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What happens when it's Windy in Denmark? An Empirical Analysis of Wind Power on Price Volatility in the Nordic Electricity Market

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WHAT HAPPENS WHEN IT'S WINDY IN DENMARK? AN EMPIRICAL ANALYSIS OF WIND POWER ON PRICE VOLATILITY IN THE NORDIC ELECTRICITY MARKET

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Abstract. This paper attempts to empirically test the effect that wind power production in Denmark has on volatility of the nord-pool wholesale electricity prices. The main result is that wind power tends to significantly *reduce* intraday volatility but *increases* volatility over larger time windows. The negative elasticity for intraday volatility is likely due to a larger-in-magnitude price effect of wind power on peak hours then off-peak hours. I suggest that this in turn is due to a steeper supply schedule at peak-loads. The positive elasticities in the wider time windows can be intuitively explained by the greater variability of the supply when large amounts of wind power are present. These finding have ramifications for investment in power generation, balancing as well as transmission capacity.

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 decade. 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. Yet the effect that substantial wind capacity has on market-based electricity systems, where prices provide the main mechanism for maintaining a balance of supply and demand is poorly understood in theory, and little researched in practice.

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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 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 an extensive dataset of hourly and daily data points from the Nordic transmission system operators (TSO), Nordpool - the central exchange, as well as other relevant data sources. The data gives a nuanced view of the effects of wind power on volatility. When looking at the volatility of prices per hour over the course of a day, wind power tends to have the effect of reducing volatility. However, when I aggregate to daily units and look at volatility over weekly and monthly periods, wind power has the effect of increasing volatility.

Given the availability of quality data, the empirical literature on the effect of wind power on market prices is relatively scarce. Focus has been especially focused on the effect of wind power on price levels - all finding that wind power has the effect of lowering prices.

Many electricity market studies use large scale programming models to evaluate cause and effect. The Econ Pøyry group [Poyry, 2008] uses its BID power market model to analyze how large scale wind development would affect the operation of the market. The Swedish government has a goal of installing 10 TWh of wind generation, and thus the authors used this as the simulated amount. The model indicated that the addition of wind would tend to lower prices significantly, but the effect on volatility was ambiguous. The simulation also stresses that the effect on the value of water in hydro power plants would be reduced - a result that, as I will explain, I am skeptical of.

Another simulation study was completed by Holttinen [2004] who found a reduction of average spot price by 2 Eur/MWH for each 10 TWh/a wind energy added. An interesting distinction that the author makes is the difference between adding wind power and adding wind power while simultaneously removing an equivalent amount of thermal-generated power production. With the latter scenario, the author finds only a slight decrease in prices. This seems to suggest that the source of the price decrease in these models is simply increased supply instead of the low-marginal-cost nature of wind power. In this case, the result of lower spot prices is banal. Again, I am skeptical of such a result and believe a data-driven approach will tend to tell a different story.

A more data driven approach was attempted by Enevoldsen et al. (in danish), but the methodology is overly simplistic and resulting conclusions sometimes unconvincing. Their approach is essentially a non-parametric approach based on binning and averaging observations by hour, month and wind power. 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 don't discuss the implications of this. They calculate that (wholesale) electricity consumers saved between 12% and 14% in western Denmark and between 2% and 5% in eastern Denmark. Yet they note a few "mysteries" in their study. They use only data for 2004 and 2005 and observe substantially different effects in those two years, which they can not explain. Furthermore they try to establish an elasticity graphically by showing the market price as a function of increasing amounts of wind penetration (by percentage). Here they note a higher "elasticity" in eastern Denmark, which again they find puzzling given the large amounts of wind in west. The first "mystery" is clearly the result of the methodology. Power prices tend to exhibit strong autocorrelations across hours, days and even months. It is not at all surprising that if one does not controll for these effects that estimates of the effect of wind power will vary significantly from year to year. Their second "mystery" confuses several issues. As they note, there is considerably less wind power present in eastern Denmark, but as my analysis shows, the prices in eastern Denmark are effected substantially from wind power from western Denmark as well.

Lower intraday volatility but higher longer-term volatility has implications for investment and system operation. Given that the lower intraday volatility is due to lower average prices at peak times, this could have adverse effects on investment in peaking generation. Since the expected payoff of such generation that is only used at peak times is now lower, less may be built solely based on signals from the market. Thus, wind power may have the strange effect of reducing average intraday volatility but in the long term this could lead to more instances of extreme stress and high price spikes when wind is not blowing at peak times.

The increased volatility at longer time-windows reflects the investment challenges of installing large amounts of intermittent generation. Consumption has been relatively flat in Denmark over the course of the last two decades. Therefor the added wind power has tended to replace older thermal generation (mostly coal plants). These plants are mothballed but often still operational and in times of stress, such as the winter of 2002-2003, they can be activated [von der Fehr et al., 2005]. In markets where generation must be built to meet growing consumption, the need for substantial backup generation is needed.

The increased price volatility caused by wind power also has interesting implications for the hydro-power producers that dominate the Nordic market. The Econ P yry groups simulation study for Sweden [Poyry, 2008] got results that indicated that the value of water would drop, and thus the profitability of these plants would decrease. Yet given enough transfer capacity, the increased volatility presents an opportunity for hydro power producers with reservoirs as they can essentially act as giant batteries.

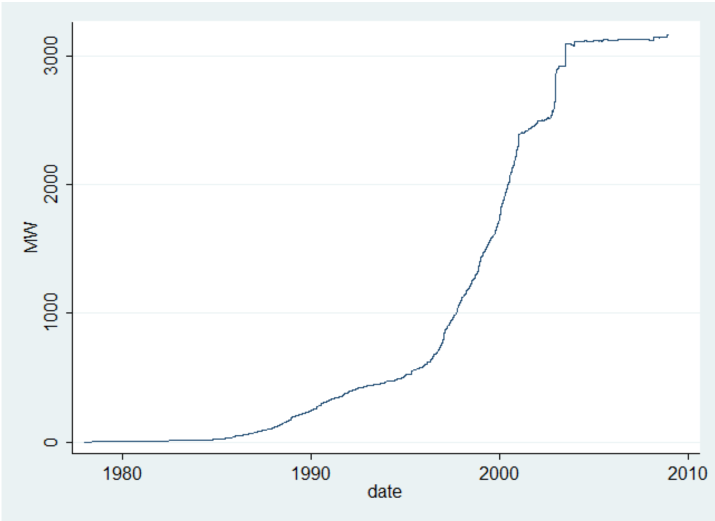
2. The Nordic Electricity Market and Danish Wind Power

Deregulation of the Nordic electricity system towards a market-based system began in 1991 in Norway. By 1996 a Norwegian-Swedish power exchange was established and the joint trading exchange Nord Pool ASA was formed. Finland joined in 1998, western Denmark in 1999 and eastern Denmark in 2000. In later years, bidding areas have also been extended to Germany (Kontek area). 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 the exact number of price areas has depended on the level of congestion. 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 different areas have different prices in practice.

