# Increasing or diversifying risk? Tail correlations, transmission flows and prices across wind power areas

Johannes Mauritzen*
BI Norwegian Business School
and
NHH Norwegian School of Economics
johannes.mauritzen@bi.no
http://jmaurit.github.io

Genaro Sucarrat
BI Norwegian Business School
genaro.sucarrat@bi.no
http://www.sucarrat.net

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**Abstract**

As wind power costs have declined, capacity has grown quickly, often times in adjacent areas. Price and volatility risk from wind power's intermittency can be mitigated through geographic diversification and transmission. But wind power generation has a fat-tailed and right-skewed distribution. In this article we aim to explore how geographic diversification of wind power and the effect of wind power on market prices varies across the distribution of production. In a case study from Denmark and Sweden, we show that during tail-end production periods, correlations between areas increases substantially as does congestion in the transmission network. This leads to highly non-linear price effects of wind power. The marginal effect of wind power on the local prices is shown to be substantially higher when wind power production is in the 90th decile. The research has important implications for valuation models of wind power projects and for operations of electricity markets with high penetrations of wind power.

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*Corresponding author

# 1 Introduction

Before wind power became a mature technology, generation tended to be built out in countries and regions that provided financial support, such as Denmark and Northern Germany in Europe and California in the United States. This often meant that wind power was geographically concentrated.

Wind power costs have come down dramatically in the previous decade, and onshore wind power is often competitive with traditional generation in many areas (Trancik, 2015; Campisi et al.; Williams et al., 2017; Wiser et al., 2019, 2020). This has meant that wind power capacity has been built up in many more locales, often in countries or regions adjacent to each other. Given available transmission capacity, such geographic dispersion can act as a form of diversification: Mitigating the risks that stem from wind power's intermittency (Grothe and Schnieders, 2011; Simoes et al., 2017; Novacheck and Johnson, 2017; Katzenstein et al., 2010; Roques et al., 2010; Schmalensee, 2016; Green et al., 2016). When there is less wind power in one place, power can be transferred from a neighboring area where the wind is blowing.

However, experience from other asset classes–both real and financial–have shown that risks that appear to be diversified away in normal times, may show strong correlations during extreme events (Hartmann et al., 2004; Ye et al., 2017). In the context of electricity markets with high penetrations of wind power, the risk that has been most explored is the systemic risk that may come from periods of low wind power generation highly correlated across a wide geographic area leading to a shortfall of generation relative to load. Yet there is also a risk of too much wind generation. If wind is highly correlated across areas at high production times, then it could have the effect of driving down the price towards the short-run marginal cost of wind power–near zero. This price risk is born by wind power producers, but also owners of other generation assets that face lower-than-expected prices and more price volatility. There is also a risk born by the power system as a whole, as excess generation can lead to increased balancing costs and expensive curtailment. The extra uncertainty around prices and electricity market operations can lead to higher cost of capital, with adverse effects on further investments in renewable energy generation.

Analyses of the effect of wind power, and in general intermittent generation on power markets and prices have become important subjects within energy economics. Increasing penetrations of renewable generation sources can fundamentally change the price formation process and risk characteristics of wholesale electricity markets. For example, power prices driven by commodity markets will tend to be random walks, while markets dominated by renewables will tend to display mean reversion and trend stationarity (Gianfreda and Bunn, 2018). Correlations between production from renewable sources and power prices may also increase with higher renewable penetrations (Ernstsen and Boomsma, 2018).

A related area of research has been devising valuation models of wind power that take into account the special characteristics of the generation technology and its effects on market prices and volatility. Many of these analyses take a real-options approach, where correctly specifying uncertainty becomes a particularly important factor in the investment decision and its timing (Tseng and Barz, 2002; Thompson et al., 2004; Munoz et al., 2011; Ernstsen and Boomsma, 2018).

Many analyses of wind power's effects on power prices use time series techniques to try to estimate a marginal average effect in electricity markets: Gelabert et al. (2011) for Spain, Ketterer (2014) and

Paraschiv et al. (2014) for Germany, and Mulder and Scholtens (2013) for the Netherlands. Wen et al. (2020) takes an explicitly spatial econometric approach to estimating the effects of wind on nodal prices in the New Zealand market, but still relies on average marginal estimates. The results of such statistical models have become important inputs in the models of transmission system operators (TSO), and wind power developers who seek to make accurate valuations of proposed projects.

But we argue that the inference from such models is incomplete. Point estimates that indicate average marginal effects are most useful when a distribution is approximately normal, with few outliers and with most of the probability mass located near the mean value. But wind power is not well approximated by a normal distribution. Instead, production tends to be better approximated by distributions with right-skewness and "fat tails" where periods of large positive production, far removed from the median value of the distribution, can be expected to happen relatively frequently. Recent analytical analyses of the wind power valuation problem, such as Ernstsen and Boomsma (2018) therefore tend to use fat-tailed and right-skewed distributions like the Weibull distribution to model wind power production. Analysis of the effects of wind power on prices that use more flexible, non-parametric, modelling such as Rivard and Yatchew (2016) for Ontario and Jonsson et al. (2010) for Denmark, tend to find non-linear effects in periods of high production. We extend this literature by devising a time-series econometric model that allows the estimates of the effect of wind power on prices to vary by decile of production.

The right-skewness and fat-tails of wind power distributions and their spatial correlation are important considerations in valuation models of wind power. Gonzalez-Pedraz et al. (2014) show how standard methods used in energy markets that tend to ignore or minimize tail behavior will tend to substantially underestimate the risk of a portfolio of generation technologies. Elberg and Hagspiel (2015) develop a stochastic wind turbine valuation model that takes into account the spatial dependence of a given wind power plant and the aggregate wind power production. They note a pronounced “upper-tail dependence”– that is that correlations increase markedly at periods of especially high production, and that this can lead to adverse effects on revenue. A model with purely linear dependence would as a consequence tend to over-value a wind power farm. The spatial character of wind power can also interact with weaknesses in the electricity market structure. Bjørndal et al. (2018) note that zonal pricing, as exists in the Nordic markets, fails to include enough locational price signals and can therefore lead to excess transmission flows due to wind power.

While it has long been acknowledged that intermittent generation will tend to be able to sell electricity at on average lower prices than dispatchable generators (Joskow, 2011), Hirth (2013) and Schmalensee (2016) point out that intermittent generation will also tend to consistently diverge from average electricity prices due to the correlations between production and prices. Hirth (2013) devises a statistic he calls a value factor to estimate this divergence. A value factor of 1 represents a situation where intermittent assets are able to sell electricity at the average price on the market. Schmalensee (2016) finds that solar power in many of the areas of the US have a value factor slightly higher than 1, however wind power tends to have value factors somewhat below 1, indicating that production tends to be correlated with low-price periods. This article contributes to this literature, showing how wind power not only is correlated with low prices, but at high penetrations and during high-production periods, can also cause prices to drop further, leading to even lower value factors.

In this article we study data from Denmark and Sweden: Two countries with large wind power penetrations, which are connected through both large physical transmission capacity as well as through the common Nordic electricity market. We use hourly data from 2016 and 2017 on wind power production, electricity prices, transmission capacities and flows. We particularly focus on the eastern price area in Denmark, called DK2, consisting of the island of Zealand, where the Copenhagen metropolitan area is located. This price area lies between and has large transmission links to both the western Danish area, which contains large amounts of wind, and the southernmost Swedish price area, which also has a high penetration of wind power.

We first present some descriptive evidence that suggests that for much of the distribution of wind power generation, geographic dispersion of wind power can have a diversifying effect. Correlations between wind power production–even in in adjacent areas–are relatively weak.

However, a marked difference appears in the 90th decile of the distribution of wind power production. Wind power production at the highest deciles in a given price area are strongly correlated with wind power production in adjacent areas. This suggests that the pattern of power flow, congestion in the network, and marginal price effects may be substantially different in these tail periods compared to average marginal effects.

To more formally explore the patterns of wind power distribution on prices and flows, we develop a flexible but also simple and robust methodology: A dynamic decile group model. We decompose the price and flow variables that serve as our dependent variable into deterministic and stochastic components. Then, instead of estimating an average marginal effect of wind power, we allow the effect of wind to vary by decile of production.

Our modeling reveals wind power's nuanced effects on pricing and exchange on the electricity market. Wind produced in DK2 at low deciles tends to have little to no effect on prices. Instead, the main effect of wind power in this area is a linear effect on net exchange towards the Swedish price area, which in turn is connected to the flexible hydro power in the Swedish northern price areas. This interaction between wind power in Denmark and transmission to neighboring hydropower areas is consistent with analysis by Green and Vasilakos (2012) and Mauritzen (2013).

However, at the highest decile, when wind power is highly correlated across areas and there is a high probability of congestion in the transmission network, wind power tends to have an out-sized effect on prices.

The results from this article are in some ways particular to the geography, generation and transmission network of the Nordic market. But the lessons from the case study are broader. The numerous statistical models of the effect of wind power on market prices that attempt to estimate an average marginal effect, poorly capture the underlying dynamics of wind power's effect on a power market. In turn, the estimates from these models may serve as flawed inputs in models of electricity market operations and wind power valuation.

There are also implications for policy and planning. As noted by Schmalensee (2016) and Green et al. (2016), many incentive schemes internationally tend to lead to a sub-optimal geographic investment decisions. For example, in the US, one of the main drivers of renewable energy investments are state-level generation mandates called Renewable Portfolio Standards (Greenstone and Nath, 2020). Likewise, many European incentive schemes often favor local investments. This article adds support to the argument that increased focus needs to go towards devising markets and policies that lead to more optimal siting decisions and greater geographic dispersion.

