Windonomics: empirical essays on the economics of wind power in the Nordic electricity market

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All errors and omissions are my own.

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Contents

Chapter 1

Introduction: the Nordic electricity market and wind power in Denmark

The following chapters in this dissertation take up three topics surrounding the interaction of wind power investment in Denmark and the functioning of the deregulated Nordic electricity market. The first two chapters take up the issue of how wind power affects prices in the deregulated market. I find that electricity price variation in the spot market is lower in days with more wind power. In the following chapter I extend this analysis to see how wind power in Denmark affects prices in neighbouring hydro power dominated Norway. I find that wind power affects the magnitude of trade between the countries asymmetrically - dependent on the net direction of trade. I also find that wind power has a slight but statistically significant negative effect on prices in Norway, likely due to a slackening of hydro power producers supply constraints. The last chapter starts with the observation that most turbines are scrapped in order to make room for a newer turbine. An opportunity cost that comes from the interaction of scarce land resources, technological change and government policy is then a dominant reason for the scrapping of wind turbines. This leads to the implication that turbines located on windier, better situated land have a higher risk of being scrapped. Policy is also shown to have a strong and in some respects unexpected effect on scrappings.

Over the last two decades two major trends have taken place in power markets around the world. The first has been a movement towards market based power systems. Vertically integrated power companies have been split into component generation, transmission and retailing companies. Generation and retailing have been opened to competition. Increasingly, regulated prices and bilateral trade are being replaced by regulated markets that establish prices through auction mechanisms.

The second trend has been investment in renewable and intermittent energy sources - notably wind power. What started as experimental projects primarily in Denmark and Germany, wind power has grown to be a major and economical power generation source in nearly all areas of the world. According to the European Wind Energy Association, by the end of 2010, more than 86 gigawatts of wind energy capacity had been installed in Europe, the equivalent in rated capacity terms of more than 80 large nuclear power reactors. Worldwide, more than 190 gigawatts of capacity has been installed (Wilkes and Moccia, 2011). Wind power investment is expected to continue to grow robustly in the coming decades. For example, the

European commission has set a goal of wind power to make up 12 % of EU electricity by 2020 (European Union Parliament, 2009).

1.1 Wind power in Denmark and electricity generation in the Nordic countries

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 (Hau, 2006).

Wind capacity growth was especially strong from the late 90's through about 2003 as figure 1 shows. A reduction of wind power feed-in tariffs in 2003 led to a levelling off of investment. Investment picked up again in 2008 due an increase in wind

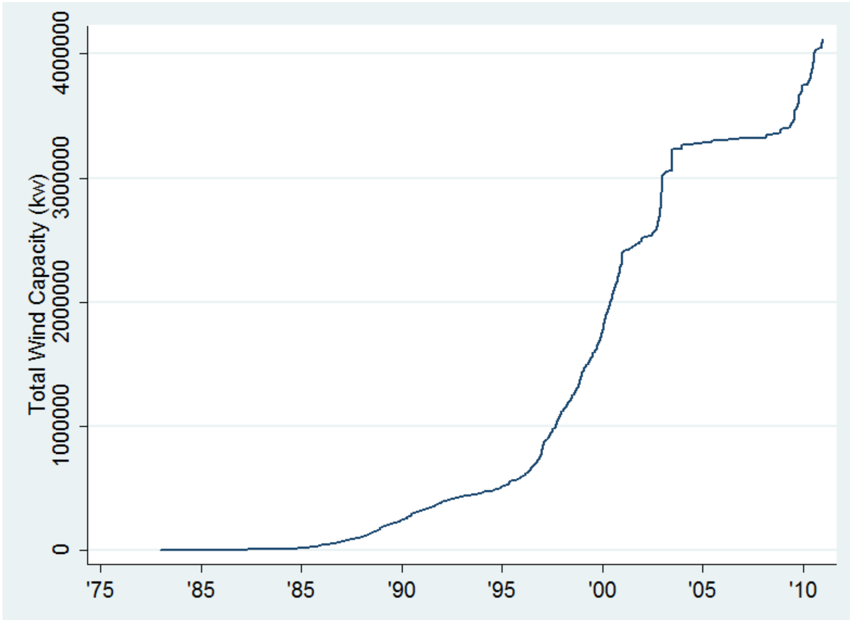

Figure 1. Shows the strong growth in Danish wind power capacity. By 2010, wind power provided approximately 20 % of the total electricity produced in Denmark

power subsidies and a new tendering system for offshore wind power (Söderholm and Pettersson, 2011). As of 2011, wind power makes up about 25% of rated generation capacity in Denmark, though its share of actual electricity produced is approximately 20% due to the intermittancy of wind. The remainder of capacity in Denmark comes nearly exclusively from thermal plants powered by coal, natural gas, and increasingly waste and biomass. Notably combined heat and power plants, which produce both electricity and district heating made up more than 60% of all thermal production in 2010 (Danish Energy Agency (ENS), 2010).

In contrast to Denmark, the other Nordic countries - Sweden, Finland and especially Norway- have large amounts of hydro power. Hydro power makes up approximately half of Swedish generating capacity with nuclear accounting for most of the remaining capacity. Finland is more diverse. About 30% of its capacity is hydro power and another 30% from nuclear while the remainder is made up of coal and natural gas. In Norway between 98% and 99% of capacity is made up of hydro power. Much of this hydro power capacity is in the form of power plants with water storage magazines. This form of hydro power is especially valuable. Power production can be controlled and adjusted quickly and nearly cost free. The downside is that supply is highly seasonal and subject to considerable weather risk.

1.2 The Nordic electricity market

The Nordic electricity market with its roots in the Norwegian electricity sector reform of 1990 is one of the oldest market based electricity systems (see Rud (2009) for a history and full description of the market reform). The Nordic market's exchanges - the day-ahead market, Elspot; the intraday market, Elbas; and the futures market - are by most accounts well developed, efficient, and liquid (see for example Amundsen and Bergman (2006)).

In the following chapters, unless otherwise noted, when referring to electricity prices I will be referring to the prices set on the day ahead "spot" market called Elspot. An independent company, Nord Pool, jointly owned by the Nordic transmission system operators, operates Elspot, which serves as the main physical exchange for power. Nord Pool also operates the intraday market, Elbas.

Elspot operates on a day-ahead basis where bids must be submitted by noon - thus bids for each hour of the day are submitted between 12 and 36 hours in advance. Producers and consumers, either large direct-consumers or electricity retailers, provide bids in the form of a supply and demand schedule for every hour of the following day. From these bids, Nord Pool establishes an aggregate supply and aggregate demand schedule from which an equilibrium system-price is established.

Though I have chosen to focus on the Elspot market due to its relatively long history and its high share of total traded volume, the Elbas market is widely expected to play an increasingly important role as wind power penetration increases throughout the Nordic market (Nord Pool Spot, 2011). When a market imbalance occurs after the close of the Elspot market, buyers and sellers can trade continuously in the Elbas market up to one hour before delivery.

Though transmission capacities in the Nordic region are relatively large, transmission congestion is common between areas and practically always present somewhere in the system. To alleviate congestion the Nordic market is split in to several price areas - two in Denmark (east and west), one for Sweden, [1] one for Finland, and several in Norway where the exact number of price areas has depended on the level of congestion. At a detailed level the mechanism for adjusting area prices to deal with congestion is relatively complex and beyond the scope of this description of the market. The basic idea is that the price will increase in the area receiving power and will be reduced in the area sending power until equilibrium is met with the available

[1] As of November 2011 Sweden will switch to having four price areas

transmission capacity. Thus, while a system price always exists, it is common that the different areas have different prices in practice.

1.3 Overview of chapters

The second chapter, titled *What happens when it's windy in Denmark? An empirical analysis of wind power on price variation* investigates the effect that wind power has on daily and weekly price variation. Here I use simple single equation dynamic distributed lag models. I find that increased wind power has the effect of *reducing* average daily price variation for both the Danish price areas as well as for the system price as a whole. This result can be explained by noting that electricity supply schedules tend to be steeper at high-load times. Periods of high wind power can be seen to shift the supply schedule and thus the negative price effect is greater at the steeper high-load end of the curve than at the base-load end. This effect only partially carries over to weekly time windows.

The third chapter titled *Dead battery? Wind power, the spot market, and hydro power interaction in the Nordic electricity market* looks at the interaction of wind power in Denmark with hydro power in Norway. It has been noted in the literature that hydro power with water storage magazines can serve as a complement to wind power, as it can quickly and cheaply adjust its output. I extend this literature by comparing the effects of wind power on spot market prices in Denmark and in Norway. My results confirm findings in previous studies that suggests that wind power will on average reduce local area prices in Denmark. My results also indicate that wind power in Denmark can be expected to have a small effect on prices in Norway by way of slackening the hydro power supply constraint and in turn reducing the option value of water in the reservoirs. Furthermore, I find that wind power has an asymmetric relation to marginal electricity trade between Denmark and Norway. The magnitude of the relation of wind power to marginal electricity trade is higher when there is net electricity exports to Norway. Finally I estimate that as much as 30 to 40 percent of Danish wind power is stored in Norwegian hydro power during periods of inflexible Danish production.

The final chapter of the dissertation titled *Scrapping a wind turbine: opportunity cost, wind resources and policy* begins by noting that most turbines in Denmark are scrapped to make room for newer and larger turbines. An opportunity cost that comes from the interaction of scarce land resources and technological change is then a major factor in the decision to scrap a wind turbine. This has implications for the pattern of wind turbine scrappings. Turbines located on land with good wind resources are likely to be at a higher risk of being scrapped and have a lower average lifetime. To test this I use a Cox regression model and a dataset of all 6754 land-based turbines constructed in Denmark between 1976 and February of 2011. I capture the wind resources of the turbines' placement indirectly through a measure of capacity utilisation. I confirm that turbines placed on land with better wind resources have a higher hazard of scrappage. I also find that policy intended to encourage the scrapping of poorly placed turbines actually has a stronger effect on well placed turbines.

Chapter 2

What happens when it's windy in Denmark? An empirical analysis of wind power on price variability in the Nordic electricity market

Abstract

High levels of wind power penetration will tend to affect prices in a deregulated electricity market. Much of the analysis in the literature has focused on the effect that wind power has on average electricity prices. This paper attempts to investigate the effect that wind power production has on the variability of wholesale electricity prices in the spot market. I use a simple distributed lag model and five years worth of hourly and daily data from Denmark, which is one of the few places with a long history of

significant wind power penetration. I show that increased wind power has the effect of reducing *intra-day variability but that this result only partially carries over to price variation over weekly time windows. I suggest that the reduction in price variability in turn is due to a steeper supply schedule at peak-load times.*

2.1 Introduction

Wind power is playing an increasingly important role in electricity systems around the world with countries from Great Britain to China planning on massive amounts of investment in the coming decades. The special nature of wind power - negligible marginal costs and an intermittent and variable energy profile - implies that the installation of large amounts of wind energy has the potential to affect the functioning of the electricity system as a whole.

The literature on the subject of wind power's effect on prices in deregulated power markets is growing. Most studies have used simulation models to analyse the effect on average price levels. Econ-Poyry (2008) uses its BID ("Better Investment Decisions") power market model to analyse how large scale wind development in Sweden would affect the operation of the market. Holttinen (2004) also uses a simulation model of the Nordic electricity market. Both find that the addition of wind capacity will tend to reduce average prices, though Holttinen notes that most of this effect simply comes from increased supply. Notably, the Econ Pöyry group finds ambiguous results when looking at price variability.

Several empirical studies also exist that look at the effect of wind power on electricity prices. Enevoldsen et al. (2002) (in danish) use a non-parametric approach - based on binning and averaging observations by hour, month and wind power generation. They also observe a lowering of the spot price at times of high wind power and note the effect is especially strong at peak times, though they do not discuss the implications of this and nor do they discuss potential causes for this effect.

In a white paper, Bach (2009) also looks at the connection between wind power and prices in Denmark. He states that wind power could have the effect of both lowering prices and *increasing* price variability. He uses correlation coefficients to conclude that the effect of wind power on prices is minimal. But both wind power and wind speed are highly volatile series, thus correlation between the two can be expected to be low. However, this does not necessarily mean that the effect of wind power on prices or price variability are economically insignificant or even "small", controlling for other factors.

Market-based electricity systems are characterized by high levels of random price volatility as well as regular foreseeable price variation. [1] Both are to a degree the result of a combination of varying load patterns and the unstoreability of electricity. The variation of prices in the market is an important factor for among other things generation investment, electricity futures and derivatives markets and electricity trade. Arguably then the effect that wind power has on price variation is

[1] The word choice here is deliberate. "volatility" tends to imply unforeseen changes in prices. Here, as mentioned, part of the variability is expected and forecastable. I thank Petter Bjerksund for pointing this out

equally important as the effect on average prices. This paper then aims to empirically identify the effects of wind power on price variability over time windows of both days and weeks.

I use a dataset of hourly and daily data from Energinet - the Danish transmission system operator (TSO) - and Nord Pool - the central exchange. I use a simple but robust and flexible empirical methodology - single equation distributed lag models with wind as an exogenous regressor. The intuition for the model is that I use the strong autocorrelations in electricity price series to control for other factors. Put simply, I use to my advantage the principle that one of the best ways to forecast the price of electricity tomorrow is to look at what the price is today and then use that correlation to control for seasonal and other factors that are not directly relevant to the analysis.

The data gives a nuanced view of the effects of wind power on variability. When looking at price variability over the course of a week the results are ambiguous. However when looking at the variability of prices per hour over the course of a day, which more reflects regular, foreseeable price variation, wind power tends to have the effect of *reducing* variability.

The mechanism for how wind power production reduces intraday variability is likely due to an out-sized effect of wind power on peak-load prices. In a competitive electricity market, the market price for any hour is set by the running cost of the marginal generation technology. When wind is added to the mix it can be seen as a shifting of the supply schedule to the right. Since the supply schedule is steeper at

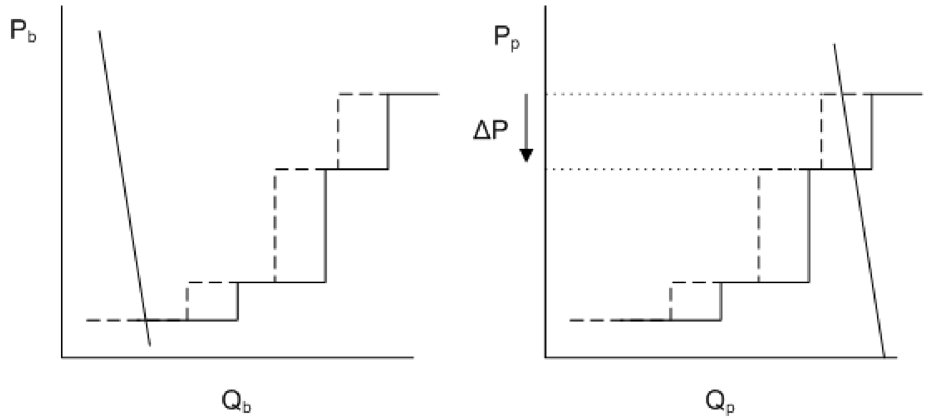

Figure 2.1 Wind power can be seen as a shifting of the supply curve to the right. Since the the supply curve is steeper at peak-load times, Q_p, than at base-load times, Q_b, the effect is to reduce intraday price variation

peak times [2] shifts in the supply curve lead to larger price decreases during the these periods. This idea is illustrated in figure 2.1, where a shift of the supply schedule to the right has little effect on the base-load price, P_b, while having a significant effect on the peak-load price, P_p.

