The Decision to Scrap a Wind Turbine: Opportunity Cost, Timing and Policy

Johannes Mauritzen

Norwegian School of Economics (NHH)
Department of Finance and Management Science
Helleveien 30
5045 Bergen, Norway
phone: +47 90 56 64 62
fax: +47 55 95 98 41

Abstract

This paper attempts to empirically identify the key factors involved in the decision to scrap a wind turbine using data from Denmark. The importance of the opportunity cost of operating an older wind turbine is shown to be a prominent factor in the decision to scrap. I show the strong effect that renewable energy policy plays in the decision to scrap a turbine. Through the use of both non-parametric and semi-parametric duration models and an instrumental variables approach I identify a strong effect for scrapping schemes put in place by the Danish government. I also obtain the, initially, counter-intuitive result that more effective wind turbines have a *higher* hazard of being scrapped.
Keywords:
Wind Power, Denmark, Empirical, Duration Models, Scrapping,

1. Introduction

The decision of when to abandon or scrap a productive good is a fundamental issue in economics. This is especially true of renewable energy technologies where the cost of the electricity generated comes primarily from capital costs and associated financing costs.

Email address: `johannes.mauritzen@nhh.no` (Johannes Mauritzen)

The expected lifetime of such investments is then of extra importance to the investment decision. In this paper, I empirically analyse the factors that determine the decision to scrap wind turbines in Denmark. The traditional economics literature on the scrapping of durable productive goods tends to focus on marginal and average running costs, and relatively more recently on price and cost uncertainty of outputs and inputs (Dixit and Pindyck, 1994). Studies of vehicle scrappings, a particularly popular subject, tend to focus on repair and replacement costs and issues of depreciation. Manski and Goldin (1983) used a data set of cars in Israel to show that vehicle scrappage rates between years 3 and 14 had much more to do with depreciation of the vehicle rather than directly due to failure proneness. An earlier paper, Walker (1968) makes a similar econometric argument. Hahn (1995) looks at the costs and benefits of automobile scrappage programs implemented in order to reduce air pollution and Alberini et al. (1995) looks at the determinants of participation in such programs.

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 and Morthorst (2008) gives a general overview and analysis of Danish wind power policy and tries 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.

I argue that when looking at the scrapping decision, wind turbines are a special case due to several factors:

- close to negligible marginal operating costs
- Importance of geographic placement
- High rate of technological change

- High level of government involvement in output price-setting and subsidies

The low, almost negligible marginal operating costs of wind turbines means that once the turbine is built, the real operating margin is nearly always positive. It is highly unlikely that a real operating loss for the turbine could be the direct reason for a scrapping. Another potential reason for scrapping is a combination of technical failure and the relative magnitude of reparation and replacement costs. However, the analysis suggests that technical failure plays only a modest role in the scrapping of wind turbines.

Instead, this article will show that the dominant reason for scrapping a wind turbine is the opportunity cost that results from a combination of scarce land resources, a high rate of technological change and government subsidies. An older turbine operating on a wind-rich location means that one can not put in its place a newer, larger and more efficient 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. [1] Other factors may also play a role in making land suited for wind turbines especially scarce, such as grid infrastructure, zoning rules, and environmental concerns.

Opportunity costs are often necessarily difficult to capture empirically. However, in Denmark, the government has had a significant role in setting the tariff for electricity from wind power (and other sources) and tariff policy has shifted abruptly several time over the course of the period studied, as shown in figure 1. The tariffs and subsidies are set up such that a turbine installed under a certain regime will receive that tariff over a defined lifetime. The shift in tariff policy then creates a sharp discontinuity in the opportunity cost. A decrease in tariffs at a certain date, for instance, means that a turbine 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

[1] A simplified energy conversion formula for wind power is $E = 1/2\Phi A t v^3$ where A is the sweeping area of the blades and v is the average wind velocity. Thus theoretical energy output from a wind turbine increases approximately *cubically* with average wind speed

turbine. Scrapping rates are shown to reflect this jump in opportunity cost.

The Danish government also launched several schemes aimed at directly encouraging the scrapping of older turbines. To test the effects that these schemes as well as other factors had on scrapping rates, I use both non-parametric and semi-parametric (Cox) duration models. One of the main reasons for using such models, alternatively called survival or time-to-failure models is the issue of censoring. Only a third of the turbines in my data set were scrapped over the period studied. These censored observations would cause biased estimators using logit or linear-probability models. In section 3 I give a brief overview of the duration models used.

My main data set consists of all 6754 turbines constructed in Denmark between 1977 and February 2011. 2279 of the turbines were scrapped before February of 2011. 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 electricity grid company, energinet (http://www.energinet.dk).

I identify the effects of the scrapping policies by using the policies cut-off points for turbine capacity as instruments. I find evidence for a large and significant effect for both the scrapping schemes. The initial scrapping scheme covering turbines under 150 kW is estimated to roughly double the hazard of scrapping. The estimated effectiveness for the second policy covering turbines under 450 kW, is more uncertain, but is nonetheless large and significant - likely increasing the hazard of scrapping by a factor of between 3 and 10. That the scrapping policy was effective at encouraging scrapping of wind turbines will likely not be surprising to policy makers, however the methods I use here provide an effective way of both visualizing the magnitude of the policies' effect as well as providing unbiased point estimates of their effect in terms of increased hazard.

Using the data available on energy produced per turbine, I create an index of effectiveness where turbine capacity is divided out. Including this term in the Cox regression leads to the finding that *more* effective turbines have a *higher* hazard of being scrapped. This finding, while initially surprising, can be explained by the importance of opportunity cost in the decision to scrap.

In section 2 I review Danish electricity policy and in particular wind power policy over the relevant period. In section 3 I give a brief overview of the duration models used and I present the results in section 4. In the concluding section I discuss some of the implications that the findings have on both energy policy design as well as on wind energy investment.