In summary, this article contributes to the literature on investment and integration of wind power in power markets in several ways: 1.) We provide evidence for geographic diversification of wind power production at moderate levels of production in the areas of the Nordic market with the highest penetrations of wind power. 2.) We provide evidence that this diversifying effect fails to hold at the highest quantiles of production when wind power production becomes highly correlated across adjacent areas. 3.) We devise a novel econometric model that takes into account the dynamics and seasonality in the power market time series while allowing the effects of wind power to vary over the distribution of production. 4.) We add support to findings of Rivard and Yatchew (2016) and Jonsson et al. (2010) of a disproportionately stronger effect of wind power on prices at the highest quantiles of production and extend these findings to show that these results are highly dependent on the pattern of transmission and congestion in the system.

In the next section we present a short overview of the Nordic Electricity Market and introduce our data sources. In section three, we present some descriptive evidence for both geographic diversification at moderate wind power production levels as well as markedly increased correlations across areas at the highest quantiles of wind power production. In the fourth section we introduce the dynamic decile econometric model, and present results for the effects of wind power on both prices and power flow. We conclude with a discussion of the implications of the findings and future avenues of research.

# 2 The Nordic Electricity Market and Data

Data consists of hourly observations from the beginning of 2016 through December of 2017 from the Nordic Electricity Market, Nord Pool. The data is openly available from the website of the Nord Pool Group[1]. A cleaned and formatted data set is available upon request.

We use the prices that are set on the day-ahead market of Nord Pool. These prices are established through an auction mechanism where producers and wholesale consumers submit supply and demand schedules by noon the day ahead of delivery. These are aggregated and an unconstrained system price is set that clears the market assuming no congestion between the price areas.

When congestion occurs between price areas, the markets become decoupled with prices being set in each market until the market clears in both price areas with the transmission constraint met. Importantly, flow on the transmission interconnectors will always flow from low price areas to high price areas.

For simplicity and tractability, we limit our analysis to three price areas in the Nordic market: The two Danish price areas, DK1 and DK2, and the southernmost Swedish price area, SE4. A snapshot of

[1] https://www.nordpoolgroup.com/historical-market-data/

Figure 1: Area power prices in southern Sweden (SE4), eastern Denmark (DK1) and western Denmark (DK2). Data from Nord Pool Group.

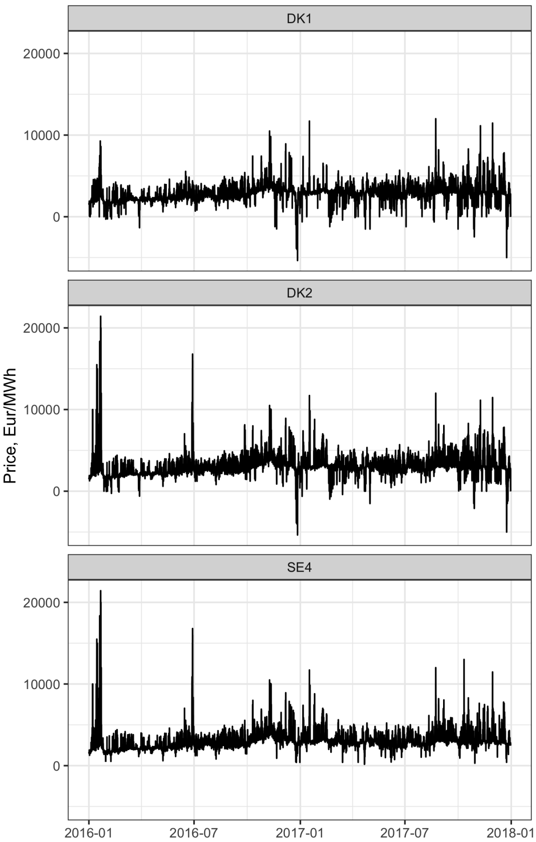
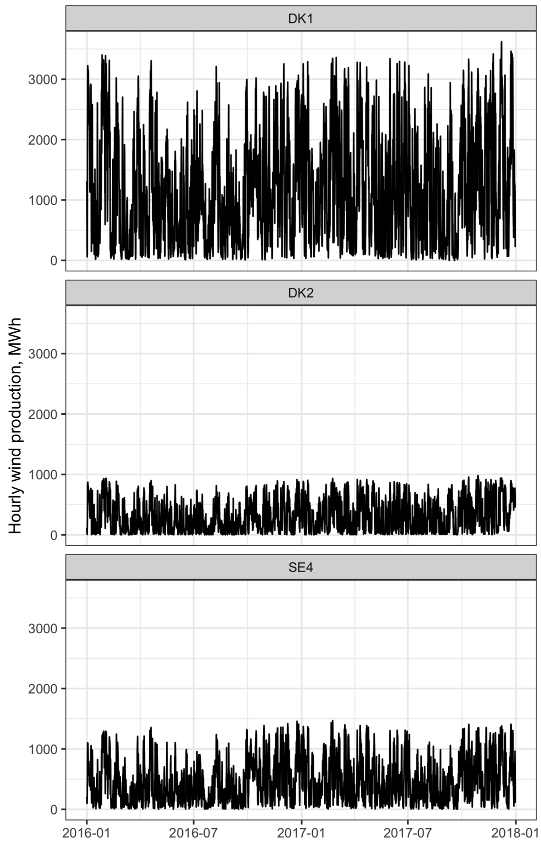



Figure 2: Wind power production in southern Sweden (SE4), eastern Denmark (DK1) and western Denmark (DK2). Data from Nord Pool Group.



these price areas from the exchange, Nord Pool Spot, is shown in figure 3. These price areas were chosen strategically. All three contain large penetrations of wind power and none contain significant hydro power generation, which provides large amounts of flexibility to energy systems. Instead, most of the generation in these areas that is not wind power comes from thermal plants, either nuclear (in southern Sweden) or gas and combined heat and power plants (Denmark). Figure 1 shows price series for SE4, DK1 and DK2.

The available transmission capacity between price areas is established by the transmission system operators (TSO) and are also announced a day before delivery.

Nord Pool also runs an intra-day market called Elbas, where power can be traded bilaterally up to an hour before delivery and producers and consumers can make up for shortfalls or surpluses from the day-ahead market. We do not analyse data from the intraday market in this paper.

Nord Pool publishes two series for wind power in the different price areas: Predicted wind power from a day-ahead based on predictive models from the transmission system operator, and realized wind power. We use actual realized wind power in this article. Figure 2 shows the time series of wind power from the three relevant price areas.

Table 1 gives some summary statistics for the three price areas over the period studied. Notice that the mean wind power production in the DK1 area is nearly four times that of the neighboring DK2 area and nearly three times that of the SE4 area. The average price is also about 5 percent lower in the DK1 area compared to the DK2 and SE4. However, the volatility of prices, measured by the standard deviation, is highest in the DK2 area. Both DK1 and SE4 areas have direct interconnections to flexible hydropower generation in Norway and the Northern price areas of Sweden. The DK2 price area, on the other hand, has no direct interconnectors to a hydropower area, and power must flow through one of the neighboring price areas. The unique geography of the DK2 price area: An area with significant wind power, sandwiched between two even bigger wind power areas, and no direct connection to hydro power, makes it a particularly interesting case study.

Table 1: Descriptive statistics from the three price areas studied

| | Eastern Denmark | Western Denmark | Southern Sweden |
|---|---|---|---|
| Price area | DK1 | DK2 | SE4 |
| Mean hourly wind power (MWh) | 1159 | 305 | 467 |
| Mean price (EUR/MWh) | 3085 | 3068 | 1224 |
| St. dev price | 1036 | 1224 | 1096 |

# 3 Wind power production: Distributions and geographic correlations

Figure 4 shows correlation coefficients between Danish and Swedish price areas. The areas are ordered according to geographic location. In general, correlations across areas of wind power production declines with distance. Correlations between adjacent areas still vary considerably, however. For example, correlation between wind power in the two Danish areas, DK1 and DK2 have a considerably higher correlation

Figure 3: A snapshot of the southern portion of the Nordic electricity market. Denmark is divided into two price areas, DK1 and DK2. SE4 is the southernmost Swedish price area, that contains the majority of Swedish wind power production. Source: Nord Pool Group

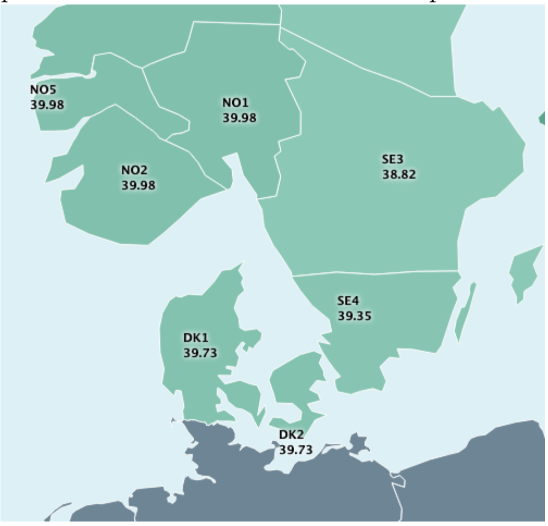
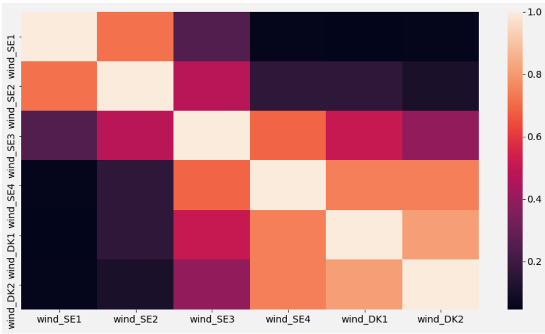



Figure 4: The figure shows a heat map illustrating the correlations between wind power production between price areas in Denmark and Sweden, ordered from areas that are adjacent to those farthest away. Correlations quickly decline with distance.




coefficient than between wind power in SE2 and SE3.

Correlation coefficients, as well as coefficients on simple regression models are calculated as average marginal effects. For processes that are well described by a normal distribution, the average effect is often times a good summary statistic as the tail of the distribution is thin, meaning that most realizations of the process happen close to the median value.