Denmark has a long history of using wind power, but the wide-scale use of wind-turbines to generate electricity for the grid trace back to around 1975, when the Arab oil embargo and a subsequent dramatic increase in fossil-based fuel prices spurred investment in alternative forms of electricity generation. Denmark has since poured considerable resources into both research and development of wind-turbines as well as providing generous subsidies to build capacity. Wind capacity

FIGURE 1. Installed Wind Capacity in Denmark



DATA SOURCE: DANISH ENERGY AGENCY

growth has been especially strong in the last 20 years as figure 1 shows.

As Figure 2 below 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 costs such as wind, hydro and coal are often sufficient in low-load times. [1]

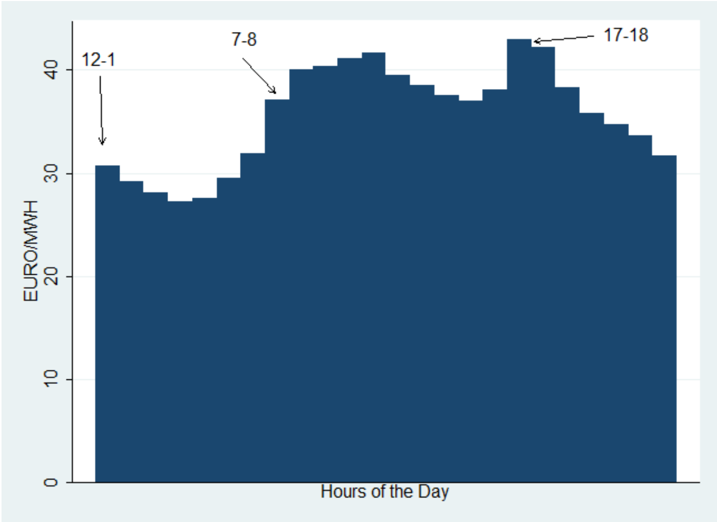
3. Data and Econometric Issues

Data was assembled from several sources. Hourly price data from 2000 through 2008 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 [ene].

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 2800 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

[1] 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.

Figure 2. Average (2000-2008) Electricity Price in Denmark-East



Data Source: Nordpool

error will exist in the dependent variable.

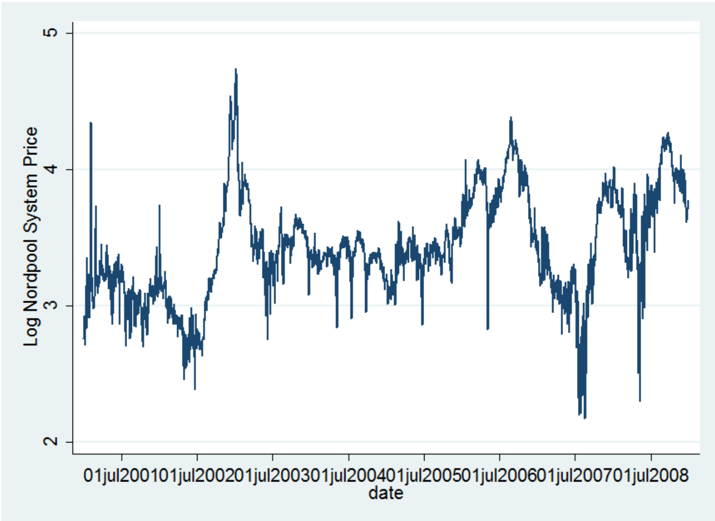
The large number of observations also makes the econometrics simpler as I can rely on the asymptotic properties of the estimators to obtain unbiased estimators and correct standard errors. In particular, robust (white) standard errors will converge to the correct standard errors asymptotically. As I 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].

Figure 3 shows a plot of the log system price. The "spiky" nature of electricity price series is immediately apparent. Many of the high peaks happen at winter time, when electricity usage is highest in the Nordic countries. Though a consistent yearly pattern is not obviously present. A closer look would however reveal a clear weekly pattern that reflects the load pattern. Fell [2008] deleted weekend observations in order to minimize the effects of this weekly seasonality. I decided to try to keep all the data and instead deal with the seasonality in the regression model.

Data source: Nordpool

I will not be using the price data directly, but instead am concerned with measures of the price volatility. One of the primary measures will

FIGURE 3. Log Nordpool System Price



be the standard deviation of intra-day prices which can be written as 3.1.

$$V_d = \sqrt{\frac{1}{24}\sum_{i=1}^{24}(P_i - \bar{P})^2} \tag{3.1}$$

The log daily price volatility as represented by 3.1 is plotted for the nordpool system price and the Denmark east area price for 2001 in figure 4. Not surprisingly the daily standard deviation displays the same spikiness as the price level series - but there appears to be a relatively quick reversion to the mean and no obvious persistence. The Denmark East local area price seems to exhibit, on average, higher daily volatility 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.

A plot of the exponentially smoothed full series (figure 5) seems to show somewhat higher volatility in the later few years - especially for the Denmark east period. Significant linear and quadratic time trend in the regressions in the next section lends support to the existence of an upward trend in the volatility in the period studied.