2. Wind and Energy Policy in Denmark

The energy crisis of the 1970's exposed the vulnerabilities of having a power system that was highly dependent on imported fossil fuels, as was the case in Denmark. Already in 1974 a Danish government commission issued a report asserting that it would be possible to generate 10% of Denmark's electricity needs by wind without causing problems for the grid (Hau, 2006). Even before the energy crisis struck, Denmark had accumulated some experience and knowledge in feeding wind power into the electricity grid, the only country to have successfully done so at that time. However this was done exclusively with small, experimental turbines in the 50-60 kW range. Still, this knowledge and experience became the kernel for a growth industry with strong government support through direct research and development aid, special tax treatment and generous subsidies.

The electricity tariffs for wind power production have changed over time as wind energy investment has grown in scale (figure 2). In 2003, Denmark also 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, which is set at a central exchange called Nordpool. The policies are shown in table 1.

The most generous tariff was provided for turbines installed from 1976 up through December 31st 2000, and provided a fixed tariff of 60 øre/kWh for electricity provided to the grid for up to 10 years. To put this in some perspective, average market prices in the wholesale market the last few years have on average been between 25 and 35 øre/kWh. After the initial 10-year period, a feed-in tariff of DKK .10/kWh above the market rate is provided for the next 20 years. With the growth in installed wind capacity, the tariff was lowered in the year 2000 to DKK .43/kWh for 22,000 full-load hours after which the normal electricity tariff yielded. In 2003, Denmark fully joined the common Nordic electricity market and transitioned to a market based tariff system. On top of the wholesale market price, a DKK .10/kwh was provided with a maximum payment set at DKK .36 /kWh. Beginning in 2004, this cap was eliminated. Starting on February 21st of 2008 a new policy was initiated which set a feed-in tariff of DKK .25 /kWh over the market price for 22,000 full-load hours.

Referring back to Figure 1, clearly turbine owners who installed after 2002 faced higher price uncertainty and, initially, considerably lower tariffs.

The government also introduced several "scrapping" schemes in order to expand wind power and "[decommission] older and less appropriately sited wind turbines" (ens, 2008). The rationale likely also involved encouraging wind turbine owners to give up the generous subsidies they received from the existing turbine. The first such 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 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. For scrapped turbines under 100 kW, the extra subsidy was provided for up to 3 times the scrapped capacity. For turbines between 100 and 150, 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.

Wind power producers were free to apply several scrapping certificates to a single new turbine. In addition, some producers chose to split the certificates and apply them to several new turbines - for example a scrapped 150 kW turbine can be made into two 75 kW certificates to be applied to two new turbines.

Other aspects of government support for wind power in Denmark include favourable tax treatment and substantial direct research and development funding - notably the Risø National Lab for Sustainable Energy. Policies have also been put in place to gain acceptance of turbines in the local communities they are placed. This includes "loss of value" rules, which provides compensation for loss of property value, the right for the local population to purchase up to 20% of a new project and subsidies to help municipalities improve scenic areas near new turbines (DEA, 2009). An environmental economist can admire the effort to put the Coase theorem in to action.

The result of all these incentives was a remarkable growth in installed wind capacity as well as often home-grown development of larger, more efficient turbines. The size (in terms of power capacity) is one easily available measure of this rapid technological improvement (figure 3). However, just as important have been advances in manufacturing efficiency and engineering quality that have brought down both capital and maintenance costs.

3. Models and Methodology

With survival analysis the goal is to identify the shape of a survival function, hazard function, and/or cumulative hazard function and the factors that shift their position up or down. See Singer and Willett (2003) for an accessible overview or Kalbfleisch and Prentice (2002) for a more thorough treatment. The basics however are fairly simple. The survivor function, $S(t)$ is simply one minus the cumulative distribution function of the hazard of exit. To put it another way, it is the probability of survival at a given time conditional on the subject having survived up to that point. The hazard function can be represented by $\lim_{\Delta t \to 0} \frac{Pr(t+\Delta t > T > t | T > t)}{\Delta t} = \frac{f(t)}{S(t)}$ (Cleves et al., 2008). It is the instantaneous rate of risk of the event occurring, and as shown above, can be expressed as the ratio of the probability distribution function (pdf) of the event over the survival function. The cumulative hazard, as the name suggests, is the accumulation of hazard over time, $H(t) = \int_0^t h(u)du$. Given a parametric form, these terms are closely linked to one another and can easily be converted. For instance, the survivor function and cumulative hazard are related by: $S(t) = e^{-H(t)}$. Other conversions follow from the definitions above.

When choosing an empirical model to analyse survival data, several options are available. A Kaplan-Meier estimate is a completely non-parametric approach. A survival function can be estimated by calculating the fraction of survivors at each failure time as in equation (1). A plot of a Kaplan-Meier estimate of the survivor function of the full set of Danish wind turbines is presented in figure 4. 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 (circa 3500 days) with an acceleration thereafter. In the results section, I will use Kaplan-Meier estimates and a policy instrument in order to identify the effect the scrapping policy.

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

While this approach has the advantage that it requires no assumptions about the shape of the hazard function, it is also limited in what information it can provide. Only a general shape can be estimated, without the ability of estimating effects beyond estimating in sub-samples. On the other end of the spectrum are parametric models, where a general shape for the hazard is assumed and parameters estimated to fit the data. This approach gives flexibility in the ability to account for effects as well as estimate an explicit hazard function. However, since I do not have any strong a priori assumptions about the shape of the hazard function, a more flexible approach is desirable.

The Cox regression model is referred to as semi-parametric in that it allows for the parametric estimation of factors that are constrained to shifting the baseline hazard function proportionally up or down. However, the baseline shape itself is obtained non-parametrically (by a similar method to the Kaplan-Meier), conditional on the included explanatory variables. Though much of the economics literature has tended to use parametric models instead of the cox model, there does not appear to be a good justification for this. Parametric models are only slightly more efficient than the Cox model when the baseline hazard is correctly specified and much less efficient when it is not (Singer and Willett, 2003).

4. Results

4.1. Effect of Tariff Policy on Scrappings

As discussed in the introduction, the opportunity cost of operating an older turbine on valuable, wind-rich land is a major determinant of whether and when to scrap. When a certain amount of technological change has taken place, an older, less efficient turbine takes up space where a newer more efficient turbine could be placed. Evidence for the importance of this effect can be seen graphically by considering the effect of a change in subsidy policy.