Wind power aggregated over a geographic area tends to be better approximated by a distribution with right-skewness and excess kurtosis ("fat tails"), such as a Weibull distribution (Carlin and Haslett, 1982). Figure 5 shows the empirical density of wind power in the DK2 area overlapped with fitted theoretical densities from the Weibull distribution and normal distribution. The vertical dotted lines represent the sample median, mean and 90th percentile of the wind data from DK2. The empirical density clearly has substantially more of its weight on the tail compared to what a half-normal distribution might suggest. The 90th percentile of observations lies far from the mean.

The fat tail of wind power distributions suggests that estimates of mean marginal effects may provide a poor summary of the effects of wind power over the full distribution. The idea of looking at average correlations between wind power areas may also be incomplete. Figure 6 shows a scatter plot of wind power in the DK2 area plotted against the wind power generated in the SE4 area. The colors represent net exchange between DK2 and SE4, with a positive value indicating net import to DK2. While there appears to be a clear correlation between wind power in the two neighboring regions for most of the range of values, there is a substantial amount of spread. At outer values of the range, however, there seems to be a bunching of values: High values of wind power in DK2 appear to be more highly correlated with high values in SE4. Visually, there also appears to be a shift in the pattern of exchange between the areas as wind power increases.

Figure 5: The figure shows the empirical density (green) of wind power. Wind power production summed over an area can be approximated by a distribution with right-skewness, such as the Weibull distribution (solid line). Large values far from the mean and median happen often relative to a half-normal distribution (dotted line). The vertical dotted lines represent the mean, median and 90th percentile of the empirical wind power distribution. The 90th percentile of observations can be seen to be far from the median and mean values.

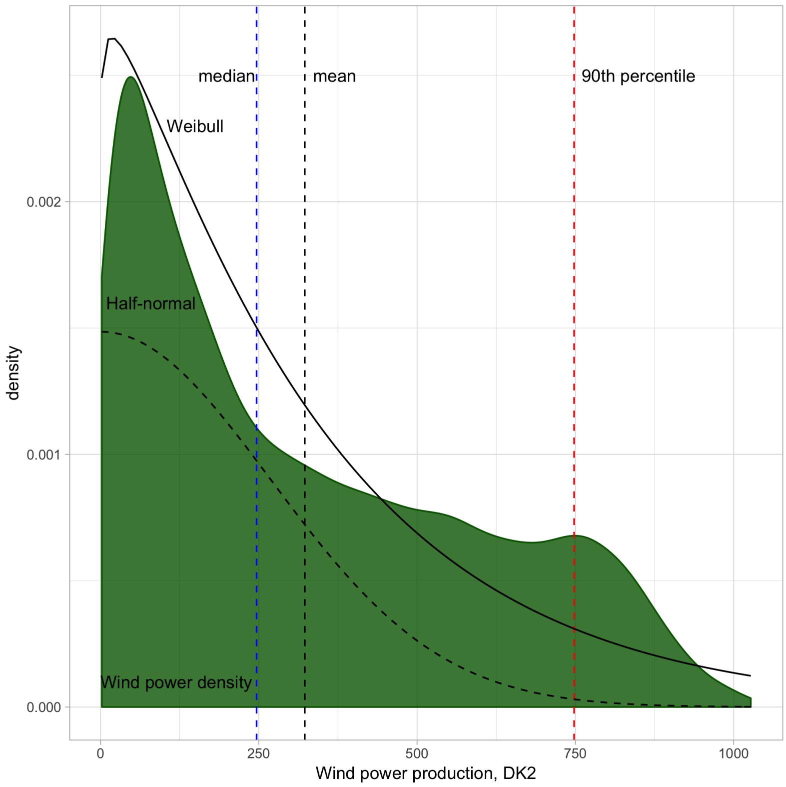


Figure 6: The left figure shows a scatter plot of wind power in the DK2 and SE4 price areas. The correlation of wind power production in DK2 and SE4 appears to increase during periods of peak wind power.

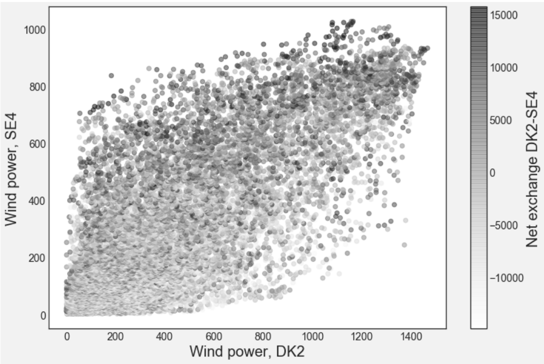
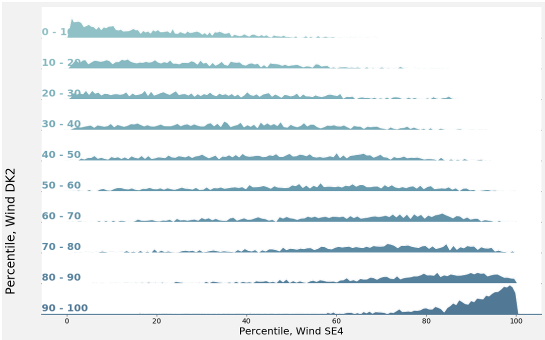



Figure 7: The right figure shows the distribution of wind power production for area DK2 conditional on the deciles of wind power in SE4. While most deciles show considerable dispersion, at the 90th percentile, the distribution is clustered in the far end, indicating a high degree of correlation at the upper decile.




The impression of higher correlations at the higher end of the range of wind power values is confirmed by figure 7. The figure shows densities of wind power production in SE4, conditional on deciles of wind power production in DK2. Most deciles are characterized by a high variance, supporting the idea of geographic diversification, consistent with previous research (Grothe and Schnieders, 2011; Simoes et al., 2017). However, the 90th decile appears substantially different. Here, the density is much more compact, suggesting a higher level of correlation between wind power in the two areas. In other words, high wind power in DK2 is strongly correlated with high wind power in SE4. This distinction between geographic diversification at mean production periods versus peak wind power production periods has not been widely explored in the literature.

The reasons for the changing correlations are related to the meteorological factors that decide wind speed and direction over a certain area (Carlin and Haslett, 1982), the details of which are well beyond the scope of this article. Intuitively, periods of high wind speed associated with weather fronts of high or low pressure moving through an area will tend to have a more uniform effect on wind speeds over a large swath of area. On the other hand, periods of moderate or low wind speed will vary more at the local level.

# 4 Dynamic decile group model

The preceding section suggests that relying on average marginal effects to summarize the effects of wind power on prices and other aspects of an electricity market can give an incomplete and perhaps misleading picture. The distribution of wind power is not well approximated by a normal distribution, and values far from the median are relatively common. More so, wind power correlations between areas appear to increase markedly in the top decile of production.

In this section, we devise an alternative methodology–a dynamic decile model–to estimate and explore price effects of wind power across deciles. The methodology is simple but also flexible and robust. In

Figure 8: The residuals of the price series for areas DK1, DK2 and SE4 after regressing on the deterministic components consisting of month, hour of day and day-of-week.

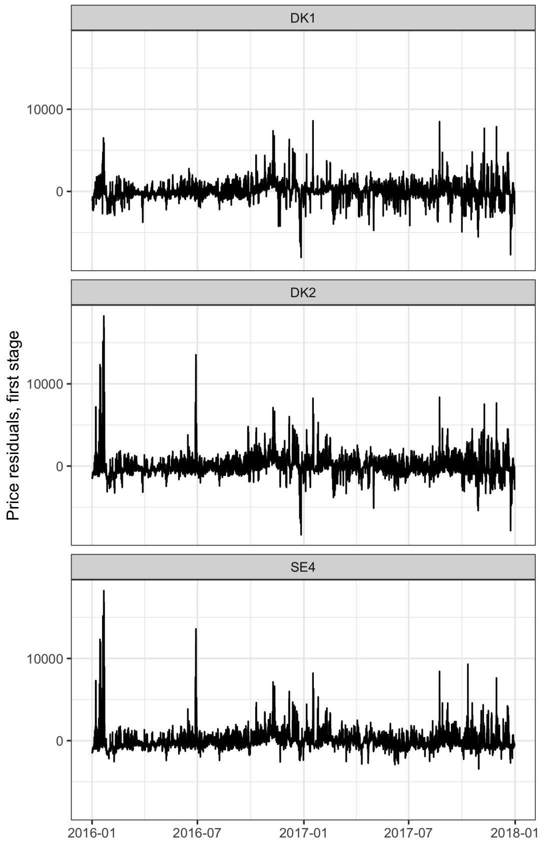
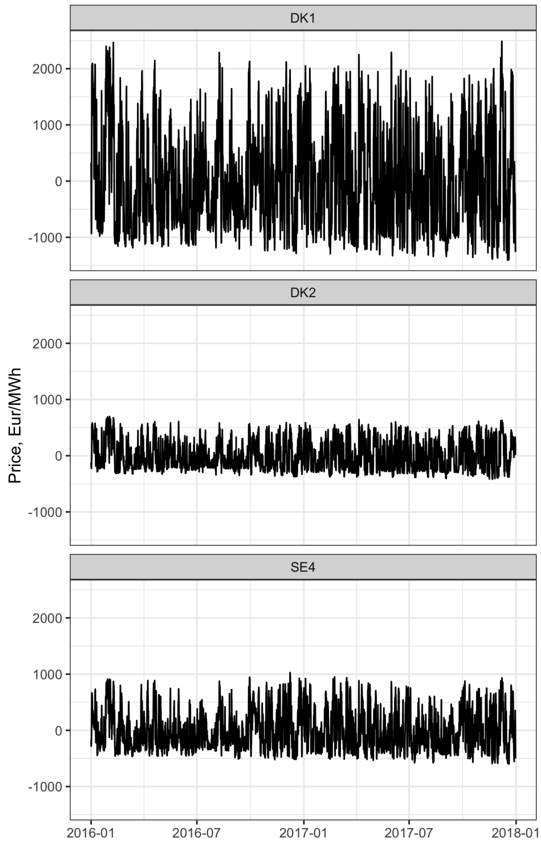



Figure 9: The residuals of the wind power series for areas DK1, DK2 and SE4 after regressing on the deterministic components consisting of month and hour of day.




specifying effects across a conditional distribution, the model is similar to quantile regression (Koenker and Bassett, 1978). However, quantile regression has primarily, though not exclusively, been applied to cross-sectional and panel data and it is the dependent variable that is generally decomposed into quantiles. Our methodology has the benefit of being easy to implement and interpret in a time series context and with standard time series software.