I use autocorrelation (ACF) and partial autocorrelation functions (PACF) of the price series to help identify appropriate ARMA specification. The ACF and PACF of the system price are displayed in respectively figure 6 and 7. The ACF displays dissipating autocorrelations with a clear weekly pattern. The autocorrelations do not die-out

FIGURE 4. Log Volatility (st.dev) of Prices

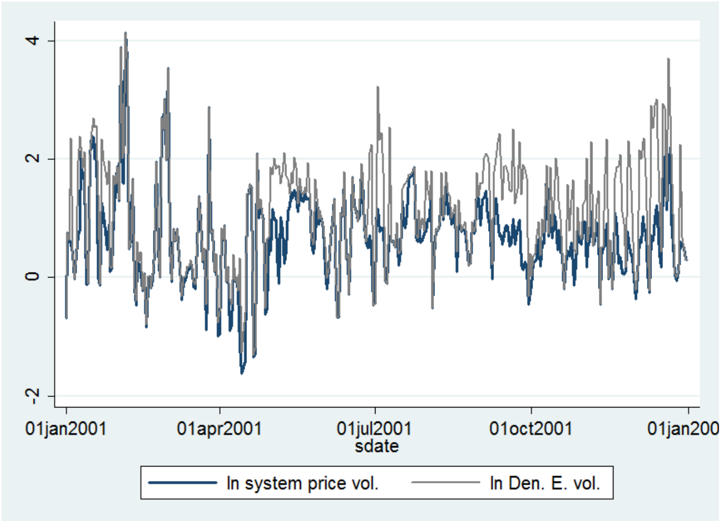
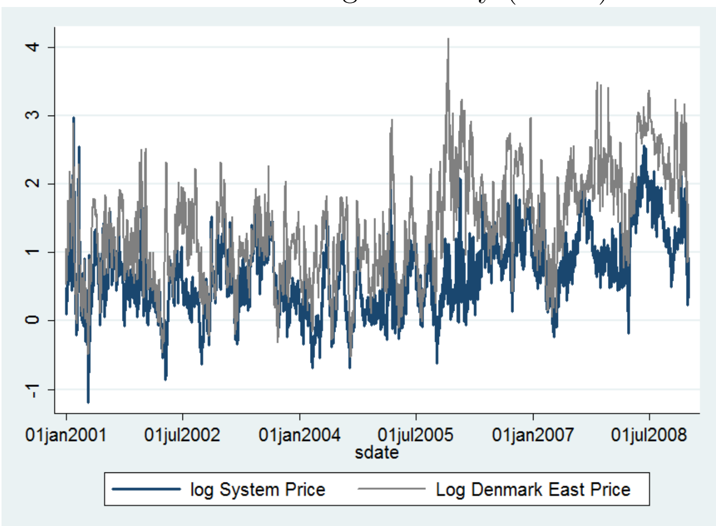


FIGURE 5. Smoothed Log Volatility (st.dev) of Prices



quickly exponentially however, thus a simple AR(1) model would probably not be sufficient. The PACF suggests however that an AR(2) or AR(3) model may be more appropriate along with a weekly moving average (MA) term.

The seasonality of the series can also be seen in the periodiogram, or the sample spectral density function, as in figure 8 where 3 years of data is used. The high densities in the very low frequencies indicates the presence of a rough yearly cycle [Enders, 2009]. The jumps in the higher frequencies relate to the weekly cycle ($\frac{1}{7} \approx .14$ $\frac{2}{7} \approx .29$, etc.)

FIGURE 6. Autocorrelation Function of System Price Volatility

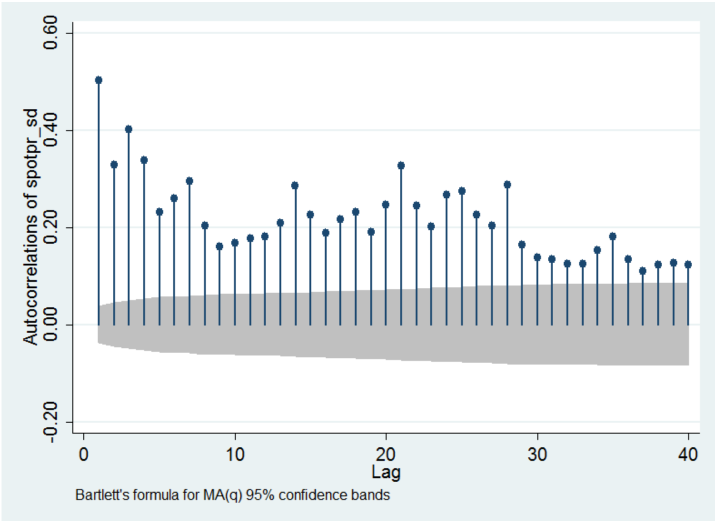
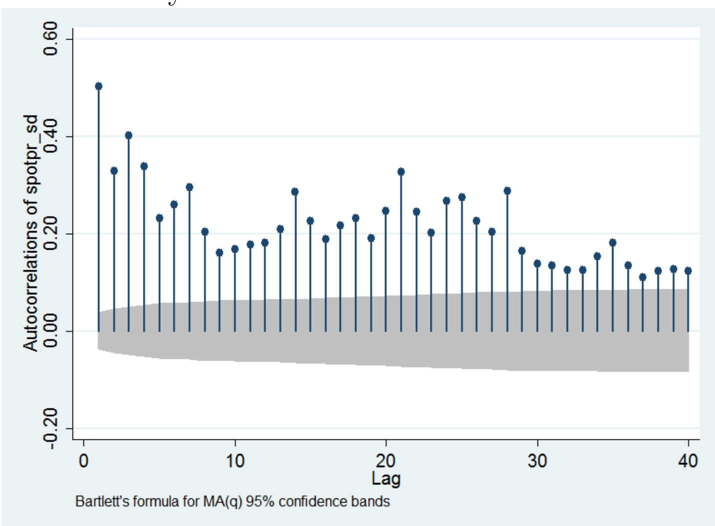


FIGURE 7. Partial Autocorrelation Function of System Price Volatility



The exogenous variable to be used in the models is the amount of wind power produced in Denmark east and Denmark west. Figure 9 shows one year of the exponentially smoothed log 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 10.

