Assessing the Impact of Wind Energy on Electricity Prices in Germany

through the usage of Markov-Switching models with time-varying probabilities

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Abstract

This thesis aims to investigate the relationship between the increased use of wind as a power source and electricity prices in Germany. After giving a short introduction on the functioning of the German electricity market, we propose an augmented version of a standard two-regime Markov-Switching model used to describe electricity prices on liberalized markets, whose switching probabilities take into account the wind-penetration of the market when forecasting prices. We then show that our model is able to describe prices agreed upon on the German electricity market better than the standard model and conclude by giving a short outlook into further research.

1 Introduction

In the last couple of decades, renewable sources of energy production (renewables) have received considerable support from both political and economic actors. For the various political actors, they represent an attractive alternative to conventional forms of energy production, as they help the actors comply with such international environmental treaties as the Kyoto Protocol and work towards achieving more sustainable forms of domestic energy security by reducing dependence on imported gas, coal, and crude oil.

The latter, economic actors, see renewables as lucrative investment opportunities, lacking the fuel cost generally associated with conventional forms of energy production and offering increasing expected returns as research and technological progresses continue to provide significant innovations in the field. Germany is prime exemplar as its recent implementation of extensive government-funded programs aimed at encouraging investments in renewable energy has resulted in the overall growth of the amount of solar panels and especially wind turbines supplying the market with electricity.

The objective of this thesis is to assess as well as analyze the impact of the growing share of electricity generated by wind and its effect on electricity prices in Germany using econometric methods on data sets provided by the German Power Market.

A number of empirical studies have already been done on the general behavior of electricity prices on liberalized markets in Germany and elsewhere, since their widespread deregulation in the late 1990's. Using data from Nord Pool, the electricity market servicing the Scandinavian and Baltic countries, Bierbrauer et al. (2004) and Weron et al. (2004) showed that prices could be described as following two distinctively different regimes: an autoregressive base regime, sparsely interrupted by a random jump regime. Working with data from the PJM, the electricity market servicing states in the northeastern United States, Mount et al. (2006) achieved similar results and explained this behavior by the unique nature of supply and demand on liberalized power markets [1]. Coming back to the German electricity market, the EEX, Bierbrauer et al. (2007) used the two-regime model that explained price behavior on

[1] Both will be further discussed in the coming sections.

the Nordic power market on German electricity prices, and demonstrated that it was also there able to explain most data characteristics by a base and jump regime. The following years yielded further research in refining the original two-regime model used by Bierbrauer et al. and other academics, incrementally improving its explanatory power (summarized in Janczura and Weron (2010)).

Our goal is to contribute to this string of improvements, by augmenting Bierbrauer et al.'s 2004 model. We do so by changing the model in such a way, that it is able to capture the effect the varying supply of wind-generated power has had on prices set on liberalized electricity markets. In recent years significant work has been done on the impact wind generated power has had on the German electricity market, with Nicolosi and Fürsch (2009), Nicolosi (2010) and Götz et al. (2014) providing a theoretical basis, Ketterer (2014), Cludius et al. (2014) and Benhmad and Percebois (2016) providing empirical investigations, and most recently Veraart (2016) proposing a regime switching framework dependent on a so called wind-penetration index.

In the following sections, we will lay out a framework to integrate Veraart's idea of regime switches dependent on a wind-penetration index in models describing electricity prices. In Section 2, we will give a first overview of the mechanisms behind the electricity market in Germany, going into supply and demand and illustrating how and where both meet. In Section 3, we give a brief introduction into Markov-Switching models and their variant with time-varying switching probabilities. In Section 4 we introduce the original time-constant version of the Markov-Switching model Bierbrauer et al. used to fit electricity prices, before building an augmented version of the model with time-varying switching probabilities dependent on a wind-penetration index (as done similarly by Mount et al. (2006) with the available reserve margin on the PJM as the dependent variable). In Section 5 we then estimate both models using data from the German electricity market and compare their performance. Finally, we conclude by discussing our results and their policy implications in Section 6.

2 The German Market for Electricity

2.1 Electricity Demand

Like many other variables dependent on human behavior, the demand for electricity follows strong seasonal patterns. In Figure 1 some of these patterns in electricity consumption become immediately visually apparent. For one a strong annual sine-wave-form pattern can be observed, peaking in the coldest winter months from December to February and troughing in the warmest summer months from June to August. This effect can partially be explained by electric heating systems utilized in winter months and by the widespread absence of air-conditioning units in most German households (which otherwise would be major energy consumers in summer months). Another seasonality which can be observed is the decreasing effect recurring major holidays have on the demand for electricity, with the christmas holidays

