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Johannes Mauritzen

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

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Johannes Mauritzen

Norwegian School of Economics (NHH)
Department of Finance and Management Science
Bergen, Norway

and

Research Institute of Industrial Economics (IFN)
Stockholm, Sweden

johannes.mauritzen@nhh.no

Abstract

This paper attempts to test the effect that wind power production has on the variability of wholesale electricity prices in the spot market. I use a simple distributed lag econometric 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 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.
Keywords:
Wind Power, Nordic Electricity Market, Empirical, Time Series

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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 effect that large amounts of wind power generation has on a deregulated market-based electricity system is then an important area of study and the literature on the subject has been growing. Most studies have used simulation models to analyze the effect on average price levels. Econ-Poyry (2008) uses its BID power market model to analyze 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 Pøyry 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. (2006) (in danish) uses 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 nor do they discuss potential causes for this effect. Furthermore, the methodology is overly simplistic and resulting conclusions sometimes unconvincing. The base problem with their approach is that their methods do not allow them to adequately control for other factors, thus their estimates are likely biased. 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. Again, however, the analysis is hindered by methodology as he relies on pure correlation coefficients to conclude that the effect of wind power on prices is minimal. [1]

Market-based electricity systems are characterized by high levels of random price volatility as well as regular, foreseeable price variation. Both are to a degree the result of a combination of varying load patterns and the unstoreability of electricity. [2] The variation and volatility 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 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.

[1]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

[2]Electricity, by its nature, can not be stored. Energy, in a form other than electricity, can of course be stored, but this can be expensive and involve technical problems. Countries and electricity systems where cheap forms of energy storage are available, for example areas with large amounts of hydro power, tend to have lower amounts of short term price variation

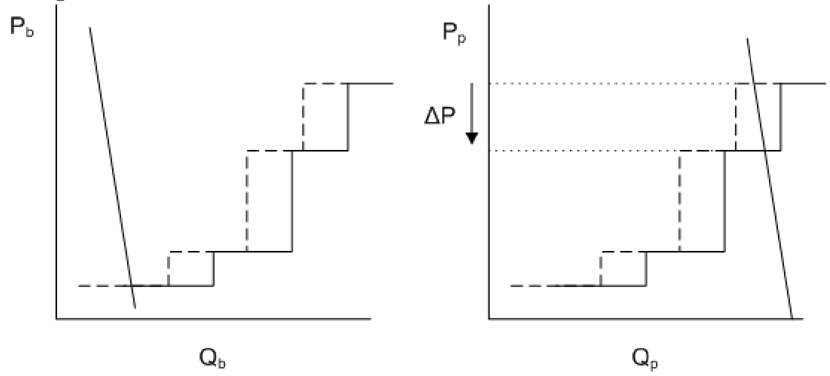
Due to the early and heavy investment by Denmark, the Nordic electricity market is one of the few places with a relatively long history with significant amounts of wind power. The Nordic system is also a market-based system with decentralized producers making bids in the wholesale day-ahead market on a central exchange. Prices are the main tool to resolve transmission constraints and balance the system across regions and countries. These attributes make the Nordic market ideal for studying the effects of wind power.

In this paper I use a dataset of hourly and daily data from Energinet - the Danish transmission system operator (TSO) - and Nordpool - 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 simple 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, supply and demand factors that are not directly relevant to the analysis.

The data gives a nuanced view of the effects of wind power on variability. [3] 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,

[3]The word choice here is deliberate. Using "volatility" may also seem natural but in economics this tends to imply unforeseen changes in prices. Here, as mentioned, part of the variability is expected and forcastable. I thank Petter Bjerksund for pointing this out

Figure 1: Effect of Wind Production on Peak and Base Load Prices



Wind power can be seen as a stochastic 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 intra-day price variation

wind power tends to have the effect of *reducing* variability.

The mechanism for how wind power production reduces intra day 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 stochastic shifting of the supply schedule to the right. Since the supply schedule is steeper at peak times, then shifts in the supply curve would lead to larger price decreases during the these periods. This idea is illustrated in figure 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.