I will also run regressions using aggregated daily prices and then calculating volatility on a weekly and monthly basis. These volatility measures are again represented as standard deviations, calculated as

FIGURE 8. Periodogram of System Price

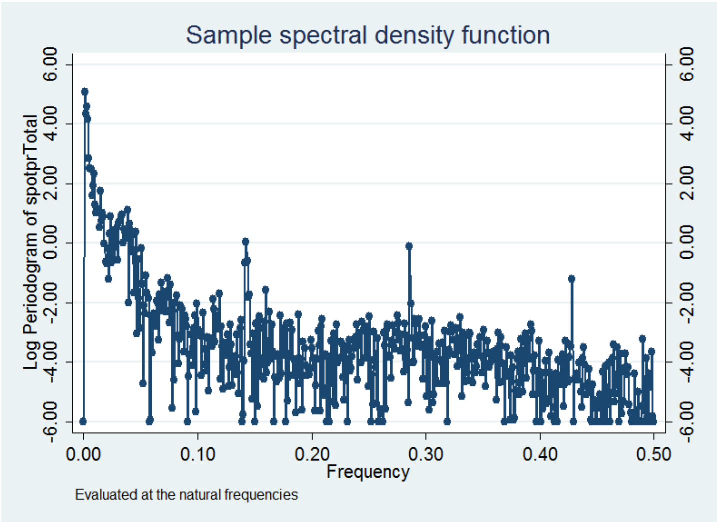
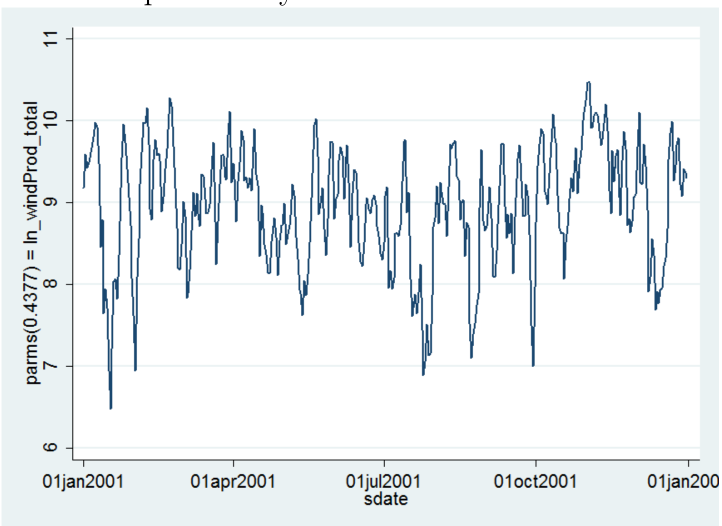


FIGURE 9. Exponentially Smoothed Wind Power in Denmark

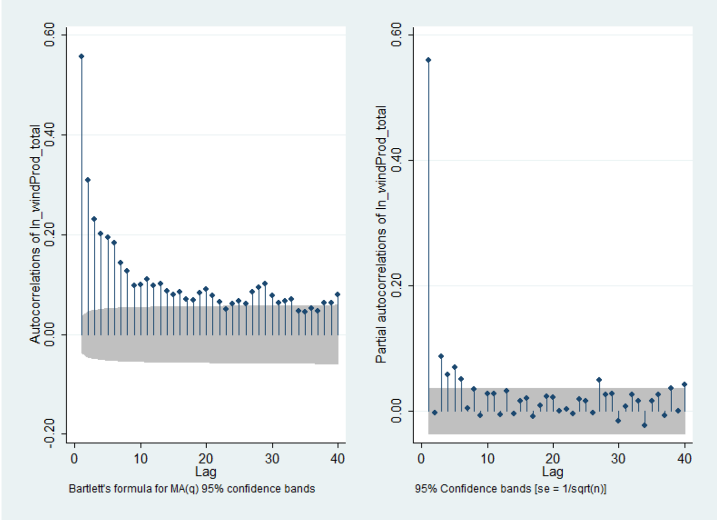


in 3.2. Monthly volatility is calculated similarly.

$$V_w = \sqrt{\frac{1}{7}\sum_{d=1}^{7}(P_d - \bar{P})^2} \tag{3.2}$$

Clearly, the number of observations is reduced by a factor of 7 for weekly volatility and a factor of approximately 30 for the monthly volatility thus I am left with 415 and 96 observations respectively. On

FIGURE 10. ACF and PACF of Wind Production Series



the plus side, the weekly seasonality that had to be modeled when using the daily volatility measures now disappears.

In order for the ARMAX 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. As mentioned, a visual inspection tends to suggest that all the series are stationary. I formally test the hypothesis with an augmented Dicky-Fuller test Hamilton [1994]. Ignoring the seasonal components for the moment, the daily System Price series can be adequately modeled as a distributed lag model with five lagged terms (ie an AR(5) model). 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 and monthly volatility are also shown to be stationary.

The other necessary assumption is that the 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 and since the marginal cost of production is near zero, the producer has little incentive to hold back production due to price signals. The wind power series used is almost certainly exogenous to prices.

Two possible exceptions to this assumption 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 [2] 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]).

Some of the regressions involve price and quantity variables of electricity - simultaneity thus becomes a potential issue. Unfortunately, finding instruments for the quantity variables (consumption/turnover) can be tricky. Weather variables that affect consumption (for instance temperature) are also likely to be correlated with supply from hydro- and wind- generation in the system. Thus they are not likely to be appropriate instruments. However, electricity demand is generally known as being very inelastic in the short run. Indeed in the regressions involving daily data, wind power appeared to be largely independent of load variables, however this does not hold in the weekly and monthly regressions. Luckily, independence of wind from demand side factors is not a necessary condition to get valid inference as long as wind power is exogenous.

4. Results

4.1. **System Price Volatility.** To establish the effect of wind power on the intraday price volatility I use a single equation transfer function (alternatively ARMAX) where the standard deviation of daily electricity prices are modeled as an ARMA process along with the exogenous wind power term.