The model is estimated in two stages. In the first stage, we decompose the stochastic and deterministic components of the series, $p_{it}$, for price in area $i$ at time $t$ (with an hourly frequency) as shown in equation 1. In this equation, the deterministic components associated with month-of-year effects, *month*, hourly effects, *hour* and day-of-week effects, *dow* are filtered out, leaving the stochastic component, $u^p_{it}$.

$$p_{it} = \alpha + \mathbf{month} + \mathbf{hour} + \mathbf{dow} + u^p_{it} \tag{1}$$

The estimated residuals for each of the three price areas is shown in figure 8.

In the second stage of the estimation, the residuals, $u^p_{it}$ are fitted to a dynamic equation in addition to a set of binary decile indicators, $I^w_{it,1}, I^w_{it,2}, \dots I^w_{it,10}$. These wind decile indicators are based on the wind power series from the three price areas, DK1, DK2 and SE4. Deterministic components from the wind

Figure 10: The stochastic component (residuals from the deterministic regression) of the wind power series for the DK2 area is shown mapped into decile categories.

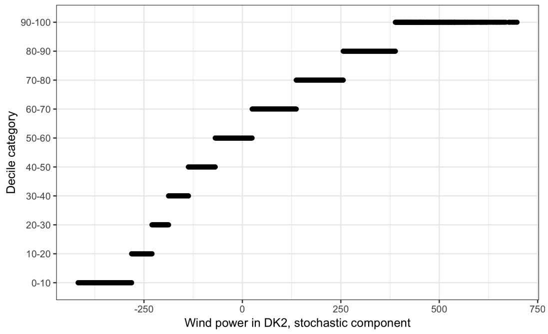
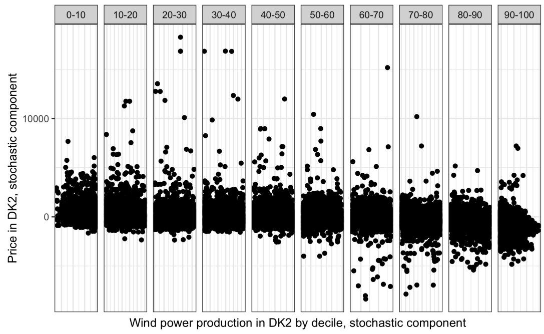



Figure 11: Prices verses wind power production, by decile of wind power in the DK2 price area.




power series consisting of daily and monthly variation are filtered out by way of estimating equation 2 with OLS. The resulting residuals, $u^w_{it}$, consists of the stochastic portion of the series. A Dickey-Fuller test rejects the null hypothesis of unit root for the series. The series of wind power residuals are shown in figure 9.

$$wind_{it} = \alpha + \mathbf{month} + \mathbf{hour} + u^w_{it} \tag{2}$$

We then estimate the empirical deciles of the wind power residuals for each area, i, which in turn are used as estimates of the unconditional deciles. Next, the deciles are used to construct the 10 indicator variables, $I^w_{it,1}$ through $I^w_{it,10}$ corresponding to the 10 deciles of wind power. Thus, if a given observation at time t in a given area i experienced wind power between the 10th and 20th quantile, then the indicator variable $I^w_{t,2} = 1$, while all other indicator variables, $I^w_{it,1} = I^w_{it,3} = ... = I^w_{it,10} = 0$.

A visualization of the mapping from the continuous series to decile indicators for the DK2 price areas is shown in figure 10. A scatter plot of the stochastic component of wind production versus stochastic component of prices in the DK2 prices is shown in figure 11. The plot shows the tendency for prices to fall under large amounts of wind power.

The equation of interest, representing the stochastic component of power prices in area $i$ at a time $t$ as a function of autoregressive terms and the wind power decile indicators, can be written as in equation 3. $\delta_{i0}$ represents the intercept term, while $\delta_{i1}, \delta_{i2}, \ldots, \delta_{i10}$ represent the coefficients to be estimated on the autoregressive terms. $I^w_{it,1}, I^w_{it,2}, \ldots, I^w_{it,10}$ represent the 10 indicator variables corresponding to the 10 deciles of wind power. $\beta^w_{it,1}, \beta^w_{it,2}, \ldots, \beta^w_{it,10}$ are coefficients on the indicator variables to be estimated.

The model is intentionally parsimonious. We do not try to fully explain price movements in the price area. We also do not include transmission flows in the model. The reason is that we interpret transmission flows as an intermediate variable. We want to start by estimating the distributional effects of wind power on prices including the effects through changes in transmission and congestion. In later specifications, we will add variables for congestion and wind power from neighboring price areas and we will also look closer at the effects of wind power on transmission flows.

$$u_{it}^{p} = \delta_{i0} + \delta_{i1} u_{it-1}^{p} + \delta_{i2} u_{it-2}^{p} + \cdots + \beta_{i1}^{w} I_{it,1}^{w} + \beta_{i2}^{w} I_{it,2}^{w} + \ldots \beta_{i10}^{w} I_{it,10}^{w} + \epsilon_{it} \tag{3}$$

Including the deciles of wind power is a simple and easy-to-interpret way of including the effects of wind power but allowing the effects to vary flexibly and non-linearly. Importantly, it makes no assumption about the normality of the distribution of wind power. Deciles provide a good balance between completeness and simplicity, having a fine-enough precision to capture the behavior at the tails, while mostly avoiding problems of over-fitting the data, which can lead to poor out-of-sample fit.

For identifying the effects of wind power, we rely on the assumption that wind power production is to a great extent exogenous to prices in the area. Wind power has a marginal cost close to zero, and thus a wind power producer generally has little incentive to curtail their own production. The exception would be periods where prices fall to below zero. This can happen in the Danish price areas but is rare.

We also check for potential issues of collinearity. Perfect collinearity would lead to numerical issues in the estimation of our model, and we see no signs of this. We could still have an imperfect collinearity problem if some of the covariates have very strong correlations - especially between non-autoregressive terms or between the autoregressive terms and other covariates. A simple way of checking for any potential problems is to look at correlation coefficients between covariates, which we have done. Besides correlation coefficients between the autoregressive terms, the correlation coefficients are estimated to be low (generally below 0.4). The highest correlations are for the top (10th) decile terms for wind power between areas (approximately 0.6), which we discuss as a feature of the analysis earlier. With the amount of data available–around 17,000 observations–these levels of correlations should not be detrimental to inference.

## 4.1 Wind power and prices in two price areas.

In the first specification we look at the effect of wind power deciles on prices within the same price area. For the dynamic part of the equation, we use a process of testing and comparing the goodness-of-fit, as measured by Akaiki Information Criteria (AIC), of different specifications. We use autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of the filtered price series in order to identify a sensible starting specification. The ACF and PACF appeared to indicate both normal autocorrelation as well as seasonal (daily) patterns. We started with a fifth order autoregressive model as well as including 21st through 29th terms in order to model the seasonal component. We then both increased and decreased the number of the autoregressive components and seasonal autoregressive components until we found a specification with the best fit as measured by AIC and BIC.[2] When AIC and BIC gave conflicting indications of model fit, we chose the specification based on BIC, as this will, at the margin, tend to favor more parsimonious specifications.

From this process, we chose a specification with first and second autoregressive terms as well as 22nd through 28th autoregressive terms. The specification is run for both the price areas DK2 and SE4. The

[2]BIC stands for Bayesian Information Criteria (Schwarz, 1978). BIC is similar to AIC in that likelihoods of nested models can be compared subject to a penalty term for the number of parameters. BIC has a larger penalty term than AIC and on the margin tends to favor more parsimonious models.

specification can be written as in equation 4.

For estimation, we use the open-source R programming language (R Core Team, 2019).[3]

$$
\begin{aligned}
u^p_{i,t} &= \delta_{i,0} + \delta_{i,1} u^p_{i,t-1} + \delta_{i,2} u^p_{i,t-2} + \delta_{i,23} u^p_{i,t-23} + \delta_{i,24} u^p_{i,t-24} \\
&\quad + \delta_{i,25} u^p_{i,t-25} + \delta_{i,26} u^p_{i,t-26} + \beta^w_{i1} I^w_{it,1} + \beta^w_{i2} I^w_{it,2} + \cdots + \beta^w_{i10} I^w_{it,10} + \epsilon_{i,t} \qquad (4)
\end{aligned}
$$

The coefficients of interest are the decile coefficients, and we show these visually in figure 12. Here the points represent the OLS point estimates, where the lines represent 95% confidence intervals. White standard errors (White, 1980) are estimated that are robust to heteroskedasticity. the first decile is left out as a comparison value. Estimated parameters for the dynamic portion of the models are shown in the first two columns of table 2.

Table 2: Columns 1 and 2 show estimated dynamic parameters of models in equations 4 where only deciles of wind power from DK2 are included. Columns 3 and 4 show the estimated dynamic parameters from models from equation 5 where wind power deciles from DK2, DK1 and SE4 are included. Columns 5 and 6 are from specifications where wind power effects are estimated conditional on congestion. White standard errors are shown in parenthesis.