Recall that the tariff for wind power was reduced from DKK .60 /kWh to .43 /kWh in January, 2000. In January of 2003 policy again changed to a feed-in tariff of DKK .10 above the market price, and as figure 1 showed, the average tariff received by power producers was substantially reduced. Knowing in advance that the new policy would be put into place, producers rushed to install turbines before the new tariff regime took effect. Figure 5 shows the frequency of turbine installations per month. The spike ahead of the policy change in 2003 is particularly apparent.

But the change in wind power tariff policy had an even more dramatic effect on scrappings (figure 6). A jump in scrappings occurred prior to the policy shift in 2000, and a dramatic increase in scrappings occurred in the months before tariffs went over to variable prices (market prices + subsidy) in 2003. What we observe is in effect a discontinuity or jump in the opportunity cost caused by the policy change. Consider the change in policy that occurred on January 1st, 2003. The tariff provided for a new turbine goes from a fixed DKK .43 per kWh to a variable rate that is on average lower. It follows then that the total asset value of that new turbine over its life shifts quite dramatically depending on whether it is installed before or after that date. In turn, the opportunity cost of operating an old turbine on optimal land also shifts, leading to the spike in scrappings. It is rare to have such a clear visual of an opportunity cost.

4.2. Effect of Scrapping Policy

The previous section demonstrated the important role that wind tariff policy plays in the decision and timing of scrapping a turbine. The Danish government has also implemented several policies with the intention of increasing scrappings. These scrapping policies can also be shown to have had a significant effect. Referring back to figure 6, notice that the frequency of scrappings goes to nearly zero in 2004 - the time period between the end of the first scrappage scheme and the beginning of the old scrappage scheme. However, estimating the effect of the scrappage scheme by way of comparing rates before and after the policy was implemented is problematic. Such an approach is likely to yield biased results since it would capture other time-varying components such as changes in tariff policy that occurred in the same period.

However both of the scrappage policies had turbine capacity cut-off provisions. In the first scheme, only turbines rated at or under 150 kW could be scrapped. In the second scheme this cut-off was raised to 450 kW. In this section I will attempt to identify the significance and effect of the scrappage policy by using these cut-offs as instruments. I compare Kaplan-Meier estimates of the survivor functions of turbines that are rated just above and below these cut-off rates. The identifying assumption is that the relatively small difference in capacities will not in themselves have a large effect on the scrappings and significant differences observed in the survival function will be due to the policy.

I extend the analysis in the context of the Cox regression model in the following section.

Figure 7 shows the Kaplan-Meier survivor functions for turbines with rated capacity between 100 and 200 kW, split into subgroups of over and under 150 kW. While both subgroups experience a fairly substantial rate of scrappage, the survival rate declines earlier for under-150 turbines and reaches near 0% at around the 9000 day mark (about 25 years). A substantial percentage of turbines between 150 and 200 kW are also scrapped, and it is important to note that they come under the later scrappage scheme for under-450 turbines. Consistent with this, the survival function stays flatter longer, dropping off steeply only after a several year delay. I can formally test the hypothesis of equal survivor functions with the Wilcox (Breslow) test. [2] The test strongly rejects the null of equal survivor functions.

Figure 8 shows the Kaplan-Meier Survival functions for turbines between 400 and 500 kW, with the split at the policy cut-off of 450 kW. Here the difference is even more pronounced. The survivor function for over-450 kW turbines remains essentially flat and can not be estimated at all beyond about 7000 days. The reason for this is not a small sample - more than a 100 turbines between 450 and 500 kW exist in my data set. Instead, almost all of such turbines were still operating at the censoring date of February 2011. Yet the group of turbines that were rated just under the cut-off capacity

[2] the Log Rank test is also used for the purpose, but the Wilcox test is shown to be a better test when the hazards are thought to vary in some way other than proportionally (Cleves et al., 2008)

experienced a sharp drop in their survival starting around 5000 days of operation. A Wilcoxon test again firmly rejects the equality of the two survivor functions.

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 scrappage policy and should therefore display a similar survival function given that my assumption that the differences in capacities does not play a significant role is correct. The chart on the right shows the initial survival functions with a sharp drop in the *over-250* group at around the 7000 day mark. A look at the data shows that several identical turbines were removed on the same day - likely a scrapping of an entire wind park. Removing this outlier, I get the the survival functions on the left. A Wilcoxon test fails to reject that these curves are the same at the 5 % significance level.

4.3. Cox Regression Model and the Determinants of Scrappage

In this section I analyse the effect of scrapping schemes along with other determinants of the hazard of scrapping using a Cox regression model. As explained earlier, the advantage of this model is that I don't need to make any assumptions about the actual shape of the hazard function. However, the validity of the estimated coefficients is conditional on the assumption that the factors shift the overall hazard function proportionally.

I include several 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. In addition I include the two policy dummies of turbines at or under 150 kW and at or under 450 kW. [3] These then represent "jumps" in the hazard that are not accounted for by the inclusion of the capacity variable and which can then be explained by the effect of policy.

Significant spatial and geographic data is available in my data set including coordinates and principality. But for simplicity of interpretation and a wish not to over-parametrise

[3] Only those turbines that remained in operation at the time of the policy implementation were included in the definition of the dummies

the model, I have chosen to limit explicit spatial data to a east/west dummy, representing turbines built in the east and west price areas. This dummy variable could capture many elements that differ between the two areas of Denmark. Referring back to figure 1, market prices for the two areas differs slightly. Factors such as wind-conditions, land value and population density could also be reflected in this variable.

I run regressions both with and without a variable that indicates the year of installation. The inclusion of this variable should *not* be taken to represent the age of the turbine - the age of the turbine is already controlled for in the model. Instead it can be read as a latent variable for turbine-specific factors that changed over time and are not otherwise accounted for. For example, this could represent increased engineering quality over time. However, I will show that the estimated coefficient for this variable is most likely picking up the uncontrolled for effects of changes in tariff policy.