Coughlin (2011) and Obersteiner and Saguan (2009) among others have noted that daily load patterns and wind power may be correlated. Windy days may for example be days with generally poor weather where people are more likely to remain indoors and use more electricity. The increased load would in turn affect power prices and price variability. Plausibly the results I obtain could then simply be a reflection of this correlation and not of any causal relationship between wind power and price variation. I attempt to control and test for this possible endogeneity problem, and conclude that it is unlikely to play a significant role.

[2] baseload plants that run nearly continuously have similarly modest to small marginal running costs. As you move up the supply schedule to plants that are used only occasionally the incremental marginal running costs increase substantially.

A recent paper by Green and Vasilakos (2010) also looks at the effects of wind power on price variability. They use wind speed data from Britain and a model of the British electricity market to predict how meeting 2020 wind power targets will affect price variability. They find that a high penetration of wind power will lead to substantially increased price variability. Their model also predicts that the effect of wind power on variability is dependent on the level of market power with increased market power leading to increased volatility. These results may at first seem to directly contradict my findings. But Green and Vasilakos approach is fundamentally different. They attempt to answer the question of what the total effect of installing large amounts of wind generation are. I am asking the much simpler and easier to test question of how price variation changes on windy days when large amounts of wind power already exist. I hope however that the answers to my question can give some insight to longer term and fundamental analysis.

2.2 Data and methodology

Data was assembled from several sources. Hourly price data from 2002 through 2007 as well as hourly turnover data was obtained from Nord Pool (Foyn, 2009). Hourly data on consumption in the two Danish price areas as well as hourly wind production in the Danish price areas was obtained from the website of the Danish TSO (energinet.dk). The period from 2002 to 2008 was chosen since the installed wind power capacity in Denmark in this period was both high, in terms of percentage of total capacity, as well as stable. [3]

One of the advantages with working with this hourly and daily data set is the size and generally good quality of the data. In the regressions where the unit of time is days I have approximately 2100 observations. Moreover, the electricity price data that underlies the dependent variable is not an estimate or measurement but the actual prices set by Nord Pool. Unless there are errors in reporting, no measurement error will exist in the dependent variable.

The large number of observations also makes the econometrics simpler as I can rely on the asymptotic properties of the estimators to obtain unbiased estimators and correct standard errors. In particular, Newey-West standard errors will converge to the correct standard errors in the presence of both heteroskedasticity and autocorrelation (Hamilton, 1994, p. 281).

I use a distributed lag model as in equation (2.1) where v_t is the measure of (log) variability with p autoregressive (AR) terms v_{t-i}, and q moving average (MA) terms, ϵ_{t-i}. a_i and β_i are then the coefficients to be estimated for respectively the AR and MA terms and σ is the coefficient on (log) wind power. X represents a vector of other included variables.

$$v_t = a_0 + \sum_{i=1}^{p} a_i v_{t-i} + \sigma w_t + \delta \mathbf{X} + \sum_{i=0}^{q} \beta_i \epsilon_{t-i} + \epsilon_t \tag{2.1}$$

As figure 2.2 shows for the Denmark-East price area, the wholesale electricity price varies substantially within a day.

[3] from 2002, the feed-in tariffs for wind power were lowered substantially, leading to steep drop-off in wind power investment. In 2008 investment picked-up again following an increase in feed-in tariffs

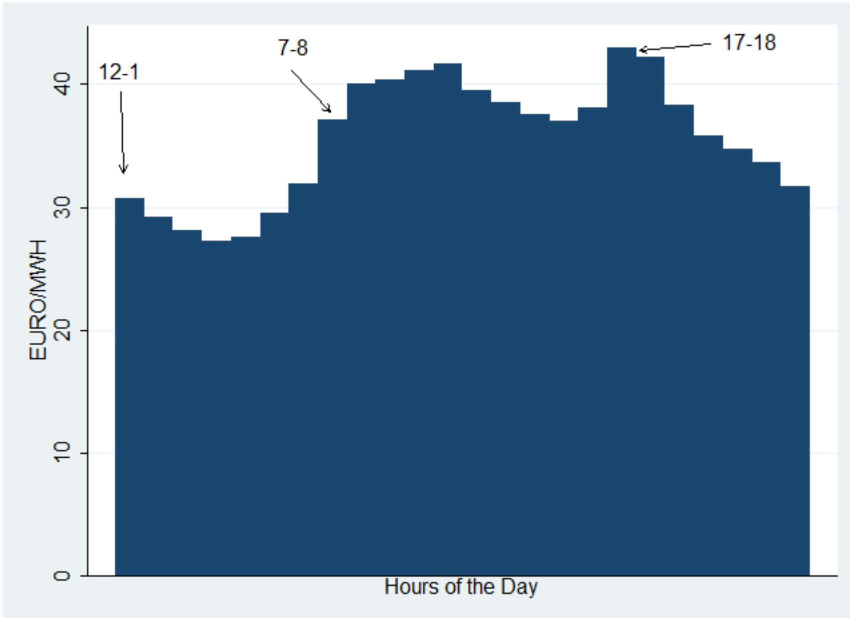

Figure 2.2 The chart shows the regular intra day pattern of electricity price variation in Denmark. Prices are low during nighttime hours and high during day-time hours, corresponding to times of low and high load.

This daily price variation tends to follow consumption patterns. At peak-times the price is set by high marginal-cost generation such as gas, while generation with lower marginal costs such as wind, hydro and coal are often sufficient in low-load times.

I measure price variability by way of simple standard deviations. Equation 2.2 shows the calculation of the intra-day (24 hour) standard deviation.

$$V_d = \sqrt{\frac{1}{24}\sum_{i=1}^{24}(P_i - \bar{P})^2} \tag{2.2}$$

Standard deviation is a simple, transparent and commonly used measure of variability. It is also flexible enough to be able to look at variability over several time-windows. In the time-series and finance literature, autoregressive conditional het-

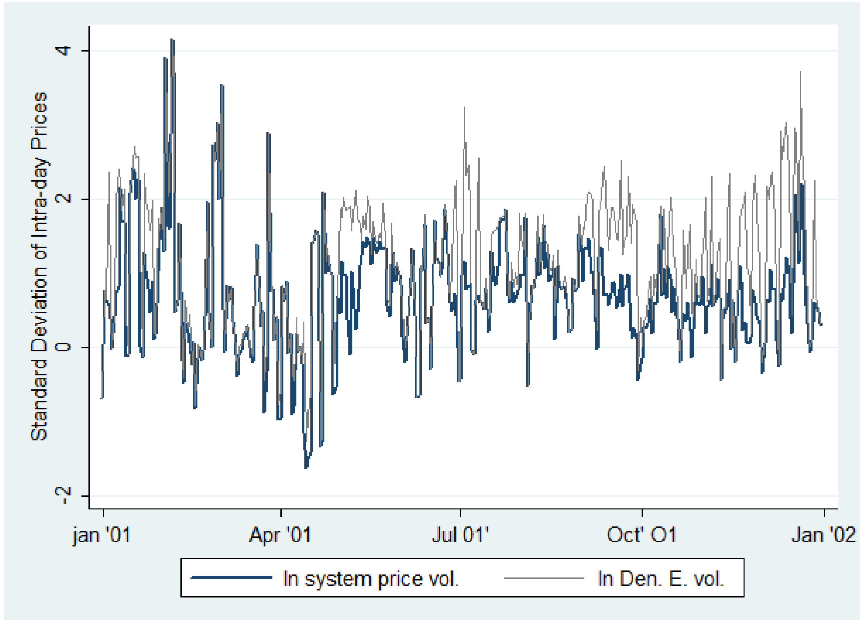

Figure 2.3 The time series of intraday standard-deviations tends to be "spiky" but appears to exhibit quick reversion to the mean and no obvious persistence. The series is shown to be stationary.

eroskedastic (ARCH) models are often used to characterize the volatility of a series. However, such models are not well suited for investigating *causal* effects on volatility or variability and thus are not used here.

The log daily standard deviation of price is plotted for the Nord Pool system price and the Denmark east area price over the year 2001 in figure 2.3.

The price series tends to be "spiky" but there appears to be a relatively quick reversion to the mean and no obvious persistence. The Denmark east area price appears to exhibit, on average, higher daily variability than the system price. This makes sense when considering that the Nordpool market as a whole has large amounts of hydro power that has a smoothing effect on prices. Denmark, on the other hand,

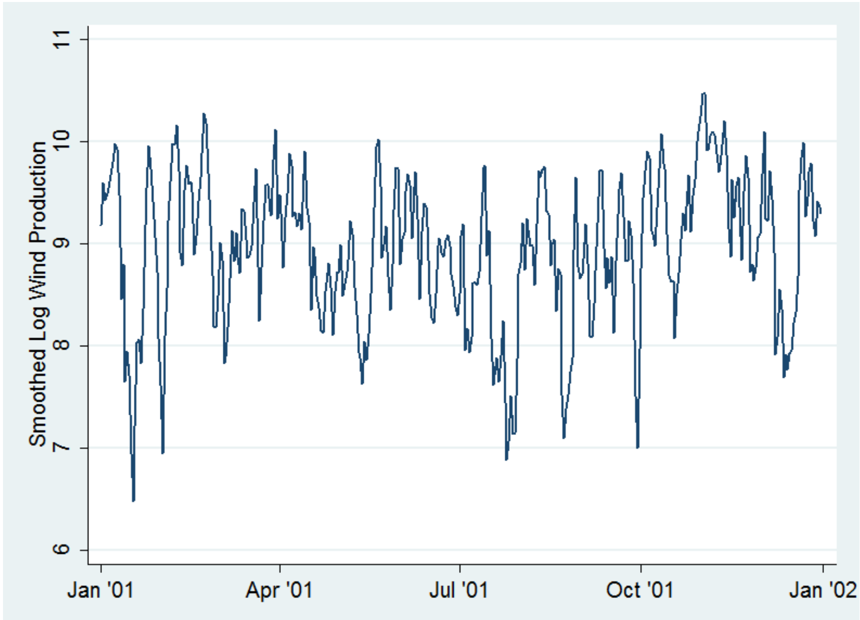

Figure 2.4 The time series of wind production from Denmark does not display persistence or trend. The series can be adequately modelled by an AR(1) representation. Note: the actual series used in the regression is not smoothed.

has none of its own hydro production. The price variation likely has some seasonal components, but these are controlled for in the regression.

To find a well fitting ARMA specification for the various price-variability series (intraday system price, local Denmark prices, intra-week, etc) I went through a process of using Wald tests, comparing Akaiki Information Criterion (AIC) as well as looking at autocorrelation (ACF) and partial autocorrelation functions (PACF) of the residuals.

The exogenous variable to be used in the models is the amount of wind power produced in Denmark east and Denmark west. Figure 2.4 shows one year of the exponentially smoothed log total wind power series.

The series does not seem to display any obvious persistence or trend. Moreover, the ACF and PACF suggest that an AR(1) representation may adequately describe the autocorrelation structure of the data. In the regressions for intraday variability I include both a contemporaneous wind power term as well as a lagged term to deal with this autocorrelation.

I also attempt to extend the analysis to variation over weekly time periods. I then run regressions where variability is calculated on a weekly basis as in equation (2.3), where the standard deviation is calculated both over all hours in the week and over averaged daily prices as in equation (2.4).

$$V_w = \sqrt{\frac{1}{168}\sum_{i=1}^{168}(P_i - \bar{P})^2} \tag{2.3}$$

$$V_w = \sqrt{\frac{1}{7}\sum_{d=1}^{7}(P_d - \bar{P})^2} \tag{2.4}$$

Clearly the number of observations is reduced by a factor of 7 for weekly variability and I am left with only 336 observations, which negatively affects the efficiency of the results. On the plus side the weekly seasonality that had to be modelled when using the daily variability measures now disappears.

In order for the regressions in the next section to be valid two key assumptions must be met. First, both the dependent series and the exogenous series need to be stationary. A visual inspection tends to suggest that all the price-variance series are stationary. I formally test the hypothesis with an augmented Dicky-Fuller test with five lags(Hamilton, 1994, p.528). The null hypothesis of at least one unit root is rejected at the 1% significance level. I run similar tests for the Denmark east and west area price data as well as the wind power series with respectively 6, 6 and 1 lags. All reject the null of at least one unit root at the 1% significance level. The series of weekly standard deviations are also shown to be stationary.

The other necessary assumption is that wind power is exogenous. One of the advantages with having wind production as the regressor of interest is that it is a passive form of generation. Wind energy is produced when there is wind. Since the marginal cost of production is near zero the producer has little incentive to hold back production due to price signals. In this sense the wind power series used is almost certainly exogenous to prices. However wind power could be correlated with load, which could be another source of endogeneity. To try to account for this I include measures of load in some of the regressions.

Two possible exceptions to the exogeneity of wind to prices should at least be mentioned. First, the system operator may order some wind off-line due to balancing concerns which might also be reflected in price. The second possible concern is the exercise of market power. A large producer with a range of generation technologies including substantial wind power may have an incentive to reduce wind power in order to benefit from higher overall prices. The former is likely a minor factor; Nordpool runs separate balancing markets and frequency regulation. Prices in the Denmark area do occasionally drop to zero, an effective price floor in the nordpool market, [4] but this is a relatively rare occurrence and is unlikely to affect the estimation. Despite a high market concentration of generation in Denmark, most studies of Danish and

[4] Nordpool introduced negative prices on the 1st of October 2009, after my sampling period

Nordic market power have failed to detect evidence of consistent market power (see for example Amundsen and Bergman (2006) and Hjalmarsson (2000)).

2.3 Results

The results from several sets of regressions are presented below. The first subsection analyses the effect of wind power on intraday price variability both for the Nordic system-wide price and for prices in the two local Danish price areas - east and west Denmark. These results constitute the main findings of the paper. However, I also wish to investigate if the results carry over to wider time-windows. Thus in the following sub-section I look at variation over week-long windows.

All of the below analysis is of variation of the prices that are set in the day-ahead ”spot” market by Nord Pool. Both Nordic-wide and national balancing markets as well as financial markets for electricity also exist, and wind power could very well have an effect on prices and price variation in these markets, but this is outside the scope of this paper.