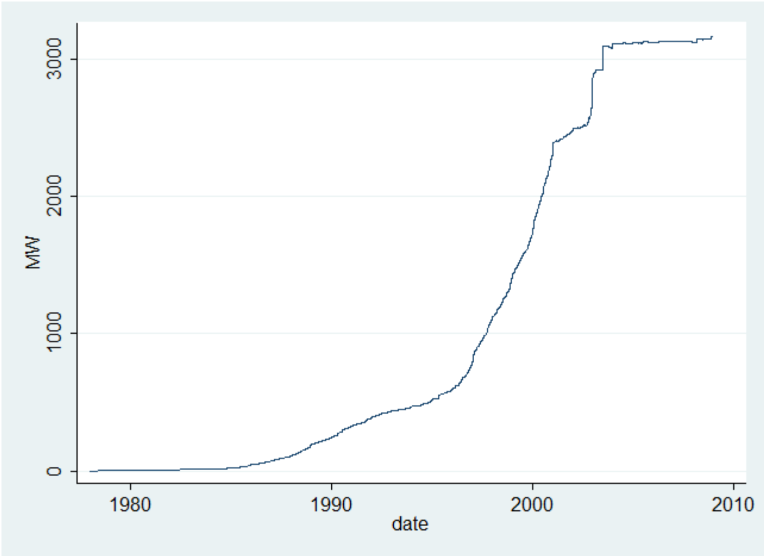
Coughlin (2011) and Obersteiner and Saguan (2009) among others have noted that daily load patterns and wind power may be correlated. Windy days may, for example, be days with generally poor weather and thus people are more likely to remain in doors and use more electricity. The increased load would in 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.

The Nordpool spot market operates on a day-ahead basis. Producers and consumers (either large direct consumers or electricity retailers) provide bids for every hour of the following day. From these bids, Nordpool establishes a supply and a demand curve from which an equilibrium system-price is established. Transfer capacities in the Nordic region are relatively large, however transmission congestion is still a common occurrence. For this reason, several price areas exist: two in Denmark (east and west), one for Sweden and Finland each, and several in Norway. [4] When congestion occurs between areas, the price increases in the area receiving power and is reduced in the area sending power until equilibrium is met with the available transmission capacity. Thus, while a theoretic system price always exists, it is common that the areas have different prices in practice.

Since the 1970's, Denmark has poured considerable resources into both research and development of wind-turbines as well as providing generous subsidies to build out capacity. Wind capacity growth has been especially strong in the last 20 years as figure 2 shows, though capacity held steady in the years studied between 2002 and 2007.

[4] the exact number of price areas has depended on the level of congestion

Figure 2: Installed Wind Capacity in Denmark



Generous government incentives led to large investments in installed wind capacity in Denmark. In the period studied between 2002-2008, wind power capacity held steady.

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 Nordpool (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. [5]

One of the advantages with working with this hourly and daily data set is

[5]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

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 Nordpool. Thus unless there are errors in reporting, no measurement error will exist in the dependent variable.

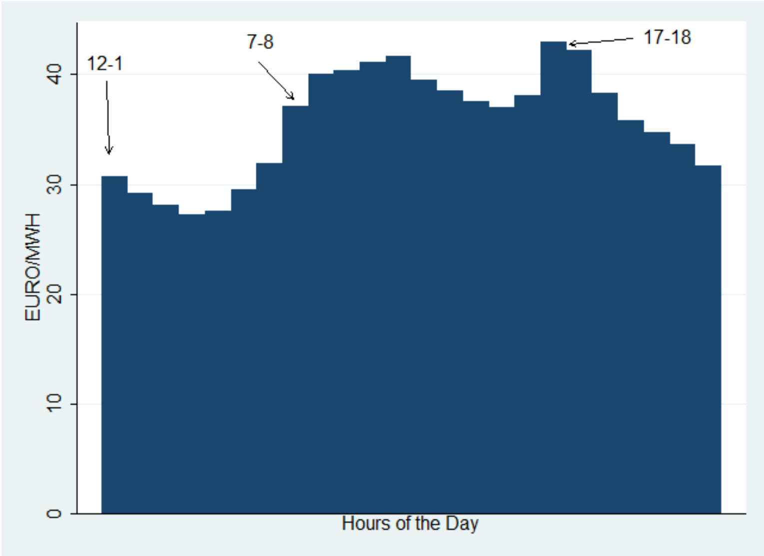
The large number of observations also makes the econometrics simpler as I can rely on the asymptotic properties of the estimators to obtain unbiased estimators and correct standard errors. In particular, robust (white) standard errors will converge to the correct standard errors. As I will show, some serial correlation will still be present in the residuals, even after accounting for the dynamics in the regression model. Happily, white standard errors are also asymptotically consistent to serial correlation (Hamilton, 1994).

I use a distributed lag model as in equation 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.

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

As Figure 3 shows for the Denmark-East price area, the wholesale electricity price tends to vary substantially within a day. 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

Figure 3: Average (2000-2008) Electricity Price in Denmark-East, by hour



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.

costs such as wind, hydro and coal are often sufficient in low-load times. [6]

In this paper I measure price variability by way of simple standard deviations. Equation 2 shows the calculation of the intra-day (24 hour) standard deviation. Calculation of standard deviation on a weekly basis is calculated similarly. Several reasons exist for using such a measure of variability. First, it 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 heteroskedastic (ARCH) models are often used to characterize the

[6]As a side note, the daily price variation in the Norwegian price areas tends to be substantially less than in Denmark due to the dominance of flexible hydro-power in the system. However Norway does tend to also experience a lot of seasonal variation due to changes in the reservoir levels.