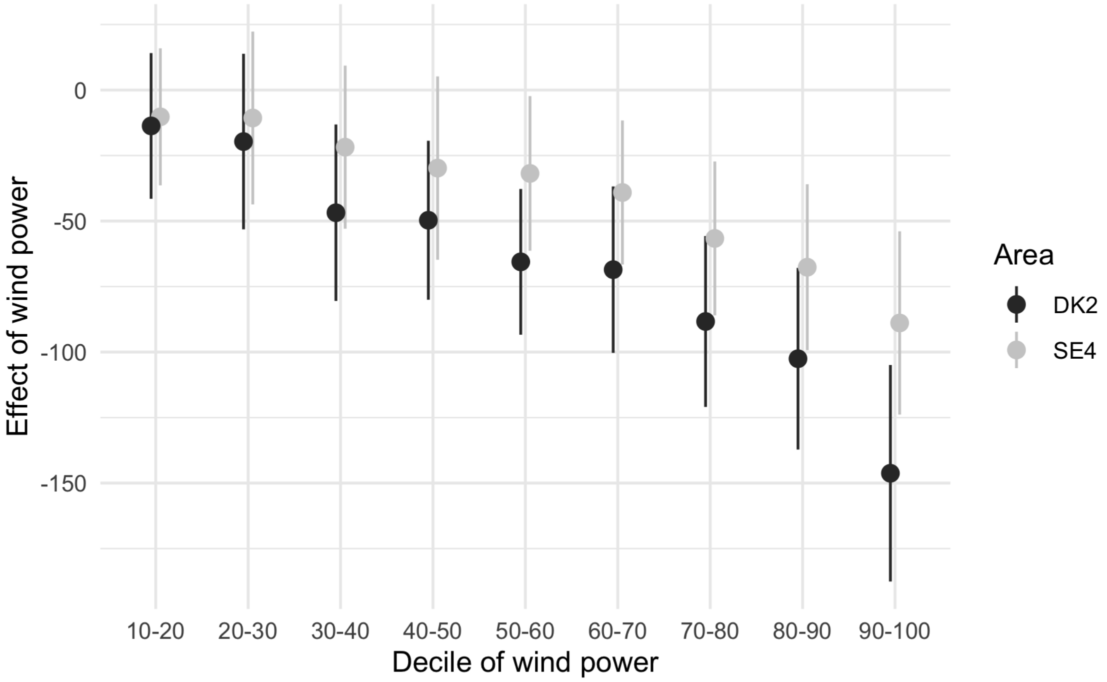
| | Wind in DK2 area | | Wind in DK1, DK2, SE4 | | Conditional on congestion |
|---|---|---|---|---|---|
| Price area | DK2 | SE4 | DK2 | SE4 | DK2 |
| Intercept | 60.31[a] | 35.93[a] | 60.31[a] | 35.93[a] | 55.56[a] |
| | (11.5) | (11.13) | (11.5) | (11.13) | (14.43) |
| ar1 | 1.07[a] | 1.07[a] | 1.07[a] | 1.07[a] | 1.05[a] |
| | (0.03) | (0.04) | (0.03) | (0.04) | (0.03) |
| ar2 | -0.23[a] | -0.23[a] | -0.23[a] | -0.23[a] | -0.23[a] |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| ar22 | -0.02 | -0.02 | -0.02 | -0.02 | -0.03 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| ar23 | 0.18[a] | 0.17[a] | 0.18[a] | 0.17[a] | 0.18[a] |
| | (0.03) | (0.04) | (0.03) | (0.04) | (0.03) |
| ar24 | 0.17[a] | 0.19[a] | 0.17[a] | 0.19[a] | 0.16[a] |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| ar25 | -0.18[a] | -0.19[a] | -0.18[a] | -0.19[a] | -0.18[a] |
| | (0.04) | (0.05) | (0.04) | (0.05) | (0.04) |
| ar26 | -0.08[a] | -0.08[b] | -0.08[a] | -0.08[b] | -0.08[a] |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| ar27 | 0.01 | 0.03 | 0.01 | 0.03 | 0.01 |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.02) |
| ar28 | 0.003 | -0.0003 | 0.0009 | -0.007 | 0.008 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |

[a]: p<0.01, [b]: p<0.05, [c]: p<0.10
White standard errors in parenthesis
17158 observations

The estimates show that in both price areas, low deciles are associated with little to no effect on prices. A modest effect on prices is estimated in the middle deciles. But an outsized large effect in the DK2 price area is estimated on the 90th percentile. For DK2, the price effect is estimated to be nearly double the

[3]Several packages are available for estimating dynamic models with exogenous regressors, but we chose the *arx* routine from the R package *GETS* (Pretis et al., 2018).

Figure 12: The points represent the OLS estimate for each decile indicator, with the lowest decile left out as the comparison value. The bands represent 95% confidence intervals. Estimates for prices in the DK2 area are shown in black and estimates for prices in the SE4 area are shown in grey.




effect of the 50th percentile.

As a whole, the estimated coefficients on the deciles do not point to a simple linear relationship between wind power and prices. Instead, significant price effects of wind power generation appear only to materialize at the mid-ranges of deciles, and then appear to be fairly steady across the deciles, while markedly higher effects are seen at the highest deciles.

From our background analysis, the regression is clearly incomplete. Wind power is highly correlated at the highest production levels, and this could potentially be driving the out-sized effect on prices in DK2 in the top decile. To get a more nuanced understanding of the distribution of effects, we estimate a new specification, as shown in equation 5 that includes deciles of wind power from both neighboring DK1 and SE4 areas.

$$
\begin{aligned}
u^p_{i,t} &= \delta_{i,0} + \delta_{i,1}u^p_{i,t-1} + \delta_{i,2}u^p_{i,t-2} + \delta_{i,23}u^p_{i,t-23} + \delta_{i,24}u^p_{i,t-24} + \delta_{i,25}u^p_{i,t-25} + \delta_{i,26}u^p_{i,t-26} \\
&+ \beta^w_{DK2,1}I^w_{DK2,t,1} + \beta^w_{DK2,2}I^w_{DK2,t,2} + \dots \beta^w_{DK2,10}I^w_{DK2,t,10} \\
&+ \beta^w_{SE4,1}I^w_{SE4,t,1} + \beta^w_{SE4,2}I^w_{SE4,t,2} + \dots \beta^w_{SE4,10}I^w_{SE4,t,10} \\
&+ \beta^w_{DK1,1}I^w_{DK1,t,1} + \beta^w_{DK1,2}I^w_{DK1,t,2} + \dots \beta^w_{DK1,10}I^w_{DK1,t,10} + \epsilon_{i,t} \qquad (5)
\end{aligned}
$$

A summary of the estimated coefficients on the wind power deciles are presented in figure 13. The estimated parameters of the dynamic portion of the model are shown in the third and fourth column of

Figure 13: The points represent the OLS estimators of each decile indicator of wind power. The bands represent 95 % confidence intervals. Estimates from wind power in DK1 are shown in black, estimates from wind power in DK2 are shown in dark grey and estimates from wind power in SE4 are shown in light grey.

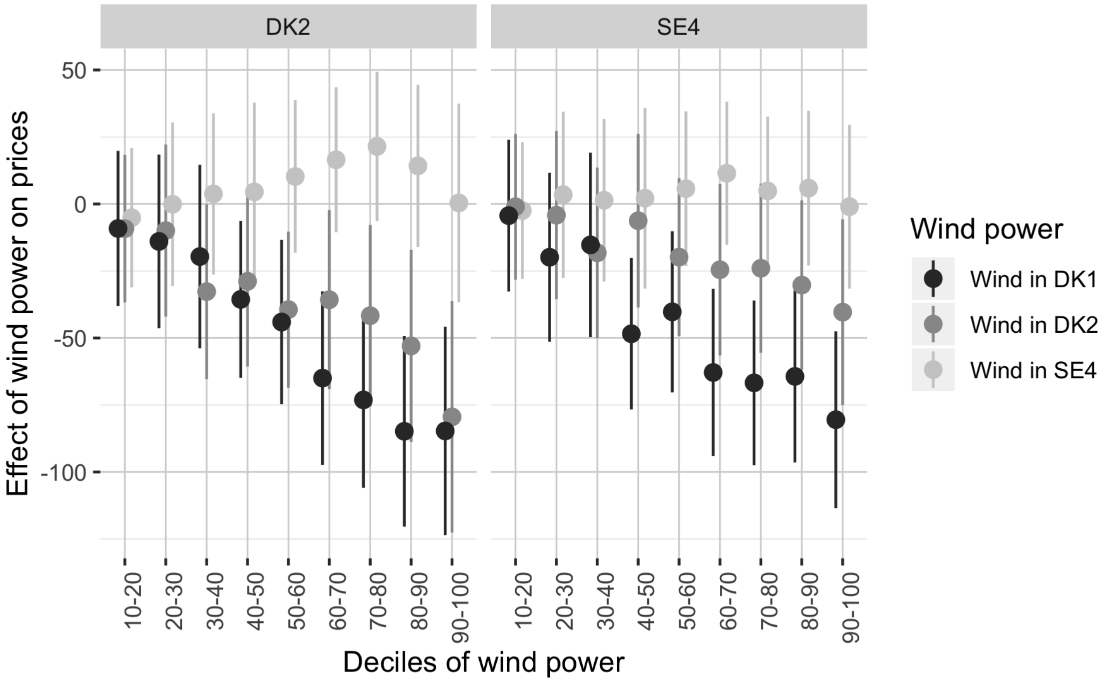



table 2. A few patterns are apparent in the figure. First, the impact of wind power within the DK2 area on its own prices is low to moderate for most of the deciles but is then shown to have a strong effect in the 8th and 9th decile. Wind in DK2 is not estimated to have a statistically significant effect on prices in the SE4 area (right panel) through the 9th decile, and is only estimated to have a moderate, statistically significant negative effect at the 10th percentile. In SE4, on the other hand, wind power seems to have little effect on its own prices or neighboring DK2 at all deciles.

