)	(0.726)
Sorø	1.232	1.155	2.000
	(0.562)	(0.690)	(0.059)
Stevns	1.179	1.173	1.463
	(0.642)	(0.653)	(0.286)
Struer	0.705	0.700	1.128
	(0.190)	(0.181)	(0.653)
Svendborg	1.235	1.299	1.812
	(0.498)	(0.401)	(0.058)
Syddjurs	1.325	1.284	1.139
	(0.308)	(0.365)	(0.638)
Sønderborg	0.515	0.506	1.044
	(0.157)	(0.147)	(0.928)
Thisted	0.827	0.935	0.975
	(0.441)	(0.786)	(0.919)
Tønder	0.641	0.629	0.914
	(0.113)	(0.099)	(0.748)
Varde	0.600	0.609	0.949
	(0.071)	(0.080)	(0.855)
Vejen	1.623	1.669	1.014
	(0.098)	(0.080)	(0.964)
Vejle	0.961	0.929	1.273
	(0.891)	(0.797)	(0.399)
Vesthimmerland	1.336	1.357	1.547
	(0.237)	(0.213)	(0.076)
Viborg	1.026	0.968	1.298
	(0.932)	(0.913)	(0.385)
Vordingborg	0.642	0.625	0.984
	(0.119)	(0.099)	(0.954)

Ålborg	1.281	1.153	2.378
	(0.323)	(0.572)	(0.001)
Århus	1.184	1.182	1.071
	(0.592)	(0.595)	(0.829)