Below is a table showing the results for the system price series. I present the coefficient of interest - wind power - for 5 specifications in table 1. In general, the various models tend to give a consistent estimate of an elasticity of around -.03 for the contemporaneous effect of wind power, a result which is significant at the 1% level for most of the models. The standard errors used are robust to heteroskedasticity,

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

but not necessarily to misspecification of the ARMA process [sta, 2007]

TABLE 1. ARMAX model results: Effect of Wind Power on System Price Volatility

	Model				
	a_1	a_2	a_3	a_4	a_5
ln(wind)	-.032	-.026	-.014^c	-.035	-.032
ln(wind)$_{t-1}$	.063	.034	.046	n/a	n/a
AIC	3325	3789	3662	3391	3378
BIC	3384	3837	3751	3427	3357

Coefficients significant at 1% level unless otherwise noted:
^{a} significant at 5% level, ^{c} not significantly different from zero

A summary of the specifications is presented in table 2. Generally, the specifications represent a trade-off between goodness-of-fit and parsimony. Dealing effectively with seasonality, which has a strong presence in power market data, was of special relevance. Including extra exogenous variables, while sacrificing parsimony, may also give a fuller picture of the causes of volatility. I use wald tests and information criterion to get the best fit for each specification.

TABLE 2. Model Specifications

Model	Specification
a_1	AR(4) SAR(3), D.O.W. fixed effects
a_2	AR(3) SAR(2) SD(1)
a_3	ARMA (2,2) SAR(2), D.O.W fixed effects
a_4	ARMA(2,1), SARIMA(0,1,1), D.O.W. ln_wind AR(1) residuals, quadratic time
a_5	a_4 + ln(load)

Both models a_1 and a_2 are distributed lag models - that is to say they rely entirely on autoregressive terms to model the dependent variable. Day of week (D.O.W) fixed-effects were also significant and improved fit in model a_1. In addition to a contemporaneous term for wind, a lagged term is also added to account for the autocorrelation in that series. The model can be written as in equation 4.1, where v_t and w_t represent the natural log of volatility (daily standard deviation) and the natural log of total daily wind power in Denmark. To try to account for potential non-linearities for the wind power, I included a squared term, but this turned out to be insignificant and thus I dropped it from the regression.

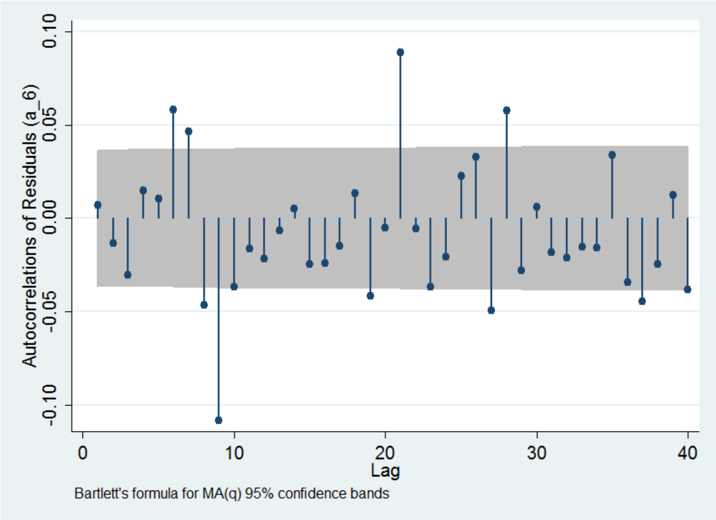
$$v_t = \sum_{i=1}^{3} \gamma_i v_{t-i} + \sum_{i=1}^{3} \gamma_{i7} v_{t-i7} + \phi_0 w_t + \phi_1 w_{t-1} + \epsilon_t (4.1)$$

Model a_2 drops the D.O.W. fixed effects and seasonally (weekly) differences all the terms. That is, the left hand becomes $v_t - v_{t-7}$, and correspondingly on the right hands side. Seasonal differencing produces a smaller (but still significant) estimated coefficient for wind power. The AIC and BIC (corrected for differencing) indicate a somewhat worse fit. Model a_3 uses a more parsimonious ARMA specification with two seasonal autoregressive terms. Here the estimate on the contemporaneous wind power term becomes insignificant while the lagged term remains positive and significant.

The estimate on the lagged wind power term should not be given any economic interpretation. That is, the estimate of .063 in model a_1, for instance, does *not* imply that an increase in wind power in one day will lead to increased price volatility in the next day. Instead the significant coefficient is most likely the result of the autoregressive character of the wind power series. Therefor, I also choose to use the residuals of an AR(1) regression on wind power as the exogenous variable in specifications a_4 and a_5, in effect filtering out the autoregession in the series. When this is done, the lagged wind term is no longer significant and the contemporaneous term is always estimated to be significant.

What models a_1 through a_3 have in common is that they generally fail to sufficiently account for the structural seasonality in the data. For instance, the autocorrelation function of the residuals from model a_3 is presented in figure 11. Notice the significant autocorrelation on the 7th lag, as well as the 21st and 28th - indicating that weekly seasonality remains in the data despite the inclusion of seasonal autoregressive and D.O.W. fixed effects. One possibility is that these relatively parsimonious models do not include enough structure to adequately model the power market data thus also making the seasonal factors ineffective.

FIGURE 11. Autocorrelation Function of Model a_3 Residuals



As suggested in the data section, it seems likely that the data has some yearly seasonality as well. For several of the models, I also added monthly fixed effects to try to account for this. However, these fixed effects turned out to be both individually and collectively insignificant. Other methods are also available to deal with seasonality of smaller frequencies, such as spectral (fourier) decomposition [Weron, 2006], though in general this seasonality doesn't seem likely to play a large role in the estimations of interest here.

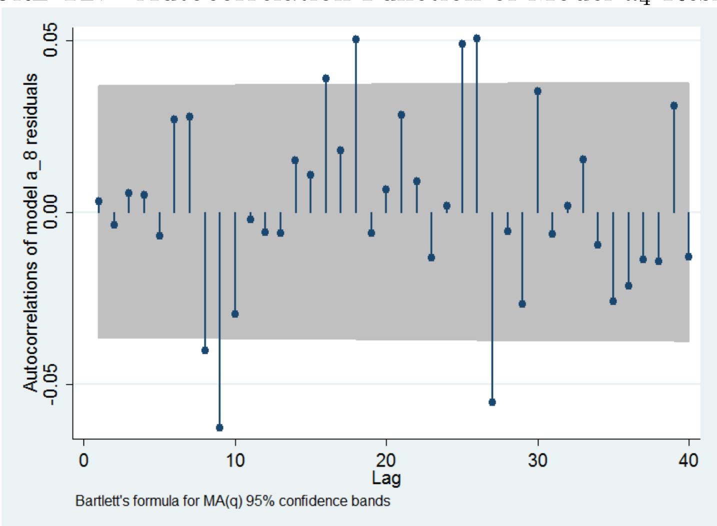
Models a_4 and a_5 are estimated by a two-step procedure. First, I regress log price volatility on a quadratic time trend and D.O.W. fixed effects. I then use the residuals of this regression to estimate a SARIMA (seasonal ARIMA) model. In both models an ARMA(2,1) dynamic was paired with a weekly differencing of the data as well as a SMA(1) term. a_5 also includes a term for the log volatility (standard deviation) of load in the nordpool market. Model a_5 can be represented by equation 4.2.