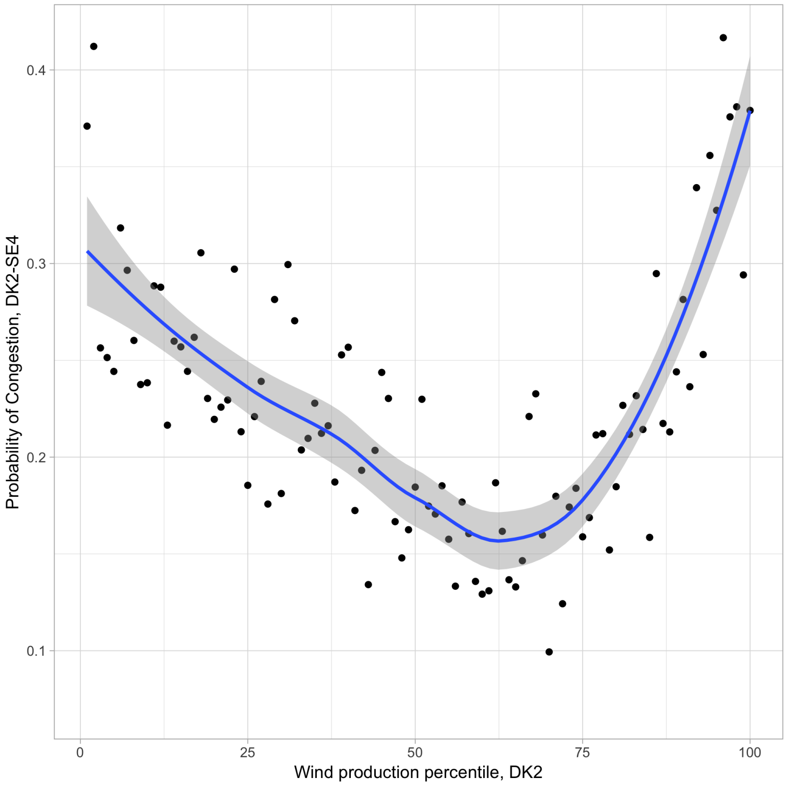
The second pattern is that wind power in DK1 significantly impacts prices in both DK2 and SE4, but the impact does not appear to be linear. The impact of wind power in DK1 on prices in DK2 and SE4 are not statistically different from zero in the first three deciles of production. The strongest negative effect is estimated at the 9th and 10th decile in the DK2 area and in the 10th decile in the SE4 area.

In this specification we have included a large number of covariates, and it may be useful to apply an algorithm that identifies covariates that do not improve the fit of the model and remove them from the estimation. We have made use of the General To Specific (GETS) frameworks that is particularly well adapted to time-series models. The results from the GETS analysis are largely in line and reinforce the results and interpretation from the full model presented in this section (Campos et al., 2005).[4] Details of the GETS analysis can be found in the appendix.

When considering wind power's effect on power flows and congestion in the system, the patterns become coherent. Figure 14 is a representation of the probability of congestion between the DK2 and SE4 price

[4]We make use of the R package *GETS*(Pretis et al., 2018) to run the routine.

Figure 14: The figure represents the probability of congestion between the areas DK2 and SE4 conditional on the percentile of wind power. Each point represents the mean of the binary variable of whether there was congestion or not for all hours in a certain percentile of wind power production. The blue line represents a smoothed Loess curve through the data points with associated 95% uncertainty band.




areas conditional on the percentile of wind power. Each dot represents the mean of the binary observation of whether there was congestion or not within each percentile. The blue line represents a Loess smoothed curve through these lines, with the grey band representing the uncertainty band of the Loess estimation.

The figure shows a pattern of reduced congestion between the price areas as wind power in DK2 increases up to approximately the 60th percentile. Wind power that increases beyond the 60th percentile is associated with sharply higher probability of congestion.

At higher deciles of wind power production, which also are highly correlated across areas, the probability of transmission of congestion is higher. This can also explain why wind power within the price areas has an out-sized effect at high deciles. A higher probability of congestion means that wind power cannot flow out and instead adds supply to the area, pressing down the price.

To formally investigate the role of congestion, we use a specification where the wind power deciles interact with an indicator variable for congestion. For simplicity, we focus on prices in the DK2 area. We can write the specification as in equation 6, where the effects of wind power in the DK1 and DK2 areas are allowed to vary by whether there was congestion between DK2 and DK1 at time t, $C_{t,DK1}$ or DK2 and SE4, $C_{t,SE4}$, where $C_{t,i}$ is an indicator variable. The design of the electricity market is such that prices between areas will only diverge when there is congestion between areas. Congestion can therefore be detected in the data by observing whether in any given hour, prices are different between areas ($C_{t,i} = 1$), or not ($C_{t,i} = 0$).

$\boldsymbol{\zeta_{DK1}}$ represents the vector of coefficients on the interaction term. For simplicity, we exclude wind power in the SE4 areas, since this was not shown to have any significant effect on prices in the DK2 area.

$$
\begin{aligned}
u^p_t = {} & \delta_0 + \delta_1 u^p_{t-1} + \delta_2 u^p_{t-2} + \delta_{23} u^p_{t-23} + \delta_{24} u^p_{t-24} + \delta_{25} u^p_{t-25} + \delta_{26} u^p_{t-26} \\
& + \alpha_{SE4} C_{t,SE4} + \alpha_{DK1} C_{t,DK1} \\
& + \beta^w_{DK2,1} I^w_{DK2,t,1} + \beta^w_{DK2,2} I^w_{DK2,t,2} + \dots \beta^w_{DK2,10} I^w_{DK2,t,10} \\
& + \beta^w_{DK1,1} I^w_{DK1,t,1} + \beta^w_{DK1,2} I^w_{DK1,t,2} + \dots \beta^w_{DK1,10} I^w_{DK1,t,10} \\
& + \zeta^{DK1}_{DK2,1} C_{t,DK1} \cdot I^w_{DK2,t,1} + \zeta^{DK1}_{DK2,2} C_{t,DK1} I^w_{DK2,t,2} + \dots \zeta^{DK1}_{DK2,10} C_{t,DK1} I^w_{DK2,t,10} \\
& + \zeta^{DK1}_{DK1,1} C_{t,DK1} \cdot I^w_{DK1,t,1} + \zeta^{DK1}_{DK1,2} C_{t,DK1} I^w_{DK1,t,2} + \dots \zeta^{DK1}_{DK1,10} C_{t,DK1} I^w_{DK1,t,10} \\
& + \zeta^{SE4}_{DK2,1} C_{t,SE4} \cdot I^w_{DK2,t,1} + \zeta^{SE4}_{DK2,2} C_{t,SE4} I^w_{DK2,t,2} + \dots \zeta^{SE4}_{DK2,10} C_{t,SE4} I^w_{DK2,t,10} \\
& + \zeta^{SE4}_{DK1,1} C_{t,SE4} \cdot I^w_{DK1,t,1} + \zeta^{SE4}_{DK1,2} C_{t,SE4} I^w_{DK1,t,2} + \dots \zeta^{SE4}_{DK1,10} C_{t,SE4} I^w_{DK1,t,10} + \epsilon_t \qquad (6)
\end{aligned}
$$

A summary of the results is shown in figure 15. The estimated coefficients on the dynamic terms are shown in column 5 in table 2. Looking at the left panel of figure 15, the effects of wind power generated in DK1 has a progressively more negative effect on prices in DK2 in periods without congestion. On the other hand, wind power in DK1 has no significant effect on prices in DK2 in periods with congestion. But the largest effect of wind power in DK2 on its own prices is in the 90th decile when there is congestion with the SE4 price area.

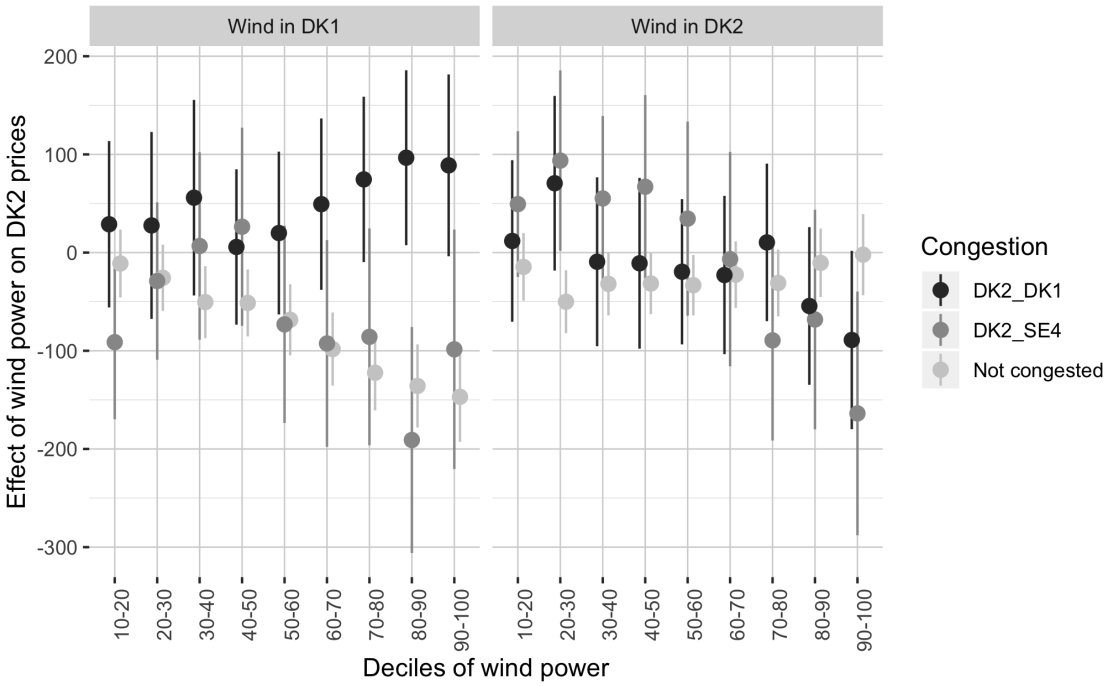
Wind power in the DK2 price area is estimated to have at most only modest effects on prices in the DK2 area over all the deciles when there is not congestion. This seems to indicate that excess wind in these periods flows to neighboring areas, rather than adding to local supply that presses down prices. With congestion, wind power in the 90th percentile is estimated to press down prices significantly.