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.

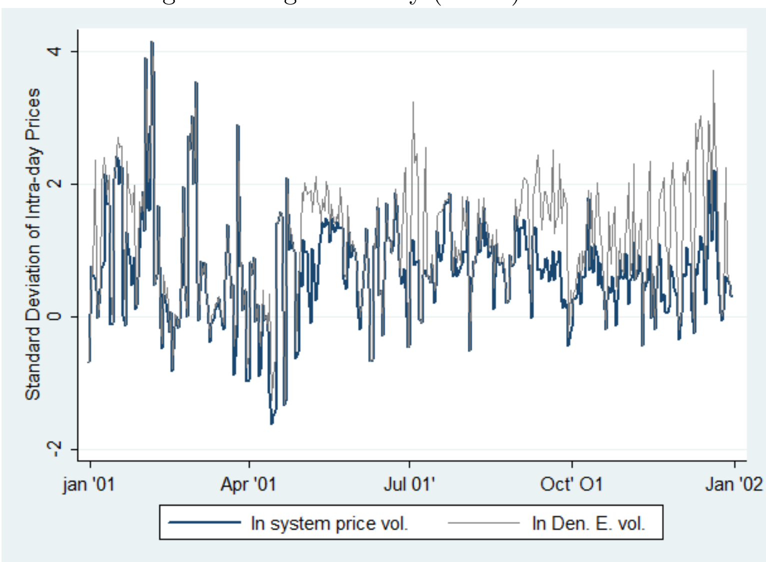
$$V_d = \sqrt{\frac{1}{24}\sum_{i=1}^{24}(P_i - \bar{P})^2} \tag{2}$$

The log daily price standard deviation series is plotted for the Nordpool system price and the Denmark east area price over the year 2001 in figure 4. 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, has none of its own hydro production.

To find a well fitting ARMA specification for the various price-variability series (intra day 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 7 shows one year of the exponentially smoothed log total wind power series. Not surprisingly 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. Thus in the regressions for intra day variability, I include both a contemporaneous wind power term as well as a lagged term to deal with this autocorrelation.

Figure 4: Log variability (st.dev) of Prices



The time series of intra day 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.

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, where the standard deviation is calculated both over all hours in the week and over averaged daily prices as in equation 3.

$$V_w = \sqrt{\frac{1}{7}\sum_{d=1}^{7}(P_d - \bar{P})^2} \tag{3}$$

Clearly, the number of observations is reduced by a factor of 7 for weekly variability and I am left with only with 336 observations, which negatively effects the efficiency of the results. On the plus side, the weekly seasonality that had to be modeled 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 (Hamilton, 1994). Ignoring the seasonal components for the moment, the intra day system price variation series can be adequately modeled as a purely autoregressive model with 5 lags (AR5). Thus I run a Dicky-Fuller test with five lags. 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. That is to say, 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, as mentioned, 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 [7] 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 Nordic market power have failed to detect evidence of consistent market power (see for example Amundsen and Bergman (2006) and Hjalmarsson (2000)).

[7] Some other markets in Europe utilize a "negative" price - essentially paying some producers not to produce

3. Results

The results from several sets of regressions are presented below. The first sub-section analyses the effect of wind power on intra day 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. As mentioned, all of the below analysis is of variation of the prices that are set in the day-ahead "spot" market by Nordpool. 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 that is important to make clear is that the prices in the day-ahead market are necessarily effected 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. It is also important to note that this does inject an extra error component into regression model, though one that is presumably random and will not bias the results.

3.1. Effects of wind on Intra day variability

As discussed briefly in the introduction, a system-wide price (I will henceforth refer to it as the system price) is established by Nordpool 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 often the case that congestion in the transmission net leads to different prices in the different price areas, the system price nonetheless represents an important bench-mark 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 I below shows the result of the distributed lag model regression of intra day system price variation in the form of equation 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 controlled for autocorrelation in the series. The estimated coefficients on the AR and MA terms are labeled 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, labeled $wind_t$ and $wind_{t-1}$. To control for the possible correlation between load and wind speed, I present results of regressions where I also include a term for consumption and its lag - approximated here by turnover in Nordpool and labeled to_t and to_{t-1}. All variables are transformed into log form in order to give the coefficients an elasticity interpretation

Table I.
Effect of Wind Power on Nordpool
System Price Intra day Variation

	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

The coefficient of interest is of course the contemporaneous wind power term, and the regressions indicate a 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 3% reduction in intra day variability of the system prices. Though this elasticity estimate is relatively small, I would argue that considering it shows the effect of Danish wind power on the system price for the entire Nordic market, that it is economically quite significant.

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, 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 correlated 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.