(4.2)

$$\begin{aligned}
p_t^v &= D + \alpha_1 t + \alpha_2 t^2 + e_t^v \\
\Delta_7 \hat{e}_t^v &= \gamma_1 \Delta_7 \hat{e}_{t-1}^v + \gamma_2 \Delta_7 \hat{e}_{t-2}^v + \phi \Delta_7 \hat{e}_t^w + \Delta_7 l_t + \beta_i \epsilon_{t-i} + \beta_1 \epsilon_{t-1} + \beta_7 \epsilon_{t-7} + \epsilon_t
\end{aligned}$$

Here D represents an array of D.O.W. fixed effects. e_t^w represents the estimated residuals of an AR(1) regression on wind power. l represents the log volatility of load in nordpool. This appears to increase the fit of the model slightly though figures 12 and 13 indicate that the autocorrelation function of the residuals appear to be almost identical. The autocorrelation functions and the partial autocorrelation functions from the latter two models do not indicate any obvious seasonality either. While some of the autocorrelations are shown as significant, this can be expected to happen by pure chance when many autocorrelations present [Enders, 2009]. A Portmanteau Q-test of the residuals however rejects the null hypothesis of white noise. Considering the relatively structured nature of power market price data, it should not be altogether surprising that a relatively simple ARMAX model with a few explanatory variables fails to filter out all but an serially uncorrelated innovation term.

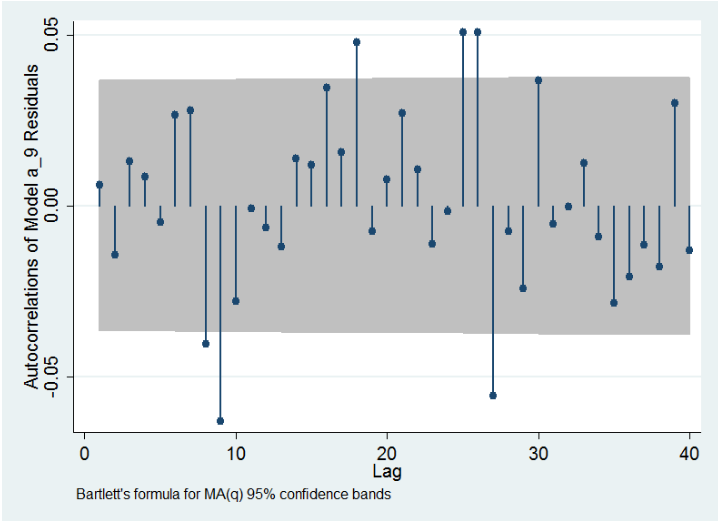
FIGURE 12. Autocorrelation Function of Model-a_4 Residuals



However, the models do seem to be able to account for a fair amount of the serial correlation as well as much of weekly seasonal patterns. More so, the estimates for the effect of wind power tend to be quite robust to specification. Taken together, the exogeneity of the wind data, the stationarity of the volatility series, and the robust results across specification make for a convincing case that wind power in Denmark has the effect of lowering the daily volatility in the nordpool system price with a elasticity of between -.03 and -.04.

4.2. **Area Price Volatility.** As mentioned earlier, the system price is not always the relevant price. Congestion in the transmission grid

FIGURE 13. Autocorrelation Function of Model-a_5 Residuals



leads to differing prices in the different areas in order to balance supply and demand. In the presence of these transmission constraints, it is reasonable to assume that the effect of wind power on volatility will be magnified. Table 3 shows the results from applying some of the model-specifications from the previous sub-section to data on Denmark's two price areas. The results tend to confirm the intuition of a higher magnitude effect of wind power on the local area prices in Denmark.

In the previous regressions, I used the total amount of daily wind power as the exogenous variable. That is, the results reflect how volatility in prices are effected by the total amount of wind. It may also be instructive to see how volatility in prices is affected by volatility in wind power. Thus in table 3 I also display results of the regressions where the daily standard deviation of wind power is used as the exogenous variable.

I used three different model specifications in this subsection, with the designations b_1, b_2 and b_3. As in specifications a_4 and a_5 The endogenous variable in all three of these specifications are De trended and I remove some of the seasonality by using the residuals of a regression with a quadratic time-term and day-of-week (DOW) fixed effects. Similarly for the exogenous wind power term, I use residuals of an autoregression to filter out the autoregressive terms of the series. When total daily wind power from Denmark east and Denmark west price areas is the exogenous variable, an AR(1) regression was sufficient for both series. However the daily standard deviation of wind power tended to have a more persistent autoregressive pattern. An AR(3) and AR(6) representations served to fit well the standard deviation of wind power

Table 3. ARMAX model results: Effect of Wind Power on Daily Danish Price Volatility

	Model					
	b_1		b_2		b_3	
	DKE	DKW	DKE	DKW	DKE	DKW
ln(D.E. Wind)	-.032^b	.014^c	-.032^b	-.017^c	-.031^b	.017^c
ln(D.W. Wind)	-.036^b	-.10	-.036^b	-.10	-.035	-.100
Total Wind	-.069	-.087	-.070	-.082	-.067	-.081
D.E. Wind Vol.	-.004^c	-.002^c	-.006^c	-.005^c	-.0024^c	-.004^c
D.W. Wind Vol.	-.038^a	-.051	-.038^b	-.04^a	-.043^a	-.043^a
Total Wind Vol.	-.039	-.045	-.039	-.041	-.041	-.042

Coefficients significant at 1% level unless otherwise noted:
^{a} significant at 5% level, ^{b} significant at 10% level
^{c} not significantly different from zero

in respectively Denmark west and Denmark east.