One important distinction is that the prices in the day-ahead market are necessarily affected by *expected* wind-power production as forecast *a day ahead*, while the series that I have access to is actual wind power produced. A correct interpretation of the results I obtain then would be of the effect of spot-market prices by forecasted wind power as approximated by actual wind power produced. If you interpret the variable of interest as expected wind power then the use of actual wind power inserts a random measurement error component into the regression. Random measurement error can be shown to bias the estimated coefficient towards zero (Greene, 2002, p. 83).

2.3.1 Effects of wind on intraday variability

A system-wide price is established by Nord Pool for the entire Nordic market. If there are no capacity constraints in the system this will also be the price for the individual price areas. Though it is practically always the case that congestion in the transmission net leads to different prices in at least some of the price areas. The system price nonetheless represents an important benchmark price. Importantly, the results can indicate to what extent Danish wind power effects price variation not just in Denmark but for the entire Nordic market.

Table 2.1 below shows the results of the distributed lag model regression of intraday system price variation.

The regression is in the form of equation 2.1 where AR 1 and 2 terms are included as well as a weekly AR 7 term to deal with the weekly seasonality in the data. Adding MA 2, 7 and 14 terms increased the fit of the model and additionally controls for autocorrelation in the series. The estimated coefficients on the AR and MA terms are labelled by respectively a_i and β_i in the tables below. I do not report standard errors for these terms in the table since the coefficients do not have economic significance, but all the estimates where significant at the 5 % level. Also included in the regression are a constant term and wind power as well as 1-day lagged wind power, labelled $wind_t$ and $wind_{t-1}$. To control for the possible correlation between load and wind speed I present results in the first column of regressions where I include a term for

	Spot	spot w/o TO
$wind_t$	-0.028	-0.029
	(.010)	(.010)
$wind_{t-1}$	0.037	0.039
	(.010)	(.010)
to_t	0.490	n/a
	(.031)	
to_{t-1}	-0.170	n/a
	[.042]	
a_1	0.522	0.529
a_2	0.212	0.147
a_7	0.093	0.16
β_2	-0.133	-0.1
β_7	0.127	0.131
β_{14}	0.178	0.213
constant	-1.71	0.627

Coefficients significant at 5% level unless otherwise noted:
[a] *significant at 10% level,* [b] *not significantly different from zero*
Variability is measured as standard deviation over the 24 hours in a day
2174 observations
All variables are in log form
Standard errors are in parenthesis

Table 2.1 The coefficient on the contemporaneous wind power term shows that on average a doubling of wind power leads to a 2% reduction ($2^{-.03} \approx .98$) in the intraday variation of the system price.

consumption and its lag; approximated here by turnover in Nord Pool and labelled to_t and to_{t-1}. All variables are transformed into log form in order to give the coefficients an elasticity interpretation

The coefficient of interest is of course the contemporaneous wind power term and the regressions indicate an elasticity of about -.03, which is significantly different from 0 at a 1% level. This can be interpreted as saying that a doubling of wind speed will on average lead to a 2% reduction ($2^{-.03} \approx .98$) in intraday variability of the system prices. Though this elasticity estimate is relatively small, I would argue that it is economically significant considering it shows the effect of Danish wind power on the system price for the entire Nordic market.

Moreover the results are robust to specification. The choice of specification comes from a balancing of fit on one side and parsimony on the other, and several feasible ARMA specifications could have been used, but the estimated coefficient for the effect of wind power is not significantly affected by changes in this specification. This includes first differencing and seasonal differencing the series to further eliminate autocorrelation in the series and adding day-of-week fixed effects to try to further control for seasonality.

Notably the addition of the turnover and lagged turnover terms in the first column, while both statistically significant, do not materially affect the results. One would expect that if the results were simply driven by a correlation between load and wind speed then the inclusion of a proxy for load would alter the results. This does not appear to be the case.

The lagged term for wind power also has a significant estimated coefficient. This term was included to control for the autocorrelation in the wind power series and the significant coefficient reflects that wind power is autocorrelated across days. This coefficient should however *not* be given any economic significance. An interpretation that wind power in one day *causes* an increase in variation the next day would be incorrect. Rather it is simply a reflection that one windy day is likely to followed by another windy day.

The price series for the two Danish price areas (east and west) represent the actual wholesale prices paid by wholesale consumers and to generators. The area price series are in this sense more important than the system price. Table 2.2 presents the results from a distributed lag model regression again of the form of equation 2.1 but where the intra day price variation is that of the series of east and west Denmark prices.

I distinguish between wind power generated from the two price areas, labelled $dw - wind$ for wind power generated from western Denmark and $de - wind$ for wind power generated from eastern Denmark. Otherwise, the form of the regression is quite similar to the regression on the system price intraday variability. I again find that a specification with AR 1,2 and 7 terms as well as MA 2, 7 and 14 provided a good fit and dealt well with the autocorrelation and weekly seasonality in the price variation data.

I display regressions with and without consumption, again as a check on possible endogeneity of wind power and load. A constant term is also included. The same warning about giving an economic interpretation to the 1-day lagged wind power

	I DE Area	II DE Area wCons	III DE Area SD of Wind	IV DW Area	V DW Area w Cons	VI DW Area SD of Wind
$dw - wind_t$	-0.072	-0.073	n/a	-0.103	-0.119	n/a
	(.026)	(.026)		(.024)	(.026)	
$dw - wind_{t-1}$	-0.023^b	-0.026^b	n/a	0.032^b	0.065	n/a
	(.025)	(.026)		(.025)	(.026)	
$de - wind_t$	-0.011^b	-0.008^b	n/a	0.031^b	0.03^b	n/a
	(.023)	(.024)		(.022)	(.024)	
$de - wind_{t-1}$	0.040^a	0.042^a	n/a	0.016^b	0.005^b	n/a
	(.024)	(.023)		(.022)	(.023)	
$dw - wind - sd_t$	n/a	n/a	-0.061	n/a	n/a	-0.044^a
			(.026)			(.027)
$de - wind - sd_t$	n/a	n/a	0.015^b	n/a	n/a	0.011^b
			(.024)			(.025)
$loc - Cons_t$	0.417^a	n/a	3.783	2.299	n/a	2.203
	(.267)		(.253)	(.132)		(.167)
$locCons_{t-1}$	-0.021^b	n/a	-1.267	-1.017	n/a	-1.098
	(.12)		(.226)	(.127)		(.161)
constant	-1.917^b	2.077	-25.045	-10.76	1.950614	-10.261
	(2.24)	(.217)	(2.731)	(1.62)	(.198)	(1.928)
a_1	-0.095	-0.07	0.412	1.474	-0.0178	1.445
a_2	0.174	0.135	0.327	-0.377	0.112	-0.340
a_7	0.772	0.806	0.128	-0.097	0.82	-0.105
β_1	n/a	n/a	n/a	-0.981	0.3	-1.109
β_2	0.081	0.503	-0.226	0.047	-0.032	-0.004
β_7	-0.465	0.092	0.035	0.103	-0.599	0.112
β_{14}	-0.080	0.5	0.077	n/a	-0.0291	0.000

Coefficients significant at 5% level unless otherwise noted:
^{a} *significant at 10% level,* ^{b} *not significantly different from zero*
Variability is measured as standard deviation over the 24 hours in a day
2174 observations
All variables are in log form
Standard errors are in parenthesis

Table 2.2 The elasticity of price variation in western Denmark to an increase in wind power from western Denmark is shown to be -.10 and -.07 in the eastern Denmark price area. Wind power generated in eastern Denmark can not be shown to significantly affect intraday price variation.

terms remains relevant. The terms were included to deal with the autocorrelation in the wind power series and a causal interpretation would not be correct.

The first two columns represent the regressions on the Denmark east price variation series. The estimated elasticity for wind generated from western Denmark is about -.07, which can be interpreted as meaning a doubling of wind power in western Denmark on average leads to a 5% decrease ($2^{-.07} \approx .95$) in intraday price variation in eastern Denmark. However, no significant effect of wind power generated in eastern Denmark is found. The results in column one are from the regression that included local consumption and a lag, labeled $loc - Cons_t$ and $loc - Cons_{t-1}$. The inclusion of these variables did not have a significant effect on the estimated coefficients on wind power production.

In the western Denmark area, represented by the 4th and 5th column, an elasticity of between -.10 and -.12 is estimated for the effect of wind power on prices. This can be interpreted as a doubling of wind generation in its own area will reduce intraday price variation between 7% and 8%. Wind power generated in east Denmark can again not be shown to have a significant effect on price variation. The 4th column shows the results when local area consumption and a lag are included. Again, this did not significantly affect the results.

In total, the effect of wind power on price variability is magnified when looking at local area prices and the magnitude of the estimated coefficients indicate that wind power has an economically quite strong effect on the daily pattern of price variation.

The main reason for the insignificance of wind power generated in eastern Denmark is most likely due to the fact that western Denmark contains approximately three times as much installed wind power capacity as eastern Denmark. Other potential explanation such as differences in international connections between east and west Denmark or other area-specific differences are unlikely since wind power from western Denmark is shown to significantly reduce intraday variation in both areas.

The insignificance of wind power from eastern Denmark on prices also strengthens the argument against the hypothesis that the significant correlations observed on wind reflects merely a correlation between load and wind patterns. If this were the case then it would be likely that the coefficients for wind from both eastern and western Denmark would be significant, assuming that the correlation would hold for both price areas. In particular one would expect that the coefficient on wind power from eastern Denmark would be significant in the regression on eastern Denmark price variability, which it is not.

The results for the Danish price areas was also robust to specification with little change in the estimated coefficients on the wind power terms with changes in the ARMA specifications.

The main challenge wind power presents for electricity systems is of course its intermittency. Thus, it is also instructive to see how price variation responds not just to daily average levels of wind power, but also to variance in the wind power in a day. Thus the third and sixth columns show regressions for Denmark east and Denmark west respectively where I use the intraday standard deviation of wind power as the exogenous regressor. The results are not radically different. A negative and significantly different-from-zero coefficient is estimated for the variation in wind power from western Denmark in both price areas, while the estimated coefficient on wind power variation from eastern Denmark is not significant.

Of course, the standard deviation of wind power over a day and mean daily wind power are correlated - the correlation coefficient for western Denmark is .71. Days with a lot of wind also tend to have a lot of variation in wind over the day, and the results likely reflect this fact.

2.3.2 Weekly variability

So far I have looked exclusively at the effect of wind power on intraday variability. This form of variability is driven in large part, though far from exclusively, by regular variation in the daily load pattern. In this section I extend the analysis by looking at variation over weekly windows. I measure variation by taking the standard deviation over week-long intervals over both hours as well as averaged daily prices. By both extending the interval window to weeks and in some of the regressions taking the standard deviation over averaged daily prices, I investigate the effects of wind power on price variation beyond that caused by the daily load patterns. The regressions show that the results found when regressing daily price variation only partly carry over to measures of weekly variation.

Table 2.3 shows the results of the regressions of wind power on weekly price variation in the east and west Denmark price areas.

Again, all the series have been transformed into log form so that the coefficients can be interpreted as elasticities. I run regressions where I use both total wind power in both areas as well as regressions where wind power from east and west

	I	II	III	IV
	DE Area	DW Area	DE Area	DW Area
$wind_t$	-0.183	0.023^b	n/a	n/a
	(.053)	(.047)		
$dw - wind_t$	n/a	n/a	-0.139^b	0.110^b
			(.166)	(.165)
$de - wind_t$	n/a	n/a	-0.025^b	-0.077^b
			(.152)	(.159)
$loc - cons_t$	1.252	-0.049^b	0.044^b	0.226^a
	(.628)	(.569)	(.110)	(.161)
$constant$	-10.150^a	1.975	2.477	-0.724
	(6.650)	(6.293)	(1.241)	(1.554)
α_1	0.373	0.281	0.381	0.289
α_2	0.225	0.219	0.228	0.213
α_3	0.136	0.217	0.128	0.217

Coefficients significant at 1% level unless otherwise noted:
[a] significant at 5% level, [b] significant at 10% level
[c] not significantly different from zero
363 Observations
Measure of variability is weekly standard deviation over averaged daily prices
All variables are in log form

Table 2.3 An elasticity of .18 is estimated for the effect of total wind power on the weekly price variability in eastern Denmark. However wind power can not be shown to affect weekly price variability in western Denmark.

Denmark are included separately. I again include local average consumption (over the week) and a constant term. A simple AR(3) specification is sufficient for dealing with the autocorrelation in the price variation series, though the results are robust to alternative specifications.

The first two columns of the table show the results of price variability in, respectively, eastern and western Denmark where the exogenous regressor used is total wind power (from both east and west Denmark) over a week. The coefficient on total wind, labeled $wind_t$, has a point estimate of -.18 for the Denmark east area and -.022 for Denmark west area, though the latter is not significantly different from zero. The former is significant at the 5% level, though one should note the relatively large standard error.

It is not immediately clear why a significant effect is found in eastern Denmark and not in western Denmark. In the regressions on daily variance the largest effect was seen in the western Denmark area, where the vast majority of wind power is located. This is a point for further research.

The third and fourth columns show the results from regressions when including separate measures of wind power from Denmark east and west. The point estimates for the effect of wind from west Denmark on variation on east and west Denmark prices are -.17 and -.06 respectively. These estimates are close in magnitude to the results when using combined wind power, but neither of the estimates is significantly different from zero due to the large standard errors. The higher standard errors are likely being driven by two factors. First, the number of observations is reduced by a factor of seven when using weekly variation. Second, and contrasting with the results for combined wind power term, wind power from east and west Denmark is highly correlated at a weekly level with a correlation coefficient of about .9. This also has the effect of inflating the standard errors (Goldberger, 1991).

The variation is measured as the standard deviation over averaged daily prices. Table 2.4 in appendix 2.5 presents the results for the regressions where variation is measured as the standard deviation over all the *hourly* prices in a week. Somewhat surprisingly, these results were not substantially different from the regressions with variation measured over averaged daily prices.

Though the results for weekly variation are to an extent inconclusive, they do provide a robustness check for the results found for daily variation. A significant negative effect on weekly price variation in eastern Denmark is found, suggesting that the effect is not purely limited to intraday variation.

2.4 Discussion and conclusion

The main finding of this paper is that wind power has both a statistically and economically significant effect on the variability of prices in the Nordic electricity market. In particular, wind power has the effect of lowering intraday variability for both the entire Nordic system price as well as in the two Danish price areas. This effect can be shown to extend to weekly variation in the eastern Denmark price area.

I argue that this effect is likely a result of an industry supply curve that is steeper at peak times than at non-peak times. Wind power then would have the effect of leading to larger decreases in prices during peak times than during non-peak times. A contributing factor could also be added supply during peak times. In Denmark, wind speeds tend to be higher during the day, which is also when load tends to be high. Thus wind speed can be seen to add more supply during peak times than non-peak times. A subject for further research would be to explicitly test these explanations by, for example, analyzing the effect of wind on hourly prices - corresponding to peak and off-peak times. The methodology suggested by Andersson and Lillestøl (2010) using vector autoregressives on electricity market price data may be useful for such research.