Finally I create a variable meant to represent the overall efficiency of a turbine, given its rated capacity. I define the variable as in equation 2. I take the average yearly energy yield (calculated by using only every full year of operation) from each turbine and dividing it by the rated capacity. This then captures factors that effect the energy production of a turbine other than its rated capacity. The most prominent such factor is likely the average wind speed at the turbine site. Given that this assumption is true, the efficiency variable then mainly represents the appropriateness of the land where the turbine is situated. A dot plot of the efficiency indicator is presented in figure 10 and gives a sense of the mean and spread of the indicator.

$$Eff_i = \frac{\sum_{t=2}^{n-1} Y_{it}^e}{(n-2) * P_i} \tag{2}$$

The Cox regression model can then be written as in equation 3. $H(t_i)$ represents the individual turbine hazards as a function of turbine lifetime. H_0 represents the baseline hazard, which is non-parametrically estimated. X represents the vector of variables, discussed above, that shift the baseline hazard up or down proportionally.

$$H(t_i) = H_0(t)e^{\beta \mathbf{X} + \epsilon} \tag{3}$$

In table 2 I report the results in terms of hazard ratios - the exponent of the estimated β's. The hazard ratios can be interpreted as the proportional effect that a one-unit change in the variable has on the baseline hazard function. The null-hypothesis for the estimated hazard ratios is then that they are equal to one (have no proportional effect on the hazard function). An estimated hazard ratio of 2, for example, would indicate that a one-unit increase in the variable would double the hazard of scrappage.

Considering first the policy variables under150 and under450, the regressions indicate that the initial scrapping policy increased the chance of scrapping by a factor of approximately two. The large standard error on the under450 policy variable makes any point-estimate quite uncertain. It is clear however, that the policy was effective, likely leading to a 2- to 7-fold increase in the hazard of scrapping and possibly higher.

In the regression where installation year is left out the estimated hazard ratio for turbine capacity, in 100 kW units, is not significantly different from 1. However when installation year is controlled for, the hazard ratio becomes highly significant, indicating that each 100 kW increase in capacity leads to a 25% ($\frac{1}{.80}$) reduction in the hazard of scrapping. This is the expected result. A larger capacity turbine produces more energy and has a higher asset value. The cost of scrapping, in the form of forgone revenues, are then higher for larger turbines.

As figure 5 showed, installation year and capacity size are clearly correlated. Given that installation year also effects the rate of hazard, the exclusion of this variable biased the capacity hazard ratio towards one in the initial regression. When installation year is included, its own estimated hazard ratio indicates that turbines built in later years had a 6% *greater* chance of being scrapped per year.

The most likely explanation for this coefficient, is that it is indirectly capturing the effect of policy change. As explained earlier, anticipation of a policy change to lower wind power tariffs led to an abrupt jump in scrappings ahead of the policy change in January 2003. Table 3 shows that the effect of a policy change in January 2003 affected the scrapping of turbines installed in the decade between 1977 and 1987 relatively evenly.

Because of the large effect that the policy change had on scrappings, turbines built in a later year - say 1987 - had a considerably shorter average lifetime than those built earlier. It follows that the hazard ratio for build-year is estimated to be significantly above one.

The positive coefficient (above-one hazard ratio) on turbine efficiency, labeled EfficInd, may initially, seem counter-intuitive. This says that a *more* efficient turbine, controlling for capacity and other factors, has a higher hazard of being scrapped. One might logically believe that a lower efficiency turbine would be at a higher risk. But again, this is forgetting the effect of the opportunity cost of operating on scarce land in the face of technological change. The variation in the efficiency metric likely has little to do with the mechanical quality of the turbine (though this could possibly play a role). Instead it likely reflects the wind resources of turbine's location.

From a theoretical stand point, the effect that better wind resources has on the hazard of scrapping is ambiguous. A wind turbine operating in an area with better wind resources produces more energy and has a higher asset value over its lifetime, thus increasing the cost of scrapping in terms of foregone revenue. This would, in turn, reduce the hazard of scrapping. However, it also has a higher opportunity cost that comes from the possibility of installing a newer, larger turbine in its place. The relative magnitude of these effects is dependent on the rate of technological change. The regression results indicates that the effect of the larger opportunity costs is dominant, reflecting a high rate of technological change.

Finally, the regression indicates that a turbine built in the western part of the country runs a 50% higher chance of being scrapped than a turbine built in the eastern part of the country. There could be several reasons for this distinction. A large majority (nearly 80%) of turbines were built in western Denmark, though this has perhaps most to do with the fact that western Denmark is substantially larger and less densely populated. Still, if it is the case that western Denmark is inherently better suited for wind power, then opportunity cost could also explain the higher hazard.

To evaluate the overall goodness-of-fit of the model, I use Cox-Snell residuals (Cox and Snell, 1968) which are defined as in equation 4 for the residual on the jth observation and where $\hat{H}_0(t_j)$ represents the maximum likelihood estimate (MLE) of the baseline cumulative hazard function and where $\hat{\beta}$ represents the vector of estimated coefficients on the explanatory shifting variables. Figure 11 shows the estimated cumulative hazard (Nelson-Aalen estimator) of the Cox-Snell residuals plotted against the values of the residuals. If the estimated Cox model has a good fit, then the Cox-Snell residuals should have a exponential distribution with a hazard function of 1 (Cleves et al., 2008). This in turn implies that the cumulative hazard function of the Cox-Snell residuals in fig 11 should roughly follow a 45 degree line. By this metric, the fit appears to be reasonably good.

$$CS_j = \hat{H}_0(t_j)e^{\mathbf{X}\hat{\beta}} \tag{4}$$

It is likely that the proportional hazards assumptions 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 5. If the proportional hazards model is satisfied, then the effect of the covariates should not vary with time in ways that are not already parametrized (Cleves et al., 2008). A violation of the proportional hazards model does not necessarily mean that the entire regression results are invalid, it does however imply that the estimates could be biased.

$$H(t_i) = H_0(t)e^{\beta\mathbf{X}+\beta_1 x_i+\phi x_i * t+\epsilon_i} \tag{5}$$

Running such regressions for the various covariates shows that the proportional hazards assumption is likely satisfied for the efficiency indicator variable as well as the west dummy variable. Not surprisingly, the policy instruments of under-150 and under-450 do not strictly satisfy the assumption, nor does the capacity indicator.