In table 3 each column represents the results from three distinct regressions. The first regression, represented by the first two rows, includes the log of wind power from both Denmark east (ln(D.E. Wind)) and Denmark west (ln(D.W. Wind)) as the exogenous regressors of interest. The second regression, represented by the third row, has total wind power as the regressor of interest. The next three rows, where the daily standard deviation of wind is used as the exogenous regressor, are otherwise identical.

Notice also that separate regressions are run for both the Denmark east (DKE) and Denmark west (DKW) price areas as the dependent variable.

Model b_1 is a distributed lag model with 4 AR terms and one SAR term (lag 7) of the dependent variable. Wind power - either in the form of separate terms from east and west, or total are the only other terms. In b_2 the data is modeled as ARMA(2,1) with SARIMA(0,1,1) terms. That is the data is differenced on a weekly basis and also includes a lag-7 ma term. b_3 keeps the ARMA and SARIMA form of b_2 and in addition adds in terms for log consumption in both Denmark east and west.

Once again, I get fairly consistent estimates across specification, though it is worth noting that in this set of regressions the models were considerably more similar to each other than in the previous section. The results indicate that wind power from the Denmark-east area has largely no role on the volatility in western Denmark but that it has an elasticitity of -.03 for the volatility in its own price area. Wind power from Denmark west on the other hand - where the large majority of wind power is located - has a substantial effect on the daily volatility in both Denmark east and west with significant elasticities of around -.035 and -.10.

When the exogenous variable is total amount of wind in both areas, the estimated elasticities are between -.067 to -.070 and and -.081 and -.087 for respectively Denmark east and Denmark west. It may at first seem surprising that this estimated elasticity is lower in magnitude than of the estimated elasticity of wind power from west Denmark. This is likely the combined result of the dominant share of wind power in western Denmark and the outsize effect that wind power has on the price area it is located in due to transmission constraints.

All the regressions in table 1 and the regressions in the first three rows of table 3 use the total amount of wind produced in a day. Yet this may not be the most relevant measure to look at. The main challenge of integrating large scale wind power in a grid is the variability of the source. Thus in the bottom half of table 3 the exogenous variable is the daily volatility (standard deviation) of wind power. The results indicate no discernible effect of variability of wind in Denmark east on price variability. On the other hand, daily variability of wind in west Denmark tends to decrease price volatility in both areas.

4.3. **Weekly and Monthly Volatility.** So far, I have looked exclusively at a fairly narrow measure of volatility - namely daily volatility. This section will show that the results from daily volatility do not carry over to volatility over longer time periods. In fact, while wind power tends to smooth the intraday (hourly) prices, it tends to increase the average (daily) price movements over weekly and monthly periods. In addition, the results suggest that the magnitude of the effect increases with the time scale used.

Table 4 shows the results from regressions using both measures of weekly and monthly volatility for prices in Denmark west, east and the Nordpool System Price. The exogenous variable here is standard deviation of total wind power in Denmark.

Table 4. ARMAX model results: Effect of Wind Power on Weekly and Monthly Volatility

	Weekly		Monthly	
	c_1	c_2	c_1	c_2
Denmark West	.165	.064[c]	.198[a]	.047[c]
Denmark East	.133	-.013[c]	.187	.339[c]
System Price	.061	-.049[c]	.12	-.10[c]

Coefficients significant at 1% level unless otherwise noted:
[a] significant at 5% level, [b] significant at 10% level
[c] not significantly different from zero
Weekly and Monthly Observations: 415, 96

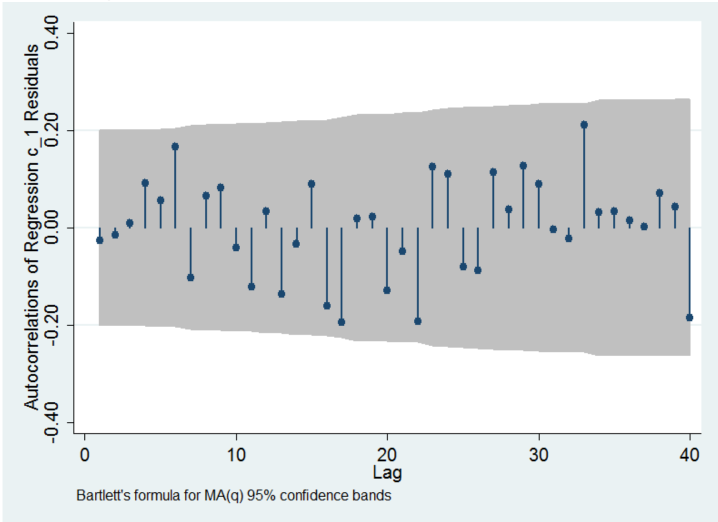
When aggregating the price data over weekly and monthly periods, many of the difficulties of dealing with seasonalities and other structure of the power market data disappears and a simple ARMA specifications seems to be sufficient. An ARMA(1,1) specification provided a good fit for all regressions on the weekly volatility as well as the regressions on monthly volatility of Denmark East prices and the Nordpool System Price. While an AR(1) model provided the best fit for the Denmark east monthly volatility regressions.

Table 4 shows two specifications: c_1 and c_2 where the only difference between them is that c_2 includes volatility of consumption as an added left hand side variable. For Denmark east and west, only volatility of consumption in their respective areas was significant in the regressions. For the regressions of the system price, I again used turnover as a proxy for consumption.

The ACF for the residuals of the c_1 regression for monthly volatility in Denmark West shows that the the simple ARMA specification adequately deals with the autocorrelation in the data. The residuals for the weekly regressions give a similar picture.

Considering the c_1 results first, all the regressions show highly significant and positive coefficients, with the greatest effect coming in the Denmark west area where the elasticity is estimated at .165 for the weekly volatility and .189 for the monthly volatility. This can be interpreted to mean that when volatility (standard deviation) of wind

FIGURE 14. Autocorrelation Function of c_1 System Price Regression



power doubles, then volatility in prices in Denmark west would increase by 16.5% on a weekly basis and 19.8% on a monthly basis. Even the estimated elasticities on the system price are both statistically and economically significant.