One important implication of reduced variability is the effect on the distribution of rents to the different generation technologies. Peaking generation - often gas turbine plants - are often only used a few hours per day and depend on high prices at those times to be profitable. Wind power - by reducing intra day volatility in the spot market - may have the effect of reducing the incentive for the investment in this type of capacity when it is exactly such peaking capacity that is needed when large amounts of intermittent generation is added to a system. Regulators and transmission system operators may have to depend more heavily on side payments or other market mechanisms to ensure adequate peaking capacity.

2.5 Appendix

	DE Area	DW Area	DE Area	DW Area
$wind_t$	-0.186	-0.022	n/a	n/a
	[.050]	[.043]		
$dw - wind_t$	n/a	n/a	-0.172	0.056
			[.147]	[.136]
$de - wind_t$	n/a	n/a	-0.012	-0.075
			[.134]	[.133]
$loc - cons_t$	1.768	0.587	1.760	0.594
	[.596]	[.480]	[.658]	[.422]
constant	-15.544	-4.033	-15.536	-4.231
	[6.311]	[5.276]	[6.907]	[4.646]
α_1	0.480	0.336	0.481	0.334
α_2	0.202	0.231	0.201	0.235
α_3	0.106	0.221	0.106	0.219

Coefficients significant at 5% level unless otherwise noted:
^{a} *significant at 10% level*
^{c} *not significantly different from zero*
363 Observations
Measure of variability is standard deviation over hourly prices
All variables are in log form

Table 2.4 Using weekly variability over hourly prices does not significantly change the results as compared to table 2.3.

Chapter 3

Dead Battery? Wind Power, The Spot Market, and Hydro Power Interaction in the Nordic Electricity Market

Abstract

It is well established within both the economics and power system engineering literature that hydro power can act as a complement to large amounts of intermittent energy. In particular hydro power can act as a "battery" where large amounts of wind power are installed. This paper attempts to extend that literature by describing the effects of cross-border wind and hydro power interaction in a day-ahead "spot" market. I use simple econometric distributed lag models with data from Denmark *and Norway. I find that increased wind power in Denmark causes increased marginal exports to Norway and that this effect is larger during periods of net exports when it is difficult to displace local production. Increased wind power can also be shown to slightly reduce prices in southern Norway in the short run. I suggest that wind power mainly affects prices in Norway not by being the marginal price setter, but by way of slackening the supply constraints of hydro power producers.*

3.1 Introduction

Wind power has grown to be a significant source of electricity supply in Europe and increasingly in North America and Asia. Its share of electricity production is likely to grow robustly in the coming decades (International Energy Agency, 2009). However, installing large amounts of intermittent energy generation presents serious risk to supply security. One proposed mitigater of this risk is to link areas with large amounts of wind power to areas with hydro power plants with magazines which are able to quickly and cheaply adjust their production while storing energy in the form of water in their magazines. Norway with its large amounts of hydro power has been referred to as the "battery" (The Economist, 2006) of Europe, especially as several large off-shore wind power projects are being proposed off Great Britain, Ireland and other areas of northern Europe (see Forewind (2011) or NOWAI (2010)).

The Nordic electricity market presents a good testing ground for the battery effect. Due to the early and heavy investment by Denmark, the Nordic electricity market is one of the few places with a relatively long history with significant amounts of wind power. As of 2011, wind power makes up about 25% of rated generation capacity in Denmark, though its share of actual electricity produced is approximately 20% due to the intermittancy of wind. The remainder of capacity in Denmark comes nearly exclusively from thermal plants powered by coal, natural gas, and increasingly waste and biomass. Notably combined heat and power plants, which produce both electricity and district heating made up more than 60% of all thermal production in 2010 (Danish Energy Agency (ENS), 2010).

The Nordic system is also a well developed market-based system with decentralized producers making bids in the wholesale spot market. Prices are the main tool to resolve transmission constraints and balance the system across regions and countries. In addition, the transmission capacity between Denmark and Norway is large and well within the scale of what has been proposed between Norway and for example the planned wind farms in Dogger Bank in the North Sea.

Wind and hydro power's complementarity has been noted in several contexts in both the economics and power systems engineering literature. Much of the literature consists of simulation studies. Belanger and Gagnon (2002) explores the amount of added hydro power that would be needed to serve as an adequate backup to a proposed large wind power installation in Quebec. Benitez et al. (2008) uses an optimisation model with parameters estimated with data from Alberta, Canada. Studies of the Nordic market also exist. Førsund and Hjalmarsson (2010) analyse the effect that a build-out of wind power in the Nordic market would have on the price of providing regulation power - primarily hydro power. Matevosyan et al. (2007) study the potential for wind power and hydro power interaction in Sweden.

Designing a market to ensure the correct signals for development and operation of intermittent energy is also an emerging area of research. Newbery (2010) gives a short overview. But at a basic level, the spot market should give the correct price signals for an interaction between wind power and hydro power. Periods with strong winds are likely to press down prices, providing an incentive for hydro power producers to cut production and store the energy in the form of water in their magazine (or in the case of magazines with pump-storage capabilities, actually pump water up hill into the magazines). When wind power production is low, prices are likely to increase, providing an incentive for hydro power producers to then increase production.

But when considering the interaction of wind power and hydro power that is geographically separated, transmission constraints play a significant role. My starting point is Green and Vasilakos (2012), who lay out a model of wind power production and power trade with two areas: one dominated by hydro power while the other, representing Denmark, has both wind and thermal capacity. The model explicitly accounts for transmission constraints and leads to several testable implications:

- Wind power production should optimally lead to increased export to the hydro power area.
- Short term variations in wind power affect local prices and and these effects are magnified when there is transmission congestion.

In addition to laying out a theoretical model, the authors take a descriptive look at price and trade data between Denmark and its neighbors and carry out regressions of the short term effect on local prices of wind power production. The authors note a high short-run correlation between wind power and exports. At a daily level they note that Denmark exports at off-peak times and argue that this is evidence for the ”storage” of Danish electricity in the hydro power magazines of their neighbors. In their regressions they confirm that wind power is associated with a reduction in prices in the local price area and this price effect is magnified when there is transmission congestion.

My methods and results are largely complementary. However I diverge in several key respects. Instead of a static regression model, I use a simple dynamic distributed lag model where wind power is used as an exogenous regressor. With this model I use the strong autocorrelation in the data to control for factors that are not of direct interest. Put simply I use to my advantage the principle that a good forecast of the electricity price tomorrow is the electricity price today. By explicitly accounting for autocorrelation, using daily-average prices and given the exogenous nature of wind power, I claim that my coefficients can be given a causal interpretation.

I also narrow my focus to the interaction between Denmark and Norway, rather than looking at the effects of trade to all of Denmarks neighbors. I focus on Norway at the exclusion of the rest of the Nordic market and other European connections because nearly all of Norwegian energy production comes from hydro production, most of which in turn comes from plants that have storage magazines.

Where Green and Vasilakos show that wind power's effect on local prices differs when there is transmission congestion, I take the approach of comparing days of net exports and imports from Denmark to Norway. The rationale is that days of net exports are more likely to be times of supple energy supply in Denmark and that extra wind power will not easily replace domestic supply. Extra wind power is not likely to curtail production from combined heat and power plants during cold winter days for example. It is during these times that the battery effect can be expected to be strongest. Marginal wind power production is more likely to lead to increased exports to be stored in Norwegian reservoirs.

I find that in periods of net exports a marginal increase of 1 megawatt-hour per hour (MWh/h) of wind power leads to .3 MWh/h higher exports to Norway. However, in days with net imports to Denmark from Norway, the marginal effect of an extra 1 MWh/h of wind power production is only to reduce net imports by about .15 MWh/h.

I also estimate the elasticity of both local Danish prices and Norwegian prices to wind power production. I estimate that a doubling of wind power production on average leads to a 5.5% decrease of prices in western Denmark and a 2% decrease in eastern Denmark. Surprisingly this effect can not be shown to differ significantly between days when there are net exports and net imports. The short term effect that wind power has on Norwegian prices is significantly smaller but is shown to differ depending on the net direction of trade. A doubling of wind power will tend to reduce prices by .5% in southern Norway on days with net exports from Denmark but only by .3% on days with net imports to Denmark.

Finally, I estimate that a 1 MWh/h increase in Danish wind power is associated with a decrease of approximately .40 MWh/h of hydro power production in the southern Norwegian price area. When discerning between periods of net exports to Norway and net imports to Denmark the respective estimates are -.46 and -

.16 MWh/h. That the effect of wind power on southern Norwegian production is estimated to be higher than the effect on marginal exports to Norway may suggest a bias in these results. One plausible explanation is that Danish wind power is correlated with wind power in other parts of northern Europe that have physical connections to Norway.

3.2 Data and Methodology

Data was assembled from several sources. Hourly price data as well as data on Norwegian hydro power production was obtained from Nordpool (Foyn, 2009). Data on daily wind energy production from both eastern and western Denmark was obtained from the website of the Danish transmission system operator, Energinet (energinet.dk).

The data can be assumed to be of high quality and with up to eight years of daily data, the econometrics becomes easier as I can rely on asymptotics to obtain consistent and unbiased coefficient estimators and standard deviations. In particular, Newey-West standard errors will converge asymptotically to the correct standard errors in the presence of heteroskedasticity and autocorrelation (Newey and West, 1987).

Figure 3.1 shows the time series of trade between Denmark and Norway.

The figure clearly shows the large seasonal and yearly variation in this series. The measure also gives a clear visualization of the transmission capacity constraints between the two countries - seen as the sharp ceilings and floors in the figure.

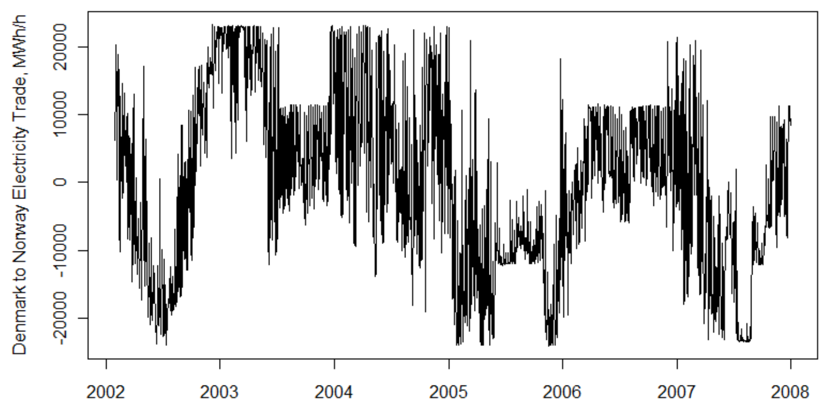

Figure 3.1 The pattern of trade between Norway varies both seasonally and yearly. Transmission constraints are visible as plateaus in both directions. Positive values represent net exports to Norway.

The general form of the distributed lag models I use throughout are as equation (3.1).

$$d_t = \sigma wind_t + \delta \mathbf{X_t} + \alpha_1 d_{t-1} + \alpha_2 d_{t-2} + \beta_1 \epsilon_{t-1} + \beta_2 \epsilon_{t-2} + \epsilon_t \tag{3.1}$$

Here d_t represents the dependent variable being modelled - trade, prices or Norwegian production - and $wind_t$ represents the daily amount of wind power produced in Denmark. $\mathbf{X_t}$ is a vector of other variables, described below. These are often not necessary in such models since the autoregressive and moving average terms serve to control for much of the variation. Still they may be useful if there is uncertainty about interpretation. In the above model I arbitrarily include autoregressive (ar) 1 and 2 terms (d_{t-1}..) and moving average (ma) 1 and 2 terms (ϵ_{t-1}...) solely for the purpose of illustration.

The actual specifications I use in the regressions are arrived at by a process of using Wald tests, charts of autocorrelation and partial autocorrelation function as well as comparison of Akaike information criteria (AIC). Notably, I often include ar 6 and ar 7 terms which are often significant and represent weekly seasonality in the data. In practice several different specification could be seen as giving a reasonable fit to such models. Therefore all of the results below have been tested to be robust to changes in specification.

Vector Autoregressive (VAR) models are increasingly being used in the context of power markets (see for example Fell (2010)), especially when analysing the interaction of several potentially endogenous series. However these models can often become complex and the results can be difficult to interpret (see for example Bernanke (1986)). I stick to the simpler single equation distributed lag models. Such single equation models may give biased results if wind power is not truly exogenous to the price and trade variables. I will discuss areas of possible endogeneity, but in the end argue that for measuring short run effects the estimated coefficients can be interpreted as causal.

Wind power will be exogenous in the sense that production is likely not sensitive to price. Wind power is produced when it is windy and a negligible marginal cost of production means that producers have little incentive to reduce production even at times of very low price.

Two possible exceptions to the exogeneity of wind to prices should at least be mentioned. First, the system operator may order some wind off-line due to balancing concerns which might also be reflected in price. This is likely a minor factor.

Nord Pool runs separate balancing markets and frequency regulation. Prices in the Denmark area do occasionally drop to zero, an effective price floor in the Nord Pool market [1] but this is a relatively rare occurrence and is unlikely to affect the estimation.

The second possible concern is the exercise of market power. A large producer with a range of generation technologies including substantial wind power may have an incentive to reduce wind power in order to benefit from higher overall prices. Despite a high market concentration of generation in Denmark, most studies of the Danish and Nordic market have failed to detect evidence of market power (see for example Amundsen and Bergman (2006) and Hjalmarsson (2000)).

Another consideration is the possibility that wind power is correlated with variations in the consumption of electricity. The estimated coefficient on wind power may then be biased. I try to control for such effects. Seasonal effects - a tendency for there to be more wind power during the summer for example - is controlled for implicitly through the distributed lag terms in the model. With the inclusion of such dynamic terms the coefficient on wind power is only being estimated based on variations between days.

At a shorter time scale, averaged electricity prices and wind power tend to have a regular pattern of variation over a day. This could also lead to bias if using hourly data. I however use average daily data, so this will not be an issue. Still, consumption can change from day to day in ways which may still correlate with wind power. For example days with high amounts of wind could be correlated with generally poor

[1] Nord Pool introduced negative prices on the 30th of November 2011, after my sampling period

weather, leading people to stay inside and use more electricity. I therefore include measures of consumption in the regressions, but they do not significantly affect the the estimated coefficient on wind power.