The specification that takes into account congestion in the grid gives a nuanced picture of how wind power effects prices in the market. On the one hand, the absence of congestion allows for wind power in a neighboring DK1 area to negatively affect prices. On the other hand, congestion also amplifies the effects of wind power's effect on its own prices at high deciles. When there is a lack of congestion from the DK2 to the SE4 area, wind power generated in DK2 has little effect on prices in its own areas. Presumably, the main effect of increased wind power would be an increased flow of electricity to the Swedish price areas.

Geography is likely a key factor behind these results. Without congestion, excess wind energy can flow into the Swedish price areas, where the hydro-power stations located in the northern price areas can flexibly adjust their production. This provides an explanation of why congestion between DK2 and SE4 areas is so important in determining the effects of wind power on prices in the DK2 area.

The results so far illustrate some of the weaknesses of simpler models that only estimate a marginal average effect. Such models will often be interpreted such that moderate amounts of wind power will press down prices. Our results show that this is not necessarily so, and that the effects of wind power on price are largely during high-production times and heavily dependent on congestion in the system.

Figure 15: The effect of wind power in deciles on prices in the DK2 price area conditional on congestion. The left pane shows the effects of wind power generated in the DK1 area, while the right pane shows the effects of wind power generated in the DK2 area. The dots represent OLS estimates, while the bands represent 95% confidence intervals. Light grey indicates estimates with no congestion. Dark grey indicates congestion between DK2 and SE4 areas, and black indicates congestion between DK2 and DK1 areas.



## 4.2 Wind power deciles and transmission flows

To further investigate the role of transmission flows, we again construct a two-stage procedure, but this time we use net exchange between DK1 and DK2, and DK2 and SE4 as the dynamic dependent variable. As before, we first decompose the dependent variable into deterministic and stochastic components by running a regression as shown in equation 7. Here, $NX_t$, represents the net exchange between two prices areas. This is sum of imports (-) and exports (+) over any given hour between two price areas.

As with the first-stage regression on prices, the deterministic elements relating to month-of-year, hour and day-of-week are estimated and controlled for, leaving the stochastic component, captured by the residual, $u_t^{nx}$.

$$nx_t = \alpha + \mathbf{month} + \mathbf{hour} + \mathbf{dow} + u_t^{nx} \tag{7}$$

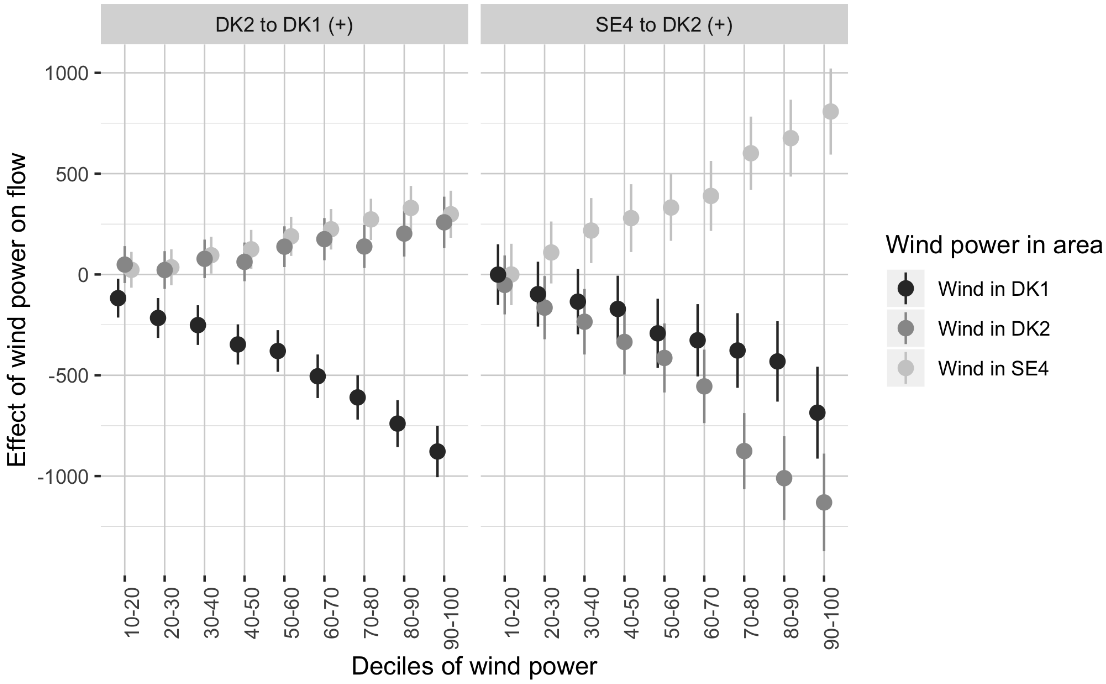
As with the estimation of prices, the stochastic component is then modelled as a dynamic process with wind power deciles, as shown in equations 8. Compared to the modelling of prices, a slightly different specification for the dynamic process is found to provide the best fit for the net-exchange time series. Three (hourly) autoregressive terms plus an autoregressive term at the 23rd hour provided the best fit. In addition to the dynamic specification, coefficients on the decile indicators for wind power from the three price areas, $(I^w_{DK2,t,1}, I^w_{DK2,t,2}, \ldots, I^w_{DK2,t,10})$, $(I^w_{SE4,t,1}, I^w_{SE4,t,2}, \ldots, I^w_{SE4,t,10})$, and $(I^w_{DK1,t,1}, I^w_{DK1,t,2}, \ldots, I^w_{DK1,t,10})$ are estimated.

$$\begin{aligned}
{u_t^{nx}}^{DK2-DK1} &= \delta_0 + \delta_1 {u_{t-1}^{nx}}^{DK2-DK1} + \delta_2 {u_{t-2}^{nx}}^{DK2-DK1} + \delta_3 {u_{t-3}^{nx}}^{DK2-DK1} + \delta_{23} {u_{t-23}^{nx}}^{DK2-DK1} \\
&+ \beta^w_{DK2,1} I^w_{DK2,t,1} + \beta^w_{DK2,2} I^w_{DK2,t,2} + \ldots \beta^w_{DK2,10} I^w_{DK2,t,10} \\
&+ \beta^w_{SE4,1} I^w_{SE4,t,1} + \beta^w_{SE4,2} I^w_{SE4,t,2} + \ldots \beta^w_{SE4,10} I^w_{SE4,t,10} \\
&+ \beta^w_{DK1,1} I^w_{DK1,t,1} + \beta^w_{DK1,2} I^w_{DK1,t,2} + \ldots \beta^w_{DK1,10} I^w_{DK1,t,10} + \epsilon_t^{DK2-DK1} \qquad (8) \\
{u_t^{nx}}^{SE4-DK2} &= \delta_0 + \delta_1 {u_{t-1}^{nx}}^{SE4-DK2} + \delta_2 {u_{t-2}^{nx}}^{SE4-DK2} + \delta_3 {u_{t-3}^{nx}}^{SE4-DK2} + \delta_{23} {u_{t-23}^{nx}}^{SE4-DK2} \\
&+ \beta^w_{DK2,1} I^w_{DK2,t,1} + \beta^w_{DK2,2} I^w_{DK2,t,2} + \ldots \beta^w_{DK2,10} I^w_{DK2,t,10} \\
&+ \beta^w_{SE4,1} I^w_{SE4,t,1} + \beta^w_{SE4,2} I^w_{SE4,t,2} + \ldots \beta^w_{SE4,10} I^w_{SE4,t,10} \\
&+ \beta^w_{DK1,1} I^w_{DK1,t,1} + \beta^w_{DK1,2} I^w_{DK1,t,2} + \ldots \beta^w_{DK1,10} I^w_{DK1,t,10} + \epsilon_t^{SE4-DK2} \qquad (9)
\end{aligned}$$

The estimates for the wind decile indicators are shown in figure 16. In the left panel, the effects on net exchange between DK2 and DK1 are shown. A positive value indicates net export to DK1. Where wind power in DK2 and SE4 are estimated to have a modest positive effect on flow from DK2 to DK1 at the higher deciles. However, the biggest effect came from wind power in the DK1 area, which is estimated to have a strong effect on flow in the direction from DK2 to DK1. The effect seems to be non-linearly stronger at the highest deciles.

In the right panel, the estimated effects of wind power on net exchange between DK2 and SE4 are shown. Both wind power in DK1 and DK2 are shown to have significant effects on flow to the Swedish

Figure 16: The effect of wind power on net exchange. The left panel shows results where flow between DK2 to DK1 is the dependent variable. The right panel shows results where flow between SE4 to DK2 is the dependent variable. The points represent OLS point estimates and the bands represent 95% confidence intervals. The light grey estimates are for wind power generated the SE4 area. The dark grey estimates are for wind power generated in the DK2 area, while the black estimates are for wind power generated in the DK1 area.




price area, especially at the highest deciles. Wind power in SE4 appears to have a substantial effect on flow from SE4 to DK2, which is approximately linearly increasing by decile.

The estimates on net exchange help support the interpretation of results from the price effects. Excess wind power will tend to lead to increased net flows in the direction of the flexible hydro power in the Swedish price areas. Transmission limits and resulting congestion led to an out-sized effect on prices at higher deciles of wind power production.

Exchange between the wind power areas tends to be one sided. This appears to be evidence against the geographical diversification hypothesis. If geographic diversification of wind power were a driving factor in the flows, then we would expect to see, for example, flows into the DK1 area from DK2 under the high wind power deciles in DK2. But this is not observed. The explanation is the high correlation of wind power at the high deciles. This leads to a flow towards the hydropower areas, and in the case of congestion, an effect on prices.