These violations of assumptions should not radically affect the validity of the results overall. As a robustness check I can slacken the proportional hazards requirement by interacting these variables with analysis time, allowing their effect to increase (decrease) proportionally through the lifetime of the turbines. The results are shown in the third column of table 3.

The coefficients for the time-interacted variables now represent effects proportional to both the baseline hazard *and* the age (in years) of the turbines. For example, the estimated hazard ratio of 1.04 on the under-150 kW indicator can be interpreted as approximately a 50 % higher hazard of being scrapped after 10 years ($1.04^{10} = 1.48$) and twice the hazard after 20 years ($1.04^{20} = 2.19$). Similarly, an under-450 kW turbine has approximately 4 to 7 times higher hazard after 10 years. The estimated coefficients on the other variables are not significantly affected.

5. Discussion and Conclusion

The findings in this paper have implications for both energy policy design and wind energy investment. The expected lifetime of a wind turbine is an important consideration in the investment decision. This paper shows that this lifetime is not just a function of the mechanical quality of the turbine, but instead highly dependent on the opportunity cost that arises from an interaction of technological change, land scarcity and government policy. Since these factors are in themselves ex-ante uncertain, the expected lifetime of a turbine (and potentially other energy investments) must be seen as inherently uncertain to a greater degree than is recognized in the literature. From a real options perspective, this uncertainty can have an adverse affect on investment.

In relation to opportunity cost, changes in government policy are shown to have strong direct and indirect effects on scrapping rates. Anticipation of tariff reductions for wind power led to large jumps in scrapping rates. This was especially true in the months leading up to the shift to market-based tariffs in 2003.

One interesting result that follows from the importance of opportunity costs is that, controlling for turbine-capacity, more efficient turbines have a higher hazard of being scrapped. This is likely due to the fact that the efficiency metric I use (average yearly energy produced per rated kW of capacity) is capturing, in large part, the wind resources of a turbine's placement.

The scrapping schemes designed to directly encourage the scrapping of older turbines in favor of newer, more advanced turbines are also shown to be highly effective. While the reports on the scheme from the Danish Energy Directorate do not explicitly say so, it is likely that a part of the rationale for the scrapping scheme was to wean producers off of the generous pre-2000 tariff scheme. Wind power policy in Denmark then serves as an interesting case study in ex-ante and ex-post optimal energy policy. A case can be made ex-ante for a generous wind power subsidy on several grounds - reduction in air pollution, energy generation diversification, technological spill-overs, etc. Instituting these policies in the form of guaranteed prices over a defined life-time may also be ex-ante optimal since this removes uncertainty that in itself may delay or reduce investment (Dixit and Pindyck, 1994).

Yet there is a time-inconsistency problem. From the point of the view of the policy maker, once the investments have been made, the technology developed, and wind power a significant contributor of energy, the generous subsidy is no longer optimal. Denmark, as in other countries with renewable energy subsidies, lowered subsidies for newer installations as capacity grew. Yet, existing turbines continued to receive the older, more generous subsidy. This, in effect, reduces the incentive for turbine owners to scrap their existing turbine in favor of a newer, more efficient turbine. The scrapping incentive is then an attempt at fixing this unintended consequence.

Energy policy agreement - 21. february, 2008. http://www.ens.dk, 2008. URL http://www.ens.dk.

Wind turbines in denmark, November 2009. URL http://www.ens.dk.

Anna Alberini, Winston Harrington, and Virginia McConnell. Determinants of participation in accelerated Vehicle-Retirement programs. *The RAND Journal of Economics*, 26(1):93–112, April 1995. ISSN 0741-6261. doi: 10.2307/2556037. ArticleType: research-article / Full publication date: Spring, 1995 / Copyright © 1995 The RAND Corporation.

Mario Cleves, William Gould, Roberto Gutierrez, and Yulia Marchenko. *An Introduction to Survival Analysis Using Stata, Second Edition.* Stata Press, 2 edition, May 2008. ISBN 1597180416.

D. R. Cox and E. J. Snell. A general definition of residuals. *Journal of the Royal Statistical Society. Series B (Methodological)*, 30(2):248–275, January 1968. ISSN 0035-9246. URL http://www.jstor.org/stable/2984505. ArticleType: research-article / Full publication date: 1968 / Copyright 1968 Royal Statistical Society.

Avinash K. Dixit and Robert S. Pindyck. *Investment under Uncertainty.* Princeton University Press, January 1994. ISBN 0691034109.

Robert W. Hahn. An economic analysis of scrappage. *The RAND Journal of Economics*, 26(2):222–242, July 1995. ISSN 0741-6261. doi: 10.2307/2555914. ArticleType: research-article / Full publication date: Summer, 1995 / Copyright © 1995 The RAND Corporation.

Erich Hau. *Wind turbines: fundamentals, technologies, application, economics.* Birkhäuser, 2006. ISBN 9783540242406.

John D. Kalbfleisch and Ross L. Prentice. *The Statistical Analysis of Failure Time Data.* Wiley-Interscience, 2 edition, September 2002. ISBN 047136357X.

Charles F. Manski and Ephraim Goldin. An econometric analysis of automobile scrappage. *TRANSPORTATION SCIENCE*, 17(4):365–375, November 1983. doi: 10.1287/trsc.17.4.365.

P. E. Morthorst. Capacity development and profitability of wind turbines. *Energy Policy*, 27(13):779–787, November 1999. ISSN 0301-4215. doi: 10.1016/S0301-4215(99)00067-1.

Jesper Munksgaard and Poul Erik Morthorst. Wind power in the danish liberalised power market–Policy measures, price impact and investor incentives. *Energy Policy*, 36(10):3940–3947, October 2008. ISSN 0301-4215. doi: 10.1016/j.enpol.2008.07.024.

Judith D. Singer and John B. Willett. *Applied longitudinal data analysis: modeling change and event occurrence*. Oxford University Press US, 2003. ISBN 9780195152968.

Franklin V. Walker. Determinants of auto scrappage. *The Review of Economics and Statistics*, 50(4):503–506, November 1968. ISSN 0034-6535. doi: 10.2307/1926820. ArticleType: research-article / Full publication date: Nov., 1968 / Copyright © 1968 The MIT Press.