When regressing prices I log-transform the variables. This is primarily in order to give the coefficients a clear interpretation in terms of an elasticity. However, doing a log-transformation also implicitly assumes a constant-elasticity relationship between wind power and prices. This is unlikely to be fully true in reality. However it is likely a better approximation than assuming a linear relationship, which is implicitly what one does when not transforming in logarithms. Work by Weigt and Hirschhausen (2008) and Twomey and Neuhoff (2010) suggest that wind power has a greater-in-magnitude effect on prices at high load times. Thus the estimation of a logarithmic average is likely to be a better approximation than a simple linear approximation.

3.3 Results

3.3.1 Effect of Wind Power on Trade

In this subsection I use distributed lag models with wind power as the exogenous regressor to explore the relationship between wind power and electricity trade between Denmark and Norway. The model is of the form of equation (3.2).

$$I_t = \gamma wind_t + \delta \mathbf{X_t} + \alpha \mathbf{I_{t-i}} + \beta \epsilon_{\mathbf{t-i}} + \epsilon_t \tag{3.2}$$

I_t represents net electricity trade between Norway and Denmark for every day t, in megawatt-hours per hour (MWh/h). A positive value means a net export to Norway and a negative value means a net import to Denmark. $wind_t$ represents the amount of wind power produced in MWh/h that day from Danish wind turbines. $\mathbf{X_t}$ represents a vector of other exogenous regressors that are included in the regression. $\mathbf{I_{t-i}}$ represents the vector of autoregressive terms while $\boldsymbol{\epsilon}_{\mathbf{t-i}}$ represents the vector of moving average terms. ϵ_t represents the contemporaneous error term.

The results for the regression are displayed in table 3.1.

Looking at the first column, the coefficient on the wind power term, labelled *wind*, is about .27 and is estimated with a relatively small standard error of .009. Since both the wind power term and the power trade term are in MWh/h units, one can interpret this to mean that for every MWh/h of wind power produced, .27 MWh/h more electricity is exported to Norway. This result is in line with both the predictions from Green and Vasilakos' model and their own empirical work. Periods with high amounts of wind power lead to increased marginal trade to the hydro power area.

In the second column I add terms for Norwegian consumption, labeled *consum*, and temperature in Norway, *norTemp*. Smaller AIC scores indicate that the addition of these terms improves the fit of the regressions but they do not substantially change the estimated coefficient on wind. This should ameliorate any concerns that the coefficient on the wind power term is capturing effects on trade from the demand side that may be correlated with wind speed.

The discussion around the battery effect suggests that the net direction of trade should be important. In the third column I estimate the effect of wind power on

	I	II	III
wind	0.269	0.276	n/a
	(0.009)	(0.010)	
win-ex	n/a	n/a	0.322
			(0.010)
wind-im	n/a	n/a	.111
			(0.012)
consum	n/a	-1.869	n/a
		(0.515)	
norTemp	n/a	-0.302	n/a
		(0.061)	
constant	-5.463	2.824	-4.832
	(2.432)	(3.121)	(2.189)
ar			
1	0.312	0.372	0.346
2	-0.193	-0.298	-0.243
3	0.192	0.281	0.237
6	0.160	0.179	0.164
7	0.469	0.410	0.435
ma			
1	0.280	0.208	0.238
2	0.320	0.425	0.363
3	-0.009	-0.066	-0.055
AIC	17715.3	17656.6	17363.1

Standard errors in parenthesis
2867 Observations

Table 3.1. Effect of wind power on trade. A one megawatt-hour per hour (mWh/h) increase in wind power is shown to increase net exports by about .30 mWh/h and to reduce net imports by about .1 mWh/h.

marginal trade during days of net import and net export from Denmark. I interact the wind power term with an indicator variable (values of 0 and 1) for net exports to Norway, *wind-ex*, and net imports to Denmark, *wind-im*. The results indicate that when there is a net export of electricity to Norway an extra 1 MWh/h of wind power leads to about .3 MWh/h of extra exports. On the other hand, when there are net imports to Denmark in a day, 1 MWh/h of wind power leads only to .1 MWh/h less of net imports.

This result is in line with the idea that Denmark will export when it is difficult for the wind power to supplant other local production. Periods of net import are likely peak periods where demand is partially met by gas turbines which can be easily turned off when extra wind power is produced. Periods of net export are more likely to be periods of base load production - primarily combined heat and power plants - which need to continue running in order to produce heat. Extra wind power production in these periods then leads to increased exports to the hydro power area.

3.3.2 The Spot Market

In the Nordic market both trade across borders and production are overwhelmingly scheduled by way of market mechanisms. The day ahead ”spot” market is the largest of such markets for the physical trade of electricity. Green and Vasilakos noted that wind power presses down spot prices in Denmark and more so at times of congestion in the transmission net. Just as important is the effect that wind power has on prices in the hydro power market. In this subsection I estimate the short-run elasticity of wind power on prices in both Denmark and Norway.

Of course actual wind power does not directly affect prices in the day-ahead market because it can not be scheduled. Instead it is forecasted wind power that producers bid on the market. The data that I have available is however realized wind power. A correct interpretation of the results I obtain then would be of the effect on spot market prices by forecasted wind power as approximated by actual wind power produced. If you interpret the variable of interest as expected wind power then the use of actual wind power inserts a measurement error component into the regression. Random measurement error can be shown to bias the estimated coefficient towards zero (Greene, 2002, p. 83). Rud (2009, Essay 5) has however pointed out that when a producer has access to both a real-time and day-ahead market they may have the incentive to underbid their expected level of production. This could lead to a systematic error term.

I do not see any good way to avoid this potential bias, but nor do I see it as being a major problem. The included variable of actual wind power produced is itself likely accurately measured and reported. Day-ahead forecasting of wind power production, while far from perfect, has improved substantially (Costa et al., 2008). Moreover, if a widespread and systematic underbidding occurred in the market it would likely be easily detectable and corrected by Nord Pool or the transmission system operator.

Consider first the effect that wind power can have on prices in its own (spot) price area. Two theoretically distinct effects can be identified. The first can be called a supply effect, illustrated in panel a of figure 3.2, where wind power can be seen to shift the entire aggregate supply curve to the right.

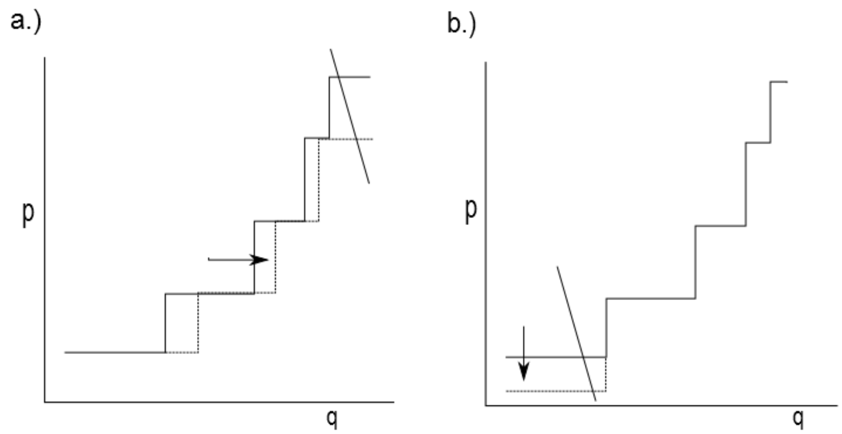

Figure 3.2. Panel a. shows the effect on prices of wind power shifting the supply curve. Panel b. shows the effect of wind power being able to underbid prices at the baseload level.

This effect implies reduced prices along the entire supply curve. But given that the high-load side of the supply curve tends to be steeper than the low-load, the price effect can be expected to be more pronounced at high-load times.

The alternative way that wind power can affect local prices is by way of its low marginal costs, illustrated in panel b of figure 3.4. Here, wind power can be seen as underbidding other forms of base-load generation. The general effect would be to lower base load prices. Of course, in reality, both mechanisms are likely at play simultaneously. Results from the previous chapter suggest that the supply effect dominates and that wind power both reduces average prices and daily price variation.

When there is congestion in the transmission net between areas, prices are reduced in the area with excess production and increased in the area with excess demand until the expected flow of electricity meets the physical transfer capacity. These transmission constraints, as well as the ability of Norwegian hydro power producers

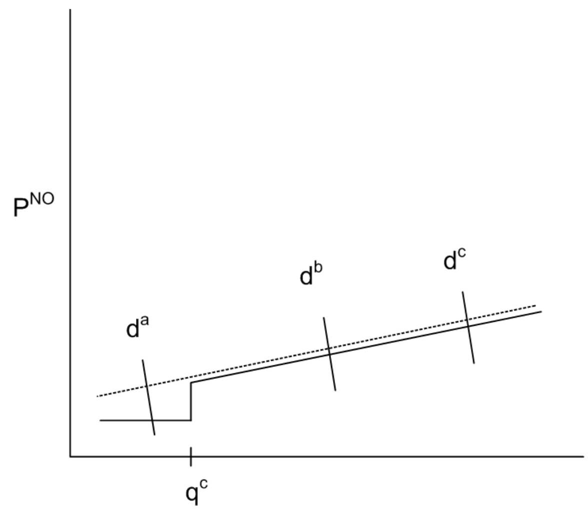

Figure 3.3 The short run effect on Norwegian prices of Danish wind power is likely to be slight due to capacity constraints and the dominance of hydro power in Norway

to store energy, makes the short-run effect on Norwegian prices to be significantly less pronounced than the effect on Danish prices.

I illustrate the idea in figure 3.3. The prices in my empirical model are average daily prices and they also represent an average over different demand levels within a day, represented in the chart by the curves d^a, d^b, and d^c. The curves are shown as being nearly vertical, reflecting the highly inelastic nature of demand for electricity in the short-run.

The dotted line represents the Norwegian supply curve without imports. It is depicted as being relatively flat, reflecting the elastic supply curve of a hydro power dominated system. In periods with heavy winds and net exports to Norway, the model shows wind power as the price setter as long as demand is below the transmission constraint, marked by q_c. If demand is higher than the transmission constraint, then it is hydro power that is the price setter. Of course, demand would have to be exceptionally low for the imported (wind) power to be the price setter. Therefore in practice it will (almost) never be wind power that is the price-setter in the Norwegian market.

Wind power can still have an effect on prices, even if it is not the price setter - but only through an indirect supply effect. The marginal cost of hydro power is first and foremost dependent on the shadow value of water in the reservoirs. Hydro producers, having produced less during high wind periods, will have more water in their magazines. Increased water in the magazines means a loosening of their production constraints, and in turn the lowering of the shadow value of the water. This in turn would lead to lower prices across their supply curve. The total average effect on prices will likely be slight however, as is depicted in the illustration.

The illustration is of course an extreme oversimplification. Optimal hydro power scheduling is in itself a complex multi-period problem. But the illustration gets across the basic idea that an extra inflow of electricity into Norway from excess wind power produced in Denmark can be expected to decrease prices by relaxing the hydro power producers supply constraints. As Green and Vasilakos point out, the transmission constraints will tend to magnify the price effect on local Danish prices. The flip side is that transmission constraints will minimize the effect on Norwegian prices.

Another testable implication is that there will be either no effect on daily price variation in Norway or a slightly positive effect. This is because the effect on prices will likely be uniform across the supply curve. A possible exception is at times when the price is set by (imported) wind power. In contrast, the effect on daily price variation in Denmark is to significantly *decrease* daily price variation as shown in the previous chapter.

To estimate the effects that wind power has on prices, I again use single equation distributed lag models where the dependent variables are prices in Denmark west, Denmark east, and southern Norway. The model is described in equation (3.3), below.

$$p_{t,a} = \gamma_x(wind_t * x_t) + \gamma_i(wind_t * i_t) + \zeta \mathbf{C_t} + \alpha \mathbf{P_{t-i}} + \epsilon_t \tag{3.3}$$

In this equation, all variables are again in logs. $p_{t,a}$ represents the average daily prices in area a. $wind_t$ is again wind power produced. The wind power term is interacted with the dummy variables x_t and i_t which represent whether there were net exports to Norway or net imports to Denmark in that day. $\mathbf{C_t}$ represents a vector of consumption variables for eastern and western Denmark and Norway. I include these to control for the possibility that wind power is correlated with daily changes in consumption, which in turn could bias the coefficient. $\mathbf{P_{t-i}}$ represents a vector of autoregressive terms. ϵ_t represents the error term.

In the spot market, the area prices are determined simultaneously. Thus I also run a regression where I estimate the models simultaneously and allow for the error terms of each equation to be correlated with each other - a so called Seemingly Unrelated Regression (SURE) model (see Greene (2002, p. 360)).

the results of the regression are displayed in table 3.2.

Wind is shown to affect prices in Norway during periods of both net exports and imports. But the magnitude of this effect is small compared to the effect on the Danish price areas. Interpreting the coefficients as elasticities, a doubling of

	I	II	III	IV	V	VI
		Sin. Eq.			SURE	
	dkw	dke	nor	dkw	dke	nor
ln-wind-ex	-0.081	-0.031	-0.008	-0.068	-0.030	-0.009
	(0.005)	(0.004)	(0.001)	(0.004)	(0.003)	(0.002)
ln-wind-im	-0.077	-0.028	-0.005	-0.066	-0.029	-0.009
	(0.006)	(0.004)	(0.002)	(0.004)	(0.003)	(0.002)
ln-DKWCons	0.850	0.614	0.023	1.088	0.735	0.278
	(0.147)	(0.179)	(0.011)	(0.080)	(0.059)	(0.034)
ln-DKECons	0.251	0.371	0.086	-0.594	-0.300	-0.165
	(0.213)	(0.122)	(0.077)	(0.111)	(0.082)	(0.050)
ln-NOCons	0.037	0.028	0.319	0.000	-0.019	0.010
	(0.021)	(0.018)	(0.111)	(0.016)	(0.013)	(0.008)
cons	-4.397	-3.780	0.334	-3.004	-2.925	-0.791
	(0.591)	(0.497)	(0.304)	(0.392)	(0.298)	(0.179)
ar						
1	0.312	0.571	0.940	0.330	0.487	0.851
2	0.165	0.036	-0.130	0.080	0.026	-0.112
3	0.089	0.120	0.106	0.105	0.103	0.122
6	0.082	0.069	0.015	0.066	0.082	0.039
7	0.181	0.117	0.071	0.153	0.149	0.069
14	0.125	0.062	-0.013	0.138	0.073	0.007

Standard errors in parenthesis
2841 Observations

Table 3.2 Effect of wind power on Danish and Norwegian prices. A doubling of wind power in Denmark is shown to decrease prices in southern Norway by on average .5% as compared to approximately 5% in western Denmark and 2% in eastern Denmark wind power will on average lead to a 5 % reduction of prices in western Denmark ($2^{-.08} \approx .95$), but only a .5 % reduction in Norway in periods with net exports to Norway and .3 % in periods with net imports to Denmark. A test for the equality of these two coefficients though fails to reject the null hypothesis of equal coefficients at the 5% level.

The results from running the SURE model are not radically different, however the point estimate of the effect of wind power on Norwegian prices is estimated to be the same in periods of net exports and net imports.