However, when I add the measures of consumption volatility, all the coefficients become insignificant. But, I argue that the c_2 coefficients of interest are likely biased downward due to simultaneity in this case and that there is good reason to believe that the coefficients of interest in c_1 can be considered valid.

Recall that in the previous discussion on daily volatility that the addition of measures of consumption did not significantly change the coefficients on wind power. In other words, in this case, wind power and consumption variables are independent. This in turn can be attributed to the low short run elasticity of power markets. What these regressions demonstrate is that when we stretch the time period from day to week and month, simultaneity becomes a serious issue and can bias supply side coefficients like wind power. In other words, consumption does not react to price fluctuations in the short term on the scale of what is caused by wind power. However, fluctuations in price over longer periods such as weeks and months caused by wind power *does* elicit a significant reaction in consumption. For instance, a large energy-intensive manufacturer may choose to increase production in a particularly windy week where electricity prices have been pressed down. Conversely, that same producer may have contract with the electricity provider to cut production and power-production in a wind-still week where supply is tight. Since I am interested in the effect of wind power *holding all other things equal* including consumption, the correct estimate is from the regression that does not include consumption.

Luckily, the validity of the c_1 regressions does not require the independence of wind power from other possibly endogenous variables. Instead, wind power needs only to be exogenous. The reasoning for assuming that wind power is exogenous - passive generation and near-zero marginal costs - do not change when widening the window to weekly and monthly volatility.

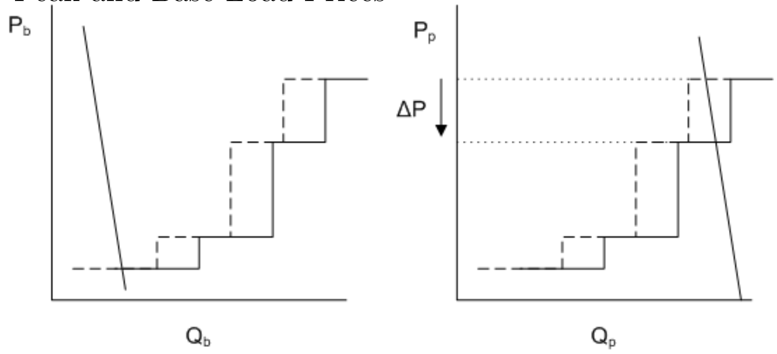
5. Discussion and Conclusion

The main finding of this paper is that wind power has both a statistically and economically significant effect on volatility, but that the sign and magnitude of this volatility is dependent on the time window studied. Intraday volatility is reduced while volatility of averaged daily prices are increased.

The mechanism for how wind power production reduces intraday volatility is likely due to an out sized effect of wind power on peak load times. In a competitive electricity market, the market price for any period is set by the marginal cost of the m̈arginalg̈eneration technology. When wind is added to the mix, it can be seen as a stochastic shifting of the supply schedule to the right. If the supply schedule is steeper at peak times, then shifts in the supply curve would lead to larger price decreases during the peak times. This idea is illustrated in figure x, where a shift of the supply schedule to the right has no effect on the base-load price, P_b, while having a significant effect on the peak-load price, P_p.

In the Nordic system, hydro, nuclear and coal generally make up the base-load capacity. The marginal costs of these generation technologies are all relatively low, thus it is likely that the left-end of the supply schedule is relatively flat. More so, there is less likely to be congestion during non-peak times, allowing for import of cheaper base-load energy from neighboring countries. This availability of imported energy, also likely keeps the left-end of the supply schedule relatively flat in Denmark. However, during peak load times, Denmark may be more dependent on its gas-fired generation which has significantly higher marginal running costs.

Figure 15. Figure 3: Effect of Wind Production on Peak and Base Load Prices



One important implication of volatility is the effect on distribution of rents to the different generation technologies. The reduction in intraday volatility means that generation used to balance supply on a daily basis - most importantly stand-by natural gas generation will on average be able to capture less of the rent and will be less profitable. In the nordpool market, standby and balancing power are compensated in markets and agreements outside of the normal spot (day-ahead) and hour-ahead markets. With increased wind power penetration in the system, use of such compensation schemes may need to be increased correspondingly.

As mentioned in the introduction, the increased volatility in longer time windows reflects the challenges of adding large amounts of intermittent wind. In the winter of 2002-03 a combination of very little rainfall in Norway and Sweden as well as cold and wind-still weather led to periods of very high electricity prices. Yet, the entire Nordic area avoided any serious disruption in power supply, thanks in part due to the activation of mothballed coal plants in Denmark. See Olsen Olsen et al. [2006], Amundsen and Bergman Amundsen and Bergman [2006] or Fehr et all von der Fehr et al. [2005] for a more in depth description. This episode demonstrated the flexibility of the nordpool market even in the face of quite extreme conditions. But it also shows the importance of having large amounts of standby power in a electricity system dominated by hydro and wind generation. This should be a particular concern for countries that build out wind generation to meet growing consumption. In this case, significant amounts of backup power would need to be built, perhaps significantly worsening the economic feasibility of wind power.

On the other hand, the combination of wind production pressing down prices and increasing volatility over longer periods in the entire nordpool system could be a boon for hydro power producers. Assuming sufficient transfer capacity, hydro power stations can shut off (or in some cases, even pump water up hill) at times of low prices, thus preserving or increasing magazine levels. They can then generate when the prices increase. In effect, the the hydro producers (in Norway and Sweden) are able to capture some of the rent created by wind power, generously subsidized by the people of Denmark. Keep in mind, that this regression accounts only for the wind power produced in Denmark. The effect of the growing amounts of wind in Sweden and Finland are not included, assuming that correlations is quite low between wind in the different areas (which there is good grounds to believe Nor [2008]) the total effect of wind is even greater and the corresponding balancing role (and profiteering) of hydro power even greater. As mentioned at least one of the simulation studies suggests that wind power, by reducing average prices, would reduce profitability of hydro stations. I believe this argument needs a closer evaluation.

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