Table 1: Wind Power Policies in Denmark

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 over 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

Table 2: Turbine Scrappage Hazard: Cox Regression Results

Variable	**w/out Ins. Year**	**w. Inst. Year**	**time inter**
capacity	1.054[a]	.798	.989*
	(.047)	(.049)	(.0035)
capacity2	1.005	1.01	n/a
	(.001)	(.001)	n/a
under150	2.37	2.093	1.04*
	(.188)	(.170)	(.005)
under450	9.48	5.15	1.19*
	(2.9)	(1.64)	(.032)
EfficInd	1.26	1.20	1.22
	(.050)	(.050)	(.050)
west	1.53	1.50	1.51
	(.087)	(.085)	(.085)
InstallYear	n/a	1.067	1.067
		(.001)	(.010)

Standard errors in parenthesis
All coefficients significant at 1% level unless otherwise noted
[a] - not significantly different from 1 at 10%
*interacted with analysis time in year-units
6754 Observations, 2279 Failures

Table 3: Turbines Scrapped in 2002 and Year of Installation

Year Built	Total # Built	#Scrapped in '02	Percent
1977	2	2	100 %
1978	10	6	60 %
1979	9	3	33 %
1980	36	18	50 %
1981	85	38	44 %
1982	91	49	53 %
1983	69	44	63 %
1984	96	65	67 %
1985	367	289	78 %
1986	291	207	71 %
1987	329	207	62 %
1988	471	145	30 %
1989	317	53	16%
1990	374	55	14 %
1991	332	22	6 %
1992	201	11	5 %
1993	127	3	2 %
1994	143	3	2.1 %
1995	160	2	1.2 %
1996	428	1	0.2 %
1997	569	1	0.1 %
1998	489	1	0.2 %
1999	469	2	0.4 %

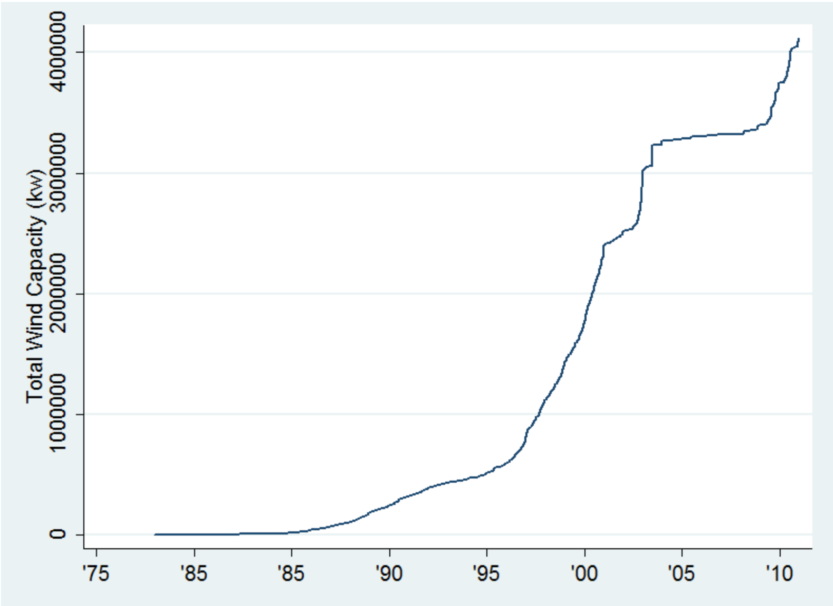

Figure 2. Strong governmental support through both research and development funding, tax breaks and generous subsidies has lead to strong growth of wind power investment.

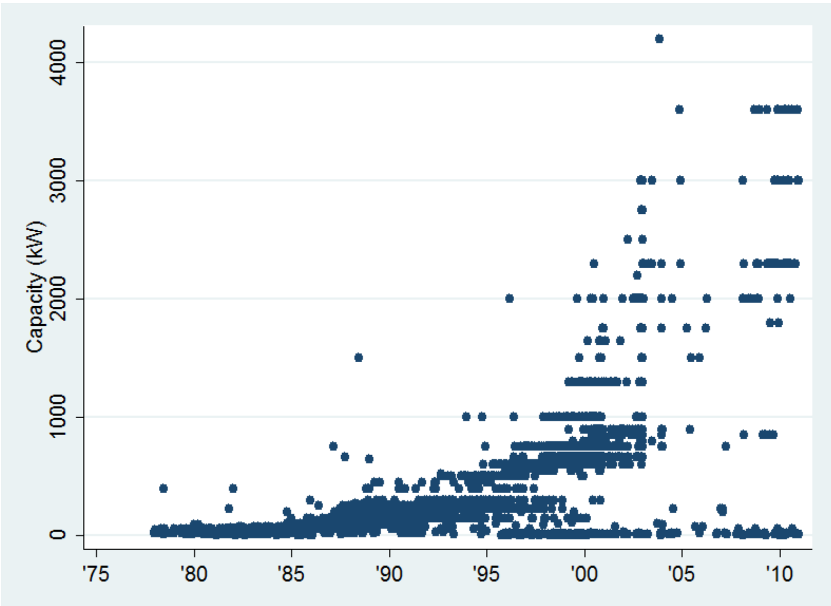

Figure 3. The increasing capacity of installed turbines reflects the rapid and substantial technological change that has occured in the industry