Electricity price series are known to not always be stationary (see Weron (2006)). In most of the specifications for the Dickey-Fuller tests however I am able to reject the null hypothesis of unit root(s). The exception is a test for the logged Norwegian price series with 13 lags. Here I can not reject the null at the 5 % level (MacKinnon approximate p-value is .08). Likewise a test for the Denmark east price series with 20 lags also fails to reject the null at a 5 % level.

As a robustness check to possible non-stationarity, I also run the regressions in first-difference format. I report the results of this regression in the appendix. It suffices to say that the estimated coefficients are nearly identical to the results of the line-by-line estimation in table 3.2.

Finally, I do a test of the implication on daily price variation as well by running a distributed lag model where the dependent variable is the standard deviation of the 24 hourly prices in the southern Norwegian price area. I report the result in table 3.3. The coefficient on log daily wind power can not be shown to be significantly different from zero, as was suggested.

ln-windProd	-0.003
	[0.010]
Intercept	0.324
	[0.109]
ar	
1	0.517
2	0.024
3	0.080
4	0.016
7	0.093
ma	
6	0.074
7	0.156
14	0.142

Standard errors in parenthesis
2641 Observations

Table 3.3. Effect of wind power on Norwegian price variation. Wind power generated in Denmark can not be shown to affect intraday price variation in Norway.

3.3.3 Production

The most direct implication of the idea of the battery effect is that changes in wind power production in Denmark should lead to changes in production in Norwegian hydro power. In particular, periods of high wind power production in Denmark should supplant hydro power production in southern Norway, in effect storing the energy in the form of extra water in Norwegian magazines. In this subsection I estimate that as much as 40 percent of Danish wind power produced is "stored" in Norwegian hydro power.

I again use a distributed lag model with the general form of equation (3.4) below.

$$\Delta NOProd_t = \gamma_1 \Delta wind_t + \gamma_2 \Delta wind_{t-1} + \sigma \mathbf{\Delta X_t} + \alpha \mathbf{\Delta NOProd_{t-i}} + \beta \epsilon_{\mathbf{t-i}} + \epsilon_t \quad (3.4)$$

Here $\Delta NOProd_t$ represents the first-difference of total production in the southern Norwegian price area per day. Since nearly 99 percent of production in Norway comes from hydro power, this can be considered a good proxy for total production of hydro power in southern Norway. $\Delta wind_t$ represents the first difference of the contemporaneous amount of wind power produced in a day and $\Delta wind_{t-1}$ is a lagged term. $\mathbf{X_t}$ represents a vector of other explanatory variables. $\mathbf{\Delta NOProd_{t-i}}$ represents a vector of autoregressive terms while $\epsilon_{\mathbf{t-i}}$ represents a vector of moving average terms. ϵ_t represents the contemporaneous error term. γ_i, σ, α, and β represents coefficients or vectors of coefficients to be estimated.

Norwegian production is highly seasonal. Household heating in Norway relies heavily on electricity and production along with demand rise substantially during the winter. This strong seasonality makes it unlikely that the series is stationary and this is confirmed by running a Dickey-Fuller test. The first-difference of the data can however be shown to be stationary. More so, first-differencing likely preserves much of the variation that I seek to capture. The wind power series is defined by high short run variability that tends to dominate any seasonal trends. The effect that wind power has on hydro power will also likely be short term and will be preserved by a first-differencing.

I show the results of the regression in table 3.4 below.

The coefficient of interest is γ_1 on the contemporaneous wind power term. In the table this is labeled $wind_t$. In the first column I show the results from the simplest

	I	II	III	IV
wind_t	-.39	-.48	-.38	n/a
	(0.05)	(0.03)	(0.021)	n/a
wind_{t-1}	0.11	.059	.01	.02
	(.05)	(.03)	(.02)	(.02)
wind-ex	n/a	n/a	n/a	-0.46
	n/a	n/a	n/a	(0.02)
wind-im	n/a	n/a	n/a	-0.16
	n/a	n/a	n/a	(0.03)
NOCons	n/a	n/a	1.08	.98
	n/a	n/a	(.03)	(.028)
NOTemp	n/a	n/a	467	177
	n/a	n/a	(180)	(175)
cons	-26	n/a	n/a	n/a
	(294)	n/a	n/a	n/a
ar				
1	.050	.41	.22	.70
2	n/a	.13	.17	-.14
7	0.469	-.33	.97	.98
ma				
1	n/a	-.49	-.44	-.93
2	n/a	.-.33	-.36	.07
7	n/a	-.87	-.80	-.81
AIC	n/a	46364	46256	46258

Standard errors in parenthesis
2158 Observations

Table 3.4. Effect of wind power on Norwegian production. A marginal MWh/h of wind power production in Denmark is associated with approximately .4 MWh/h of reduced power production in Norwegian hydro power production. This suggests a strong battery effect between the two countries.

of distributed lag models. I include a single autoregressive term as well as the wind power term and a lagged wind power term. The coefficient on the wind power term is estimated to be -.39. Since both southern Norwegian production and Danish wind production are in MWh/h units, this coefficient can be interpreted to mean that for ever MWh of wind power produced, production is reduced by .39 in Norwegian hydro power plants. With production held back, extra water is preserved in the reservoir, in effect storing the energy.

The coefficient on the lagged wind power term should not be given any economic significance. It is included in the model to account for the fact that wind power tends to be autocorrelated and the positive and significant coefficient simply reflects this relationship and not any causal relationship between lagged wind power and production.

The simple AR(1) structure of the model is not adequate for modelling the dynamics of the series and the residuals from the regression are highly correlated. I therefore use Newey-West standard errors that are robust to autocorrelation.

In the second column I show the results of a regression where I try to more completely account for the dynamics of the first-differenced Norwegian production series. I find that including AR 1, 2 and 7 terms as well as MA 1,2 and 7 provides a relatively good fit as measured by a low AIC. Here the coefficient on the wind power term is estimated to be about -.47.

In the third column I add variables for Norwegian consumption and Norwegian temperature. The rationale is again that the coefficient on wind power may be capturing some weather variable that affects both wind power and consumption and demand in Norway. The coefficient on wind power is reduced slightly to approximately -.39. But in general, all the estimates from the first three specifications are similar in magnitude.

In the fourth column I differentiate between times of net export to Norway and periods with net imports to Denmark. As might be expected, the magnitude of the effect of Danish wind production on Norwegian production is considerably higher at periods of net export to Norway. In periods of net export, the coefficient is estimated to be -.46 where it is only -.16 in periods of import to Denmark. This mirrors the results from the regressions on the effect of wind power on marginal export to Norway. At times of plentiful base load production in Denmark, wind power can not easily supplant local production and more power is exported. In turn flexible Norwegian production is reduced and energy is stored in the form of water in hydro power magazines.

The estimated coefficient of approximately .40 for the effect of Danish wind power on Norwegian hydro power production should however be seen as an upper bound. If wind power in Denmark is correlated with, for example, wind power in Sweden, then the estimated effect of Danish wind power will be biased upward. The fact that the effect of wind power on marginal exports to Norway was estimated to be approximately .30 gives some evidence for the existence of such a bias.

3.4 Discussion and Conclusion

Wind power in Denmark clearly and significantly affects the pattern of trade between Denmark and Norway in the short run, with increased wind power having the effect of significantly increasing marginal exports and in turn reducing production in Norwegian hydro power plants. The magnitude of that effect is dependent on the net direction of trade. Green and Vasilakos note that exports are most strongly correlated to the operation of thermal plants in Denmark, in particular combined heat and power plants. The results from this study suggests that there is a strong interaction effect. At times of plentiful base load production, like during winter days when combined heat and power plants run primarily to provide heat, extra wind power leads to increased net exports to Norway and a reduction of production in Norwegian hydro power plants. At these times, the estimates suggest that an extra MWh/h of wind power can lead to .30 MWh/h of increased exports and as much as a .40 MWh/h of reduced production in Norwegian hydro power production.

The mechanism by which this trade happens is through prices set in the Nordic electricity market. I estimate elasticities for the effect of wind power on the two Danish price areas, but I also investigate whether wind power can have an effect on southern Norwegian prices. My empirical models suggests that wind power does slightly affect prices in southern Norway in the short run. But unlike in the local Danish market wind power can not be shown to affect the daily distribution of prices. This slight price effect likely comes from a slackening of the hydro power producers supply constraint.

Though the interaction of wind power in Denmark and hydro power in Norway appears to be strong, congestion in the transmission net between the countries is nonetheless a common occurrence and limits the interaction. Installing more transmission capacity would have the effect of decreasing the effect of wind power on prices in Denmark and increasing the effect on prices in Norway. In turn, the Norwegian hydro power producers would have an increased incentive to alter their production.

It has been argued that Denmark's large penetration of wind power is only possible due to its close proximity and large transmission connections to its hydro power heavy neighbors. to a certain extent, this study supports that point. When wind power can not supplant local production, power can be exported and stored in the hydro power magazines of its neighbors. More so, the Nordic electricity market appears to provide the correct price signals for this interaction to occur. The ability to store excess wind power would clearly be an advantage for the planned wind power projects off the coast of Britain and northern Germany. Whether the benefit outweighs the cost of investing in the necessary expensive transmission infrastructure to connect these areas is of course a question that requires a careful cost-benefit analysis.

3.5 Appendix: Affect of wind power on prices, first-difference

	dwt	det	nor
ln-wind-ex	-0.080	-0.030	-0.008
	(0.005)	(0.004)	(0.001)
ln-wind-im	-0.077	-0.027	-0.005
	(0.006)	(0.004)	(0.001)
ln-DKWCons	0.813	0.453	0.022
	(0.136)	(0.176)	(0.010)
ln-DKECons	0.293	0.449	0.082
	(0.208)	(0.120)	(0.076)
ln-NOCons	0.042	0.025	0.327
	(0.021)	(0.018)	(0.109)
cons	0.000	0.000	0.000
	(0.002)	(0.002)	(0.001)
ar			
1	-0.584	-0.360	-0.026
2	-0.354	-0.285	-0.154
3	-0.207	-0.160	-0.020
6	-0.043	-0.013	-0.042
7	0.052	0.119	0.049
14	0.065	0.057	0.112

Standard errors in parenthesis
2625 observations

Table 4. The price series are likely stationary, but as a robustness check I first-difference the variables and run regressions. The estimated coefficients are not significantly affected.

Chapter 4

Scrapping a wind turbine: opportunity cost, wind resources and policy

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 and technological change. This has implications for the timing of turbine scrappings and the effects of 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.

4.1 Introduction

The scrapping and replacing of productive goods is a fundamental issue in economics and management science. The scrapping decision for wind turbines is distinct from many other productive goods due to several reasons:

- Near 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.

In a study on Danish wind turbines by Jensen et al. (2002) it was found that of those turbines that were scrapped the largest single reason given for the scrapping - 40 percent- was to make room for newer turbines. Only 12 percent were reported to be scrapped due to mechanical defect or due to wear. The author suggests that making room for newer turbines is also the reason for scrapping of most of the remaining 47 percent where the reason for scrapping 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 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. 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, Φ is a constant and v is the average wind velocity. Thus energy output from a wind turbine increases approximately *cubically* with average wind speed. 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.

This leads to some testable implications about the pattern of wind power scrapping. First, policy changes that effect investment will also have a direct affect on scrapping and the role of opportunity cost suggests that 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 4.1.

Consider first the top panel in the figure. The vertical height represents instantaneous cash flow from a turbine while the horizontal distance represents time. The jagged dotted line represents the instantaneous cash flow that could be obtained by investing in a newer turbine. The line is drawn step-wise increasing to represent a discrete process of technological change. The turbine owner would choose to scrap turbine 1 at a point at which turbine technology has advanced so that the total expected revenue from the new turbine less the revenue lost from scrapping the old turbine is greater than the cost of investing in a new turbine, represented by the shaded region. In the drawing, this point is shown as being at t*.

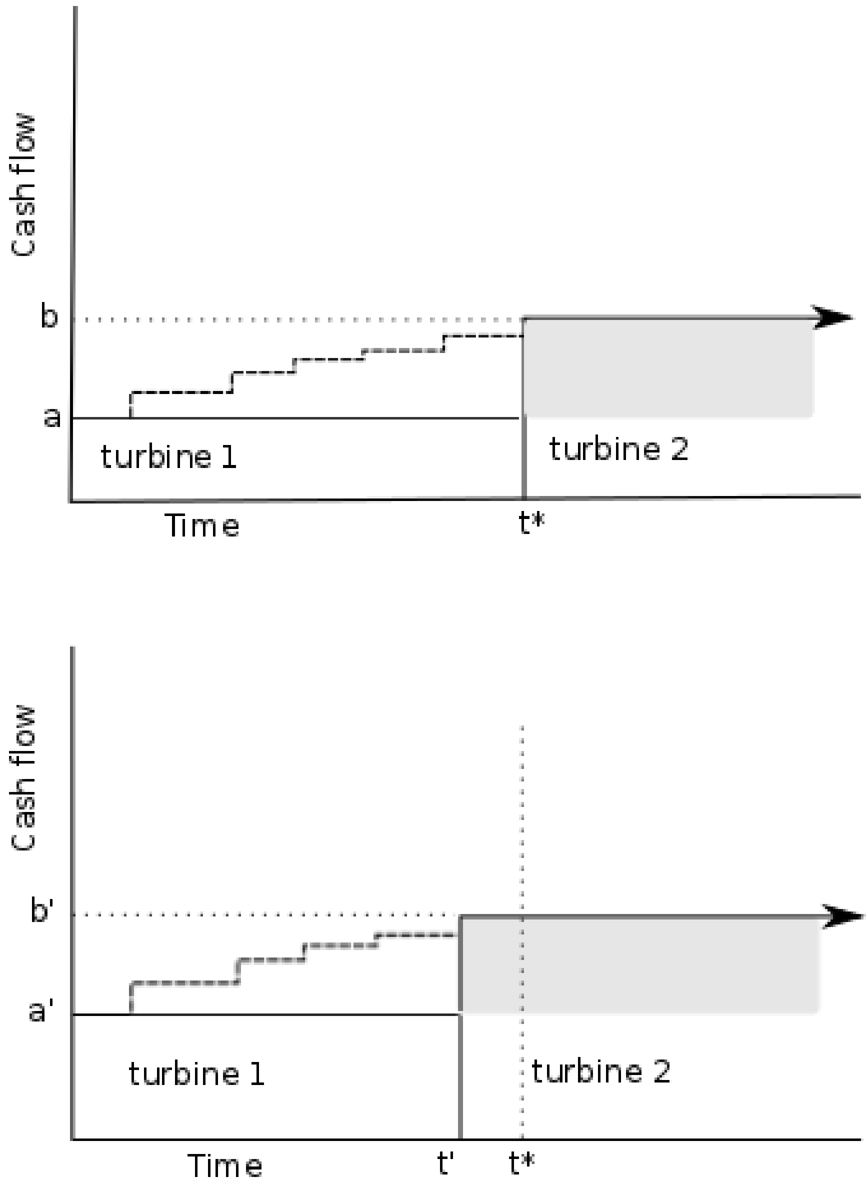

Figure 4.1 In the presence of technological change and scarce land resources, turbines placed on better, windier land can be expected to be replaced earlier. This is because the expected lifetime asset value of the newer turbine is worth more in a windier piece of land.