# 5 Conclusions

Geographic diversification of wind power with sufficient transmission capacity between areas is seen as one of the primary ways of mitigating the technology's inherent intermittency. With a case study from the Nordic electricity market, we show evidence for the diversifying effects of geographic separation at moderate levels of wind power production. There tends to be low correlations between wind power production in different price areas, and this correlation quickly goes towards zero as distance increases. Furthermore, at moderate levels of wind power, extra generation can be exported through the transmission network, leading to only moderate effects on prices.

However, we also document how wind power correlations across areas increase markedly at high quantiles of wind power production. Combined with the effects of congestion at times of high wind power, this can lead to non-linearly large effects on prices. This effect has the potential to increase risk for actors in the power market under large penetrations of wind power, as prices are pressed down to low levels, and leading to less price certainty for investors and other actors on the market.

Denmark and southern Sweden consists of three interconnected price areas with large amounts of wind power and provides a useful case study in how wind power affects power prices and flow between areas. The results of this study are in some ways particular to the geography and generation profile of the Nordic electricity market. But the study presents some important broader lessons. First, statistical and econometric models of wind power's effect on prices that rely on estimating a single point estimate representing an average marginal effect overlook the significant variation across the distribution of production. Another broad point is that wind power can be expected to have a complex effect on prices in a power market: The effects are highly dependent on factors such as geography, congestion in the transmission network, and the composition and generation in the market. Finally, the diversifying effects of geographically dispersed wind power that is evident at moderate periods of generation, should not necessarily be expected to hold at more extreme periods, where wind power tends to be more highly correlated across geographies and transmission capacity more limited.

The results have implications for electricity market design and policy. The Nordic market relies on a zonal market with a uniform price within predefined areas. However, such aggregated price areas can lead to substantial inefficiencies if there are substantial geographic variations in the marginal cost of generation within these areas, something our analysis suggests is likely. In other markets, such as the PJM market in the US, nodal systems are used that in theory provide the correct match between the price and marginal cost of electricity at any point in the network given all the technical and physical constraints (Hogan, 1992; Green, 2007; Bjorndal et al., 2014). Bjørndal et al. (2018) proposes a hybrid zonal-nodal approach as an optimal market solution under high penetrations of wind power. Such nodal or hybrid systems system that better provide locational marginal price signals would also provide better incentives for the optimal location of wind farms Lewis (2010).

The findings in this article also underlines the importance of arguments presented by among others Schmalensee (2016) and Green et al. (2016) that incentive schemes should to the greatest extent possible be geographically neutral, allowing investors to base their locational decisions on wind conditions and market prices. Many incentive policies at the state and national level lead to inefficient placement of wind power. The article also underlines the importance of investing in long-distance transmission with large penetrations of wind power as well as designing appropriate financial instruments–such as Financial Transmission Rights (Hogan, 1992)–that provide the correct incentives for both optimal geographic investment in wind power as well as transmission capacity.

There are important considerations such as the role of market power, market design (as discussed above), and the role of financial markets that we do not explicitly consider in this article. In addition, we have restricted ourselves to effects on prices in the day-ahead market. Undoubtedly, wind power will also effect the shorter term markets such as the hour-ahead market and balancing market. These are all promising avenues for future research.


# 6 Acknowledgments

We thank the editor, Adonis Yatchew, and four anonymous referees for comments and suggestions that have helped to improve this article. We also wish to thank Jonas Andersson and Afzal Siddiqui for helpful advice. Feedback from participants at the 2018 International Conference on Computational and Financial Econometrics in Pisa and the 2019 International Association for Energy Economics conference in Montreal was also helpful. All errors and omissions are of course our own.


# A GETS Analysis

In the main sections of the article we present the full results of our models, including parameter estimates that were not significant. In this section we present alternative specifications using an algorithm based on the General To Specific (GETS) procedure (Campos et al., 2005).

The GETS procedure is particularly well adapted as a variable selection procedure for time series models. The basic intuition for the algorithm is that it iteratively removes the least significant covariate from a base model, compares information criteria (AIC) of the new model with the old, and then repeats the process until an optimal model, as measured by AIC, is reached. In addition, the algorithm includes robustness mechanisms that vary the order of removal.

In general we found the process of GETS modelling to reinforce our stated results. We provide details about the GETS results below.

We start with model written in equation 5, which is the first model with a substantial number of covariates. Table 3 shows the results from the optimal model selected by the algorithm for both regressions where prices in the DK2 and SE4 areas are the left-hand-side variables.

Not surprisingly, the deciles for wind power in the SE4 area are removed as covariates. These deciles were not shown to be significant in the full model. However, when the SE4 deciles were removed, it had the effect of also slightly attenuating the estimates for the DK2 deciles, several of which were significant in the full model, leaving only the highest decile of wind power for the DK2 area as significant. This model provides some strengthening of one of the main findings: That the highest deciles of wind power can have a disproportionately large effect on prices.

However, as a matter of interpretation, the GETS model is not materially different from the full model presented in the main text. We report the AIC value of the optimal model as well as the "one-cut" model–which represents the model where all non-significant (at the 5% level) covariates are removed from the full

Table 3: GETS model

| | DK2 | | SE4 | |
|---|---|---|---|---|
| | coef | std.error | coef | std.error |
| ar1 | 1.07[a] | 0.03 | 1.06[a] | 0.04 |
| ar2 | −0.22[a] | 0.03 | −0.22[a] | 0.03 |
| ar23 | 0.16[a] | 0.02 | 0.15[a] | 0.03 |
| ar24 | 0.17[a] | 0.04 | 0.20[a] | 0.04 |
| ar25 | −0.18[a] | 0.04 | −0.20[a] | 0.04 |
| ar26 | −0.07[a] | 0.02 | −0.05[a] | 0.02 |
| (Intercept) | 43.57[a] | 5.34 | 38.32[a] | 5.15 |
| wind_DK1_deciles40_50 | −32.00[a] | 10.06 | −43.06[a] | 9.40 |
| wind_DK1_deciles50_60 | −40.85[a] | 9.98 | −36.13[a] | 9.23 |
| wind_DK1_deciles60_70 | −63.62[a] | 10.86 | −61.33[a] | 9.92 |
| wind_DK1_deciles70_80 | −74.84[a] | 10.56 | −67.88[a] | 9.61 |
| wind_DK1_deciles80_90 | −90.13[a] | 12.66 | −68.05[a] | 10.56 |
| wind_DK1_deciles90_100 | −93.75[a] | 14.81 | −86.42[a] | 11.88 |
| wind_DK2_deciles90_100 | −38.51[a] | 12.94 | −17.39[a] | 7.94 |

[a]: $p<0.01$, [b]: $p<0.05$, [c]: $p<0.10$
AIC: 14.904
AIC ("One-Cut"): 14.904

model. The AIC values are equivalent up to 3 decimal points. This provides support for relying on an interpretation of the full model, where non-significant covariates are disregarded. In this one-cut model, the wind power terms from DK2 are still included

We also complete a GETS analysis of the model written in equation 6 where the deciles are interacted with dummy variables representing whether there was congestion between the price areas. Only prices in the DK2 areas were used as the left-hand-side variables in this regression. Results of the sparsest specification are shown in table 4. Though, it should be noted that several other specifications, with a larger number of covariates included were found that had identical AIC statistics (to the third decimal).

As a matter of interpretation the GETS modelling again reinforces the results from the full model discussed in the full section. The upper 5 deciles of wind in the DK1 area during uncongested times have a unambiguous negative effect on prices in the DK2 area. When there is congestion between the DK2 and SE4 area, wind power in DK2 also has a strong negative effect on prices in the three top deciles of wind power production. All these results are in line with the full model presented in the main section.

Three positive terms for wind power deciles are also included in this specification, but these are of dubious value in terms interpretation. Two are estimated with a p-value of between .01 and .05 and one has a p-value of over .10. When we run the algorithm, setting the critical value to .01 all three disappear from the specification. Even without this change, all three terms are absent in other specifications that give an equivalent AIC value. In terms of theory there is little logic that would indicate that more wind power production could drive prices higher. Instead, the estimated point coefficients seem likely to be driven by the positive effect on prices of congestion that is not fully controlled for by the congestion dummies.

Table 4: GETS model

| | coef | std.error |
|---|---|---|
| ar1 | 1.05[a] | 0.03 |
| ar2 | −0.22[a] | 0.03 |
| ar23 | 0.15[a] | 0.02 |
| ar24 | 0.17[a] | 0.04 |
| ar25 | −0.18[a] | 0.04 |
| ar26 | −0.07[a] | 0.02 |
| (Intercept) | 21.03[a] | 5.17 |
| DK2_DK1Congested[a] | 65.77 | 7.85 |
| wind_DK1_deciles40_50[a] | −42.84 | 10.11 |
| wind_DK1_deciles50_60[a] | −49.07 | 9.90 |
| wind_DK1_deciles60_70[a] | −64.82 | 10.96 |
| wind_DK1_deciles70_80[a] | −80.00 | 10.47 |
| wind_DK1_deciles80_90[a] | −90.19 | 13.77 |
| wind_DK1_deciles90_100[a] | −106.73 | 13.42 |
| DK2_SE4Congested | 47.31[a] | 13.04 |
| DK2_DK1Congested:wind_DK1_deciles80_90 | 41.36[b] | 20.42 |
| DK2_SE4Congested:wind_DK2_deciles70_80 | −150.71[a] | 36.04 |
| DK2_SE4Congested:wind_DK2_deciles80_90 | −126.39[a] | 36.73 |
| DK2_SE4Congested:wind_DK2_deciles90_100 | −217.26[a] | 37.33 |
| DK2_SE4Congested: wind_DK1_deciles40_50: | 82.86[b] | 38.00 |
| DK2_SE4Congested:wind_DK1_deciles80_90 | −115.67[a] | 34.73 |
| DK2_DK1Congested:wind_DK2_deciles20_30 | 55.58 | 36.62 |

[a]: $p<0.01$, [b]: $p<0.05$, [c]: $p<0.10$
AIC: 14.888

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