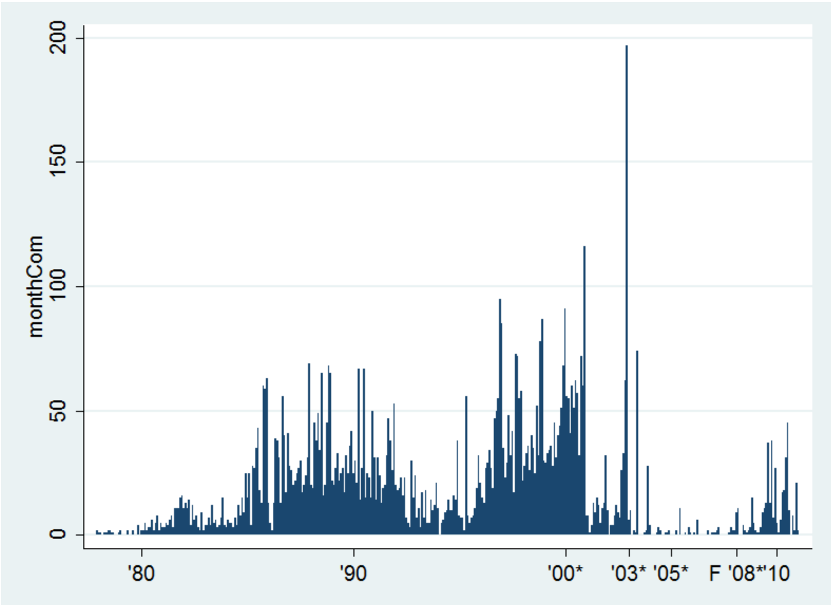

Figure 5. The chart shows the number of commissions of new wind turbines per month. Turbine owners rushed to install new turbines ahead of a shift to lower tariffs in January of 2000 and January 2003

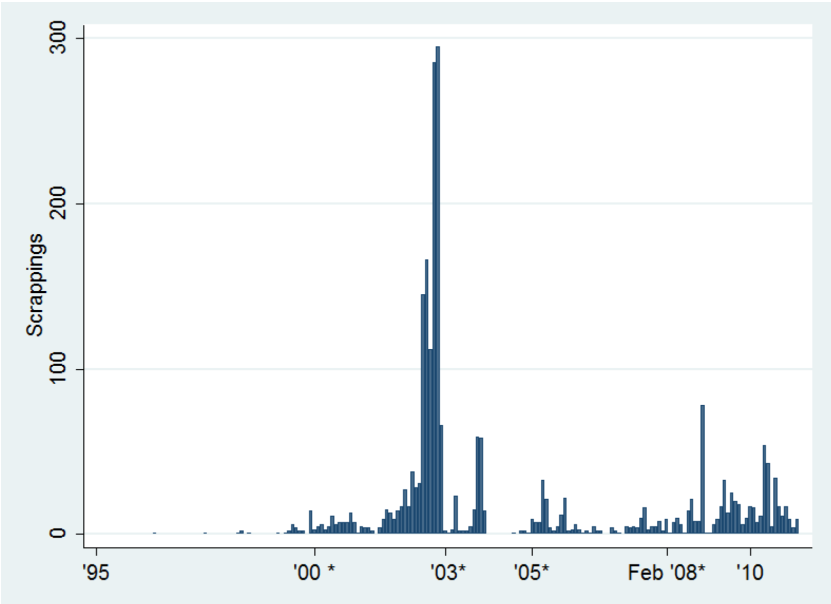

Figure 6. Scrappings of old wind turbines jumped ahead of the shift to lower tariffs in January 2000, and dramatically ahead of the shift in 2003. This demonstrates the strong role that opportunity cost has in the decision to scrap a wind turbine.

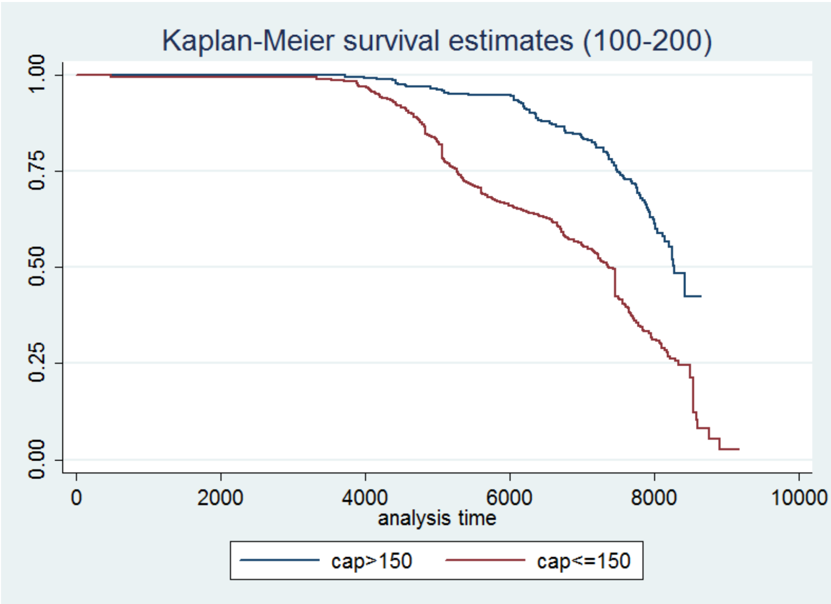

Figure 7. Kaplan-Meier estimates of the survival function for turbines between 100 and 200 kW in subgroups of over and under 150 kW. Turbines that are rated at or under 150kW - which are those affected by the policy - show a markedly steeper drop in the survivor function.

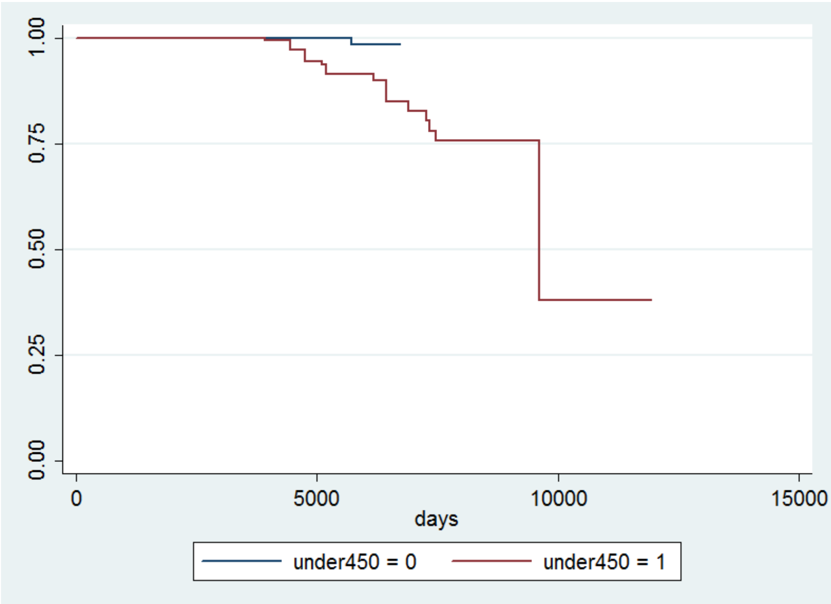

Figure 8. Kaplan-Meier estimates of the survival function for turbines between 400 and 500 kW i subgroups of over and under 450 kW. Turbines affected by the policy - those under 450 kW - display a drop in the survival function after about 10 years, while nearly all those over the cut-off continue to operate as of February 2011.