Now consider the effect of higher average wind speeds, as illustrated in the lower panel. Assume that higher average wind speeds affects the cashflow of both the existing turbines as well as the cashflow from technologically more advanced turbines proportionally. When replacing a turbine, the foregone revenue from the scrapped turbine is more than in the less windy situation. However the benefits of technological change are in absolute terms even higher. Assuming that the cost of investing in the new turbine is fixed, then the investment will take place at an earlier phase.

The figure of course represents an extreme simplification of the actual replacement decision. Discounting and the effects of uncertainty are not considered and the process of technological change is a vast oversimplification. But 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. I take the average yearly energy produced from each turbine and divide it by the rated capacity of the turbine. I then normalize this statistic to be between 0 and 1. This indicator, which can be interpreted as a type of capacity utilisation likely reflects the wind conditions of a turbine's placement. The results show that turbines with a higher capacity utilisation, representing a higher opportunity cost have a *higher* hazard of being scrapped.

Government policy is shown to have a strong effect on scrapping and to interact with the placement of turbines. Government policy meant to encourage the scrapping of older, poorly placed turbines is actually shown to have a greater effect on turbines in wind rich locations.

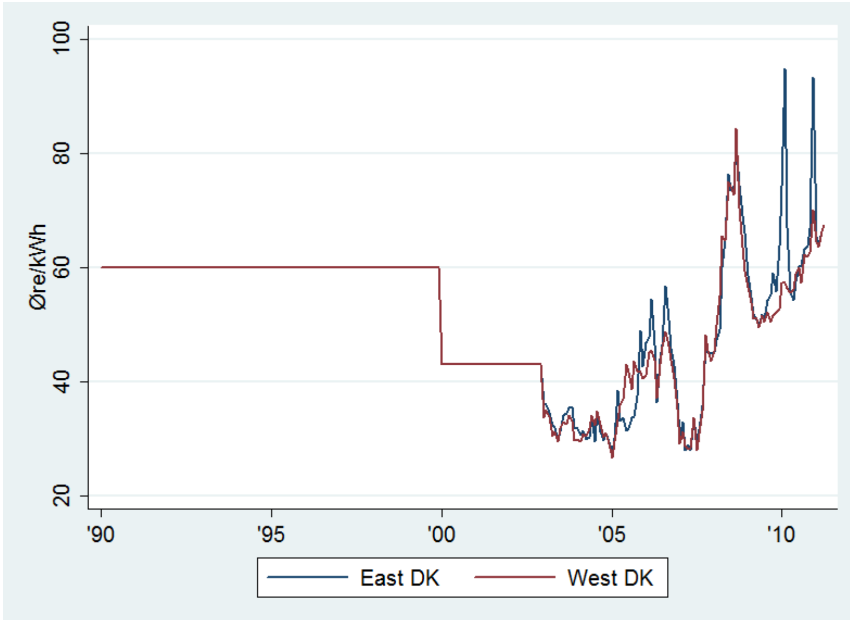

Figure 4.2 The tariff paid to wind power producers has shifted sharply several times. Notably in 2003, when Denmark fully joined the Nordic electricity market and tariffs were set at the market rate plus an added feed-in tariff.

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 4.2.

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 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 4.3. I attempt to control for these effects in the regression model.

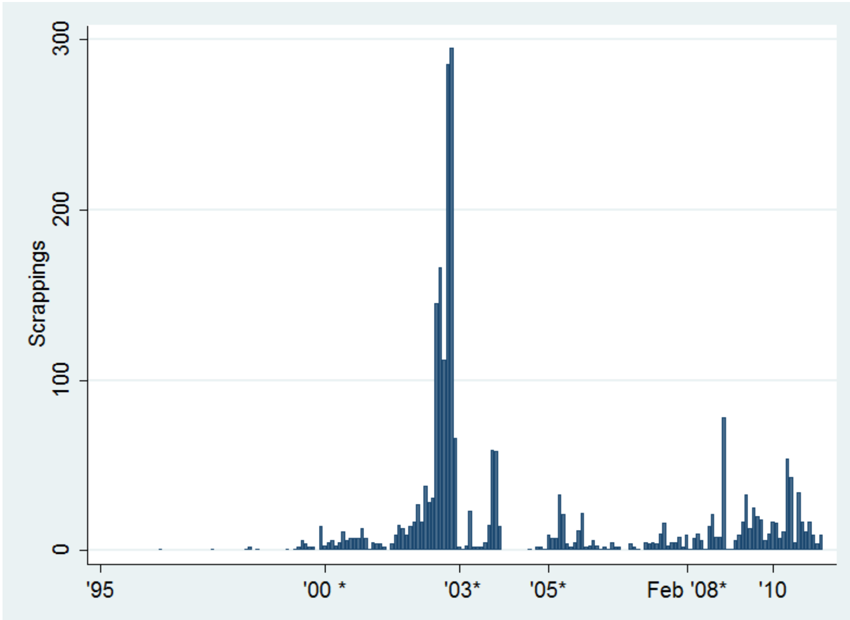

Figure 4.3 Scrappings of old wind turbines jumped ahead of the shift to lower tariffs in January 2000, and dramatically ahead of the shift in 2003. This demonstrates the strong role that opportunity cost has in the decision to scrap a wind turbine.

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 abandonment is taken up by Gaumnitz and Emery (1980) among others. Empirical studies of vehicle scrappings are a particularly popular subject and tend to focus on repair and replacement costs and issues of depreciation. See Manski and Goldin (1983) and Walker (1968) for example.

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 and Pindyck (1994) focuses on output and input price uncertainty on the decision to scrap. Subsequent work has recognized that technological change is also ex-ante uncertain and can affect the timing of investment decisions. See for example Murto (2007) or Huisman and Kort (2000).

This article is mainly descriptive in scope. I do not attempt to explicitly estimate or test aspects of real option 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 and 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.

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 energy directorate (http://www.ens.dk).

While I assert that the scrapping decision of a wind turbine is a special case, it is an important special case. In 2011 38 gigawatts of wind power was installed all over the world (Global Wind Energy Council, 2010), the equivalent of roughly 38 large nuclear power reactors. In a world where carbon emissions must be constrained, wind power looks to play a large role.

4.2 Methodology and data

I choose to use a semi-parametric Cox regression model to analyse the scrapping event. See Singer and Willett (2003) for an accessible overview or Kalbfleisch and 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 likely highly non-linear and not well approximated by a linear or quadratic form. The other main factor is sensoring. As of February 2011, approximately two-thirds of all the turbines in my data set were still operating. In a regression where time-to-event is the dependent variable, this censoring will bias the results (Greene, 2002, p. 790). A cox regression model effectively deals with both of these issues.

The Cox regression model can be written as in equation 4.1.

$$H(t|X) = H_0(t)e^{\beta \mathbf{X}+\epsilon} \tag{4.1}$$

$H(t|X)$ represents the individual turbine hazards as a function of turbine lifetime, t, conditional on X. H_0 represents a baseline hazard over lifetime. X represents the vector of variables, discussed below, that shift the baseline hazard up or down proportionally. β represents a vector of parameters on the X. These are estimated simultaneously with the non-parametric baseline hazard by a semi-maximum likelihood method that is detailed in Kalbfleisch and Prentice (2002, p.95).

Though much of the economics literature has tended to use purely parametric models where the general shape of the baseline hazard is given, 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 and Willett, 2003).

My main variable of interest is the proxy for the wind conditions of a turbines location. I create the variable as in equation (4.2).

$$CAPUTIL_i = \frac{\sum_{t=2}^{n-1} Y_{it}^e}{(n-2) * K_i} \tag{4.2}$$

I take the average yearly energy yield Y_{it}^e for every full year of operation from each turbine and divide out the rated capacity. This then captures factors that affect 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 capacity utilization variable then mainly represents the appropriateness of the land where the turbine is situated.

I then normalize the index to be between 0 and 1 by dividing the variable by its maximum as in equation (4.3).

$$caputil_i = \frac{CAPUTIL}{max(CAPUTIL)} \tag{4.3}$$

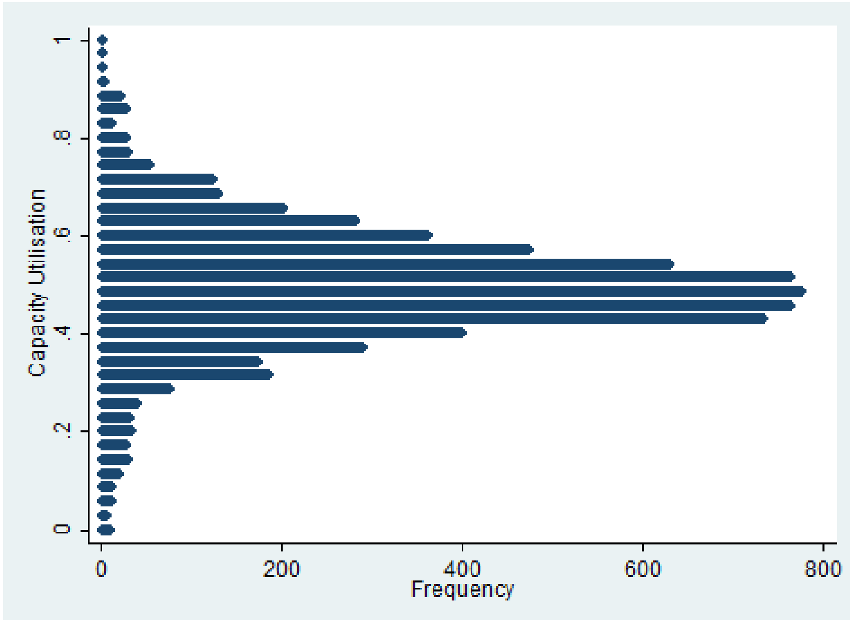

Figure 4.4 A dot plot of the capacity utilisation indicator showing the distribution of the indicator. The indicator likely mainly reflects differences in average wind speed at the site of the turbine.

A dot plot of created capacity utilisation variable is shown in figure 4.4 and gives a sense of the distribution of the indicator, which appears roughly normal.

I further multiply the index by 10 so that the estimated hazard ratio on the variable can be interpreteted as the effect on hazard per .10 increase in capacity utilisation.

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. 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 the model, I have chosen to limit explicit spatial data to an east/west dummy, representing turbines built in the east and west price

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 4.1. Tariffs provided for wind power in Denmark have changed several times over the course of the period studied. Notably, in 2003 the tariff for wind power changed from a fixed price per kWh to a market price plus a feed-in tariff.

areas. This dummy variable could capture many elements that differ between the two areas of Denmark. Market prices for the two areas have differed slightly for example. Factors such as wind-conditions, land value and population density could also be reflected in this variable.

As noted, wind power tariff policy has had a large effect on scrappings and I attempt to control for this in the regression. The electricity tariffs for wind power production have changed over time as wind energy investment has grown in scale. In 2003, Denmark also fully transitioned 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 4.1.

I do not include fixed effects for the different periods of tariff policy because such period dummies are 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 and the inclusion of such time varying variables in the regression can lead to erratic estimation (Singer and Willett, 2003). Instead I attempt to partially control for the effects of wind power tariff policy by including year of installation - dummies representing years 1977 through 1999. 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 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.

The government also introduced several "scrapping" schemes in order to expand wind power and "[decommission] older and less appropriately sited wind turbines" (Danish Energy Agency, 2008). 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.

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 these cut-off rates. The identifying assumption is that the relatively small differences 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.

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 (4.4).

$$\hat{S}(t) = \prod_{j|t_j \leq t} \left(\frac{n_j - d_j}{n_j} \right) \tag{4.4}$$

Here $\hat{S}(t)$ represents the estimated survival function over time, t. d_j represents the number of "deaths" at each time of failure, 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 4.5.

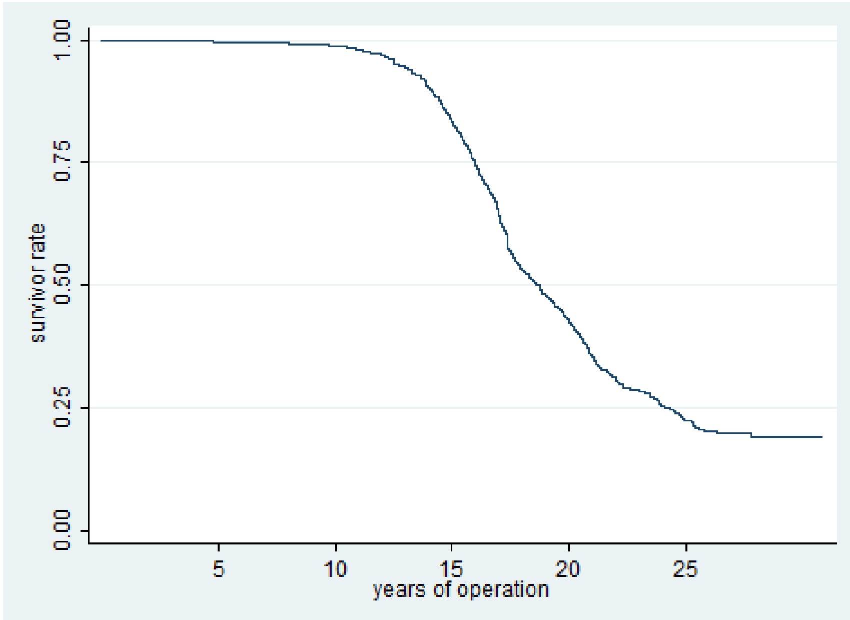

Figure 4.5 A Kaplan-Meier estimate of the survival function for the full set of Danish wind turbines. The shape appears reasonable with the the risk of scrappage being very low early in the life of the turbine and sharply increasing at approximately the 10-year mark.

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.