As mentioned earlier, several price areas exist within the Nordic market and when congestion occurs in the transmission net prices will increase in the importing area and decrease in the exporting area until the expected electricity trade meets the physical transmission capacity. The price series for the two Danish price areas (east and west) then represent the actual wholesale price paid by consumers and to generators in that price area and in that sense, the area price series are the more important series.

Table II. presents the results from a distributed lag model regression again of the form of equation 1 but where the intra day price variation is that of the series of east and west Denmark prices. I also distinguish between wind power generated from the two price areas.

Otherwise, the form of the regression is quite similar to the regression on the system price intra day 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 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.

Looking at the first two columns, which represent the regressions on the Denmark east price variation series, the coefficients of interest are wind power from Denmark east and Denmark west, labeled $de - wind_t$ and $dw - wind_t$ respectively. The estimated coefficient 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 7% decrease in intra day price variation in eastern Denmark. However, no significant effect of wind power generated in eastern Denmark is found. In the western Denmark area, represented by the 4th and 5th column, wind generated in its own area reduced intra day price variation between 10% and 12% while again wind power generated in east Denmark can not be shown to have a significant effect on price variation. Not surprisingly, the effect of wind power on price variability is magnified when looking at area prices and the magnitude of the effects indicate that wind power has an economically quite strong effect on the daily pattern of price variation.

Table II.
Effect of Wind Power on Intra day Danish Price Variability

	DE Area	DE Area wCons	DE Area SD of Wind	DW Area	DE Area w Cons	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

2174 Observations

Measure of variability is standard deviation over the 24 hourly prices in a day

all variables are in log form

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 intra day 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. As a further check, I again include consumption, this time in the form of actual electricity consumption in both areas. This does not significantly change the results. Thus the negative coefficients on wind power from western Denmark is likely not just a reflection of a correlation between the daily wind power pattern and daily load pattern, but reflects a real causal effect of wind power on price variability. More so, 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 intermitancy. 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 where I use the intra day standard deviation of wind power as the exogenous regressor. However, the results are not radically different. A negative and significantly different from zero coefficient is estimated for the variation in wind power from Denmark West 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. That is to say, 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.

As an added robustness check, I ran the regression on western Denmark price variability on a year-by-year basis. The table of results can be found in the appendix. With only 365 data points for each yearly regression, the standard error is significantly larger and the point estimates, not surprisingly, vary substantially. However, negative coefficient estimates on the effect of wind from western Denmark are found at the 5 % level in 3 of the 6 years, where the remaining 3 estimates are not found to be significant.

3.2. Weekly Variability

So far, I have looked exclusively at the effect of wind power on intra day 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 to looking at variation over weekly windows. I measure variation by taking the standard deviation over a 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 try to test what the effects of wind power has 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 III. below shows the results of the regressions of wind power on weekly price variation in the east and west Denmark price areas. The variation is here measured as the standard deviation over averaged daily prices. In the appendix, a table is presented with 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, so I do not present them here.

Table III.
Effect of Wind Power on Weekly Danish Price Variability

	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

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 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 such as, for example, ARMA(1,1) that also provide good fit for the series.

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). 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 than 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. Recall that 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 then 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).

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 intra day variation.

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 intra day 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 Lillestl (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 perverse 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 TSO's may then have to depend more heavily on side payments or other market mechanisms to ensure adequate peaking capacity.

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Appendix A.

Table IV.
Effect of Wind Power on Weekly West Danish Price Variability, by Year

	2002	2003	2004	2005	2006	2007
$dw - wind_t$	-0.145	0.050	-0.104	-0.279	-0.004	-0.102
	[.093]	[.084]	[.080]	[.091]	[.059]	[.083]
$dw - wind_{t-1}$	0.231	0.126	0.037	0.015	-0.015	0.073
	[.092]	[.076]	0.075	0.079	0.064	0.070
$de - wind_t$	-0.014	0.048	0.143	-0.019	-0.016	0.014
	[.080]	[.078]	[.079]	[.076]	[.057]	[.073]
$de - wind_{t-1}$	-0.088	-0.067	0.109	-0.002	0.041	-0.022
	[.071]	[.071]	[.072]	[.070]	[.056]	[.063]
$constant$	1.478	0.246	-0.295	4.440	1.949	2.252
α_1	0.510	0.397	0.362	0.359	0.221	0.482
α_2	0.018	0.067	-0.153	0.067	0.164	0.046
α_3	0.026	0.006	0.110	-0.001	0.167	0.050
α_4	0.109	0.064	0.017	0.082	0.089	0.089

Coefficients significant at 1% level unless otherwise noted:

[a] significant at 10% level

[b] not significantly different from zero

364 Observations

Measure of variability is standard deviation over hourly prices

All variables are in log form

Table V.
Effect of Wind Power on weekly Danish Price Variability, measured over hourly prices

	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