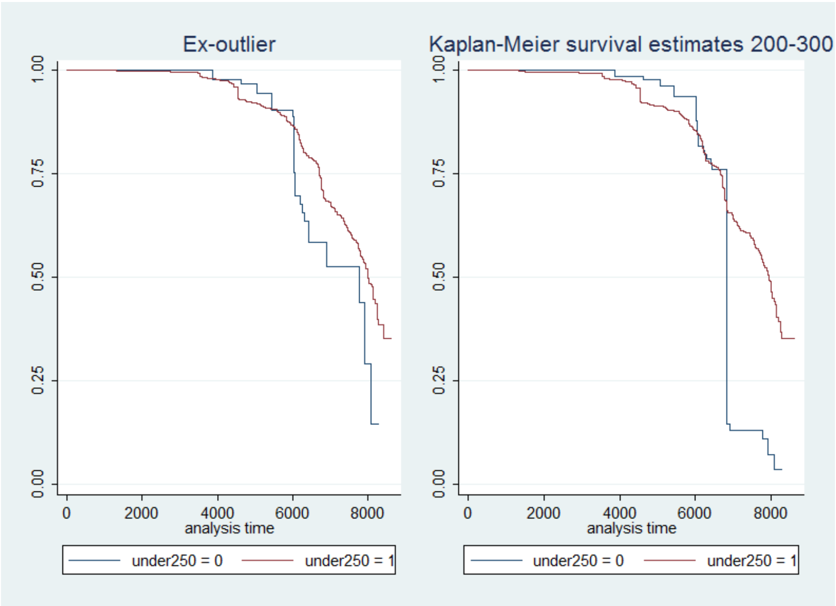

Figure 9. Kaplan-Meier estimates of the survival function for turbines between 200 and 300 kW in subgroups of over and under 250 kW. Turbines from both sub-groups come under the same policy, and after removing a group of outliers, the survival function estimates are not significantly different from one another.

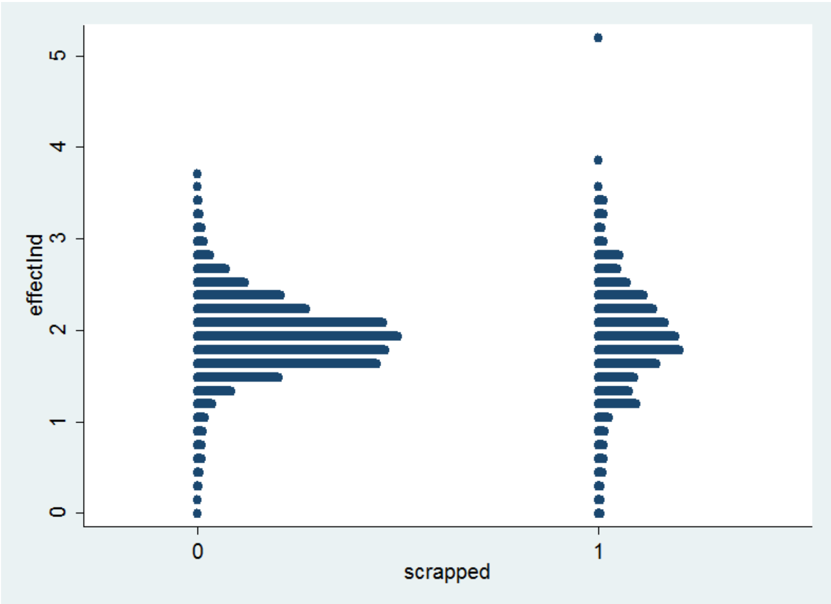

Figure 10. A dot plot of the efficiency indicator in subgroups of turbines that were scrapped and those that remain in operation as of February 2011. The indicator likely mainly reflects differences in average wind speed at the site of the turbine.

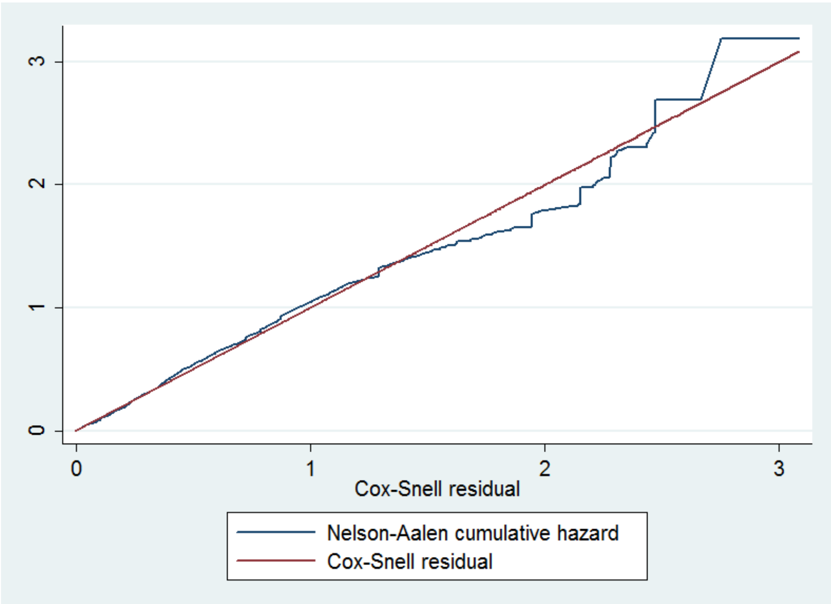

Figure 11. Nelson-Aalen estimate of the cumulative hazard of the Cox-Snell residuals plotted against the Cox-Snell residuals. A cumulative hazard that approximately follows a 45 degree line indicates a good fit to the data.