Figure 4.6 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 sub-groups 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

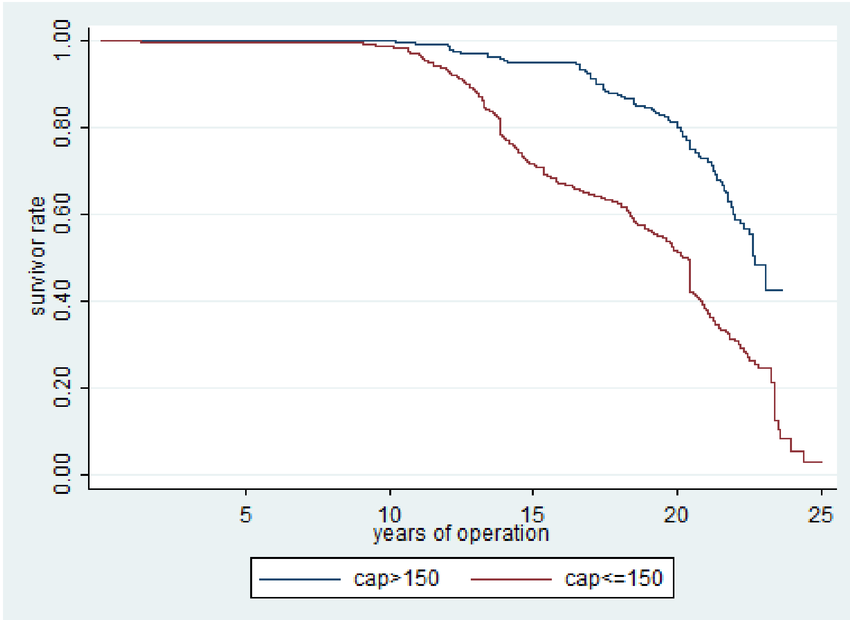

Figure 4.6 Kaplan-Meier estimates of the survival function for turbines between 100 and 200 kW in subgroups of over and under 150 kW. Turbines that are rated at or under 150kW - which are those affected by the policy - show a markedly steeper drop in the survivor function.

formally test the hypothesis of equal survivor functions with the Wilcox (Breslow) test. The test strongly rejects the null of equal survivor functions.

Figure 4.7 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 experienced a sharp drop in

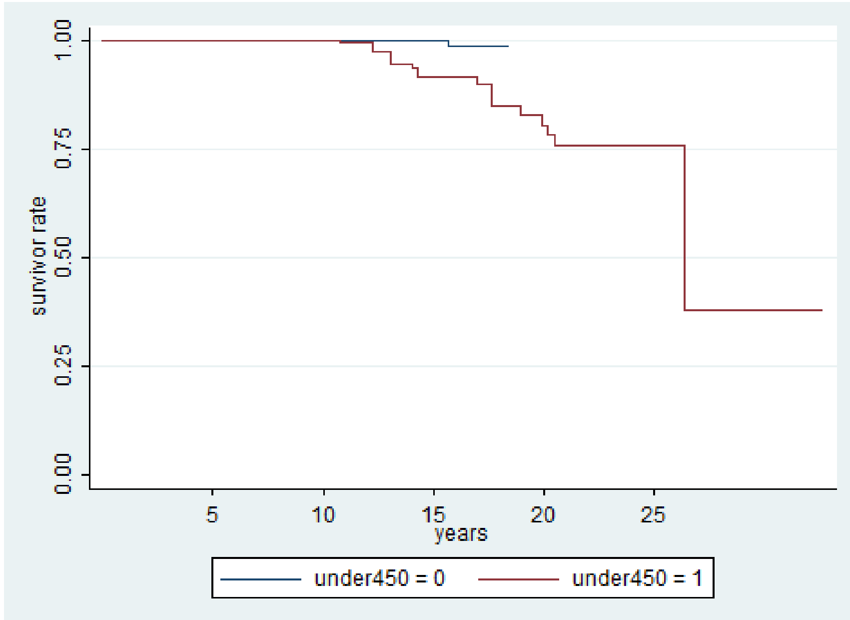

Figure 4.7 Kaplan-Meier estimates of the survival function for turbines between 400 and 500 kW in subgroups of over and under 450 kW. Turbines affected by the policy - those under 450 kW - display a drop in the survival function after about 10 years, while nearly all those over the cut-off continue to operate as of February 2011.

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 (figure 4.8).

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 in figure 2.8 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

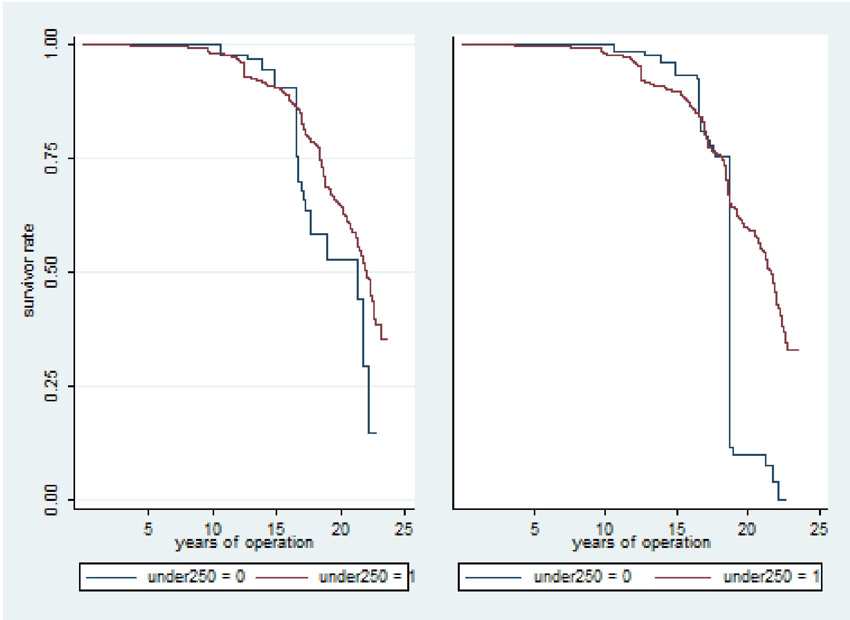

Figure 4.8 Kaplan-Meier estimates of the survival function for turbines between 200 and 300 kW in subgroups of over and under 250 kW. Turbines from both sub-groups come under the same policy, and after removing a group of outliers, the survival function estimates are not significantly different from one another.

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.

In the Cox regression I include a dummy variable representing turbines that have a capacity under 150 kw and were operating at the time of the start of the scrapping policy. 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 the policy. I also run regressions where I include interaction terms with the capacity utilisation variable to show how the effects of this policy varied with the wind resources of a turbines location. Unfortunately, because nearly no turbines

	I No Install Year	II Install Year[a] Dummies	III Interaction Terms	IV Time[a] interaction
cap-util	1.12	1.033	.77	1.036
	(.051)	(.045)	(.035)	(.046)
capacity	0.82	0.67	.66	0.98[b]
	(.027)	(.03)	(.03)	(.003)
capacity2	1.009	1.013	1.014	n/a
	(.001)	(.001)	(.001)	
under150	1.85	1.574	.421	1.022[b]
	(.14)	(.122)	(.10)	(.005)
west	1.47	1.471	1.16	1.469
	(.083)	(.084)	(.21)	(.083)
under150Xcap-util	n/a	n/a	1.32	n/a
			.064	
westXcap-util	n/a	n/a	1.05	n/a
			.041	

Standard errors in parenthesis
[a] *estimated coefficients on install-year dummies omitted*
[b] interacted with analysis time in year-units
6754 Observations, 2279 Failures

Table 4.2 The cox regression results show that a higher capacity utilisation significantly increases the hazard of scrappage. This is evidence for the role that opportunity cost has for the scrapping of wind turbines

rated over 450 kw were scrapped, including a dummy for turbines rated under 450 kw leads to severe numerical problems in the estimation.

4.3 Results

In table 4.2 I report the results in terms of hazard ratios - the exponent of the estimated β's.

The hazard ratios can be interpreted as the 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 scrappage.

The first and second columns show the results when install year dummies are not and are included. The estimated coefficients on the install-year dummies do not have any meaningful economic interpretation so I do not report them here.

The estimated coefficient on the capacity utilization variable that is meant to capture wind resources is labelled $cap - util$. In the first column where install-year dummies are left out, the coefficient on capacity utilization indicates that a .1 increase in capacity utilisation leads to a 12% increase in the hazard of scrapping, which is statistically significant at the 1% level. Controlling for install-year as a proxy for the effects of changes in wind power tariff policy as in column two leads to an estimated hazard ratio of 1.033. A .1 increase in capacity utilisation leads to a roughly 3% increase in the hazard of scrapping.

That the estimated coefficient on capacity utilization 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 wind power tariff policy that created jumps in the opportunity cost of operating an old wind turbine. The effect of capacity utilization likely interacts with the effect of changes in wind power tariffs. When investors rushed to replace older turbines with newer ones before tariffs were lowered in 2000 and 2003 they likely chose to replace turbines situated in locations with better wind resources over more marginally situated turbines. This explains the larger coefficient on capacity utilization when the install-year dummies are not included.

A plausible alternative explanation for the positive coefficient on capacity utilization exists. Turbines with higher capacity utilization may wear out sooner and therefore be at a higher hazard of scrapping. But given the evidence that most turbines are scrapped long before the end of their physical lifetimes and given the correlation with the install year dummies, this explanation seems less convincing.

The hazard ratio for capacity is also highly significant. The estimate from the second column where install-year is controlled for is likely the more reliable estimate. The estimated coefficient indicates that each 100 kW increase in capacity leads to a 50% ($\frac{1}{.65}$) 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. The positive and significant coefficient on the squared capacity term, labelled $capacity2$, indicates that the effect of rated capacity on scrapping hazard is decreasing with scale. The difference in the hazard of scrapping between a 500 and 600 kW turbine is less than the difference between a 100 and 200 kW turbine.

The estimated coefficient on the dummy variable that represents turbines affected by the first scrapping policy, labeled $under150$, indicates that the policy increased the hazard of scrapping by approximately 55 percent. The magnitude of this estimate is roughly in line with the Kaplan-Meier estimates in the previous section.

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. It is unclear what the exact reason for this is. One potential explanation is that the most suitable land is in the geographically larger western Denmark. If this were the case, we would expect significant interaction with the capacity utilisation term.

In the third column, I show the estimates from a regression where the capacity utilisation term is interacted both with the under-150 policy dummy, labelled $under150Xcap - util$ as well as the east-west dummy labelled $westXcap - util$.

The results from this regression indicate that there is a strong interaction between the scrapping policy and the wind resources of a turbines placement. In particular, the estimated hazard ratio of 1.3 on the interaction variable suggests that the effect of the scrapping incentive policy was much greater for turbines located in wind rich locations.

In fact, after stripping away the interaction component between the scrapping policy and the capacity utilisation term, the estimated hazard ratios on both the individual variables are no longer above 1. About 80% of the turbines that were scrapped in the period studied were rated under 150 kW and came under the scrapping policy. The story that is most consistent with these results is then that the introduction of the turbine policy led many producers to replace out their old turbines, but that this had a disproportionally large effect on producers who had old turbines located in prime, wind rich areas.

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 (4.5).

$$H(t_i) = H_0(t)e^{\beta\mathbf{X}+\beta_1 x_i+\phi x_i * t+\epsilon_i} \tag{4.5}$$

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).

Running such regressions for the various covariates shows that the proportional hazards assumption is likely satisfied for the capacity utilisation variable as well as the west dummy variable. Not surprisingly, the *under150* policy instrument does not satisfy the proportional hazards 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 fourth column of the table.

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 1.02 on the under-150 kW indicator can be interpreted as approximately a 20 % higher hazard of being scrapped after 10 years ($1.02^{10} = 1.20$) and 50% higher hazard after 20 years ($1.02^{20} = 1.49$). Similarly a 100 kw increase in capacity reduces the hazard of scrapping by 25% over 10 years ($.978^{10} = .80$) and by about 55 percent over 20 years.

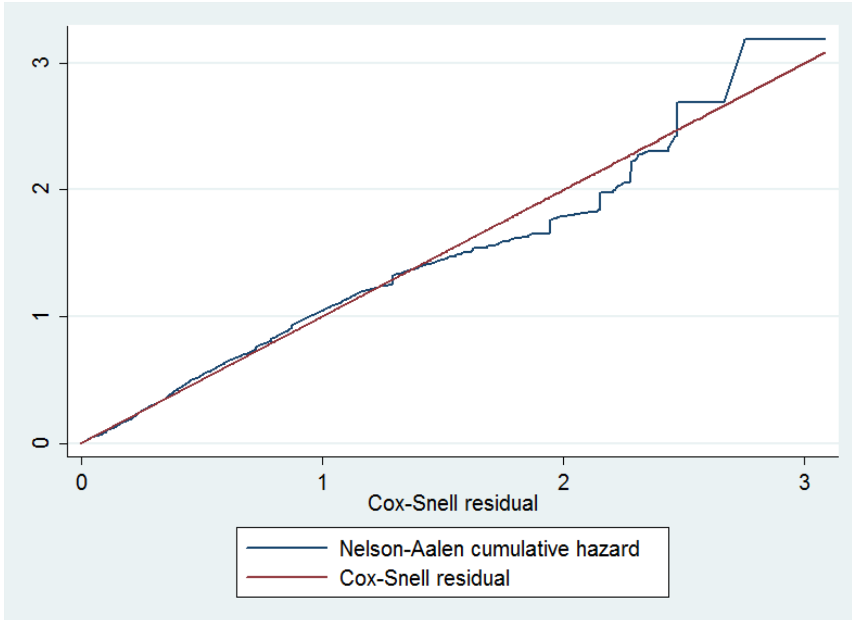

Figure 4.9 Nelson-Aalen estimate of the cumulative hazard of the Cox-Snell residuals plotted against the Cox-Snell residuals. A cumulative hazard that approximately follows a 45 degree line indicates a good fit to the data.

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 (4.6).

$$CS_j = \hat{H}_0(t_j)e^{\mathbf{X}\hat{\beta}} \tag{4.6}$$

CS_j represents the residual on the jth observation. $\hat{H}_0(t_j)$ represents the maximum likelihood estimate (MLE) of the baseline cumulative hazard function and $\hat{\beta}$ represents the vector of estimated coefficients on the explanatory shifting variables. Figure 4.4 shows the estimated cumulative hazard (Nelson-Aalen estimator) of the Cox-Snell residuals plotted against the values of the residuals for the regression in the second column.

If the estimated Cox model has a good fit, then the Cox-Snell residuals should have an 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 figure 4.9 should roughly follow a 45 degree line. By this metric, the fit appears to be reasonably good.

4.4 Conclusion

In Denmark and presumably elsewhere, the most common reason for replacing a wind turbine is to make way for a newer and larger turbine. An opportunity cost that comes from a combination of scarce land resources and technological change is then a dominant reason for the scrapping of turbines. The importance of this opportunity cost has implications for the pattern of turbine scrapping and the effects of policy. Turbines located in areas with better wind resources are shown to have a higher hazard of scrapping. Policies meant to encourage the scrapping of older poorly placed turbines actually have a higher effect on turbines located in good locations.

The theoretical literature on the abandonment of capital goods recognizes that uncertain future policy and uncertain technological change can affect the timing of the scrapping and replacement decision. The expected lifetime of a wind turbine and potentially other renewable energy investments with high rates of technological change must then be seen as inherently uncertain to a greater degree than is generally recognized in the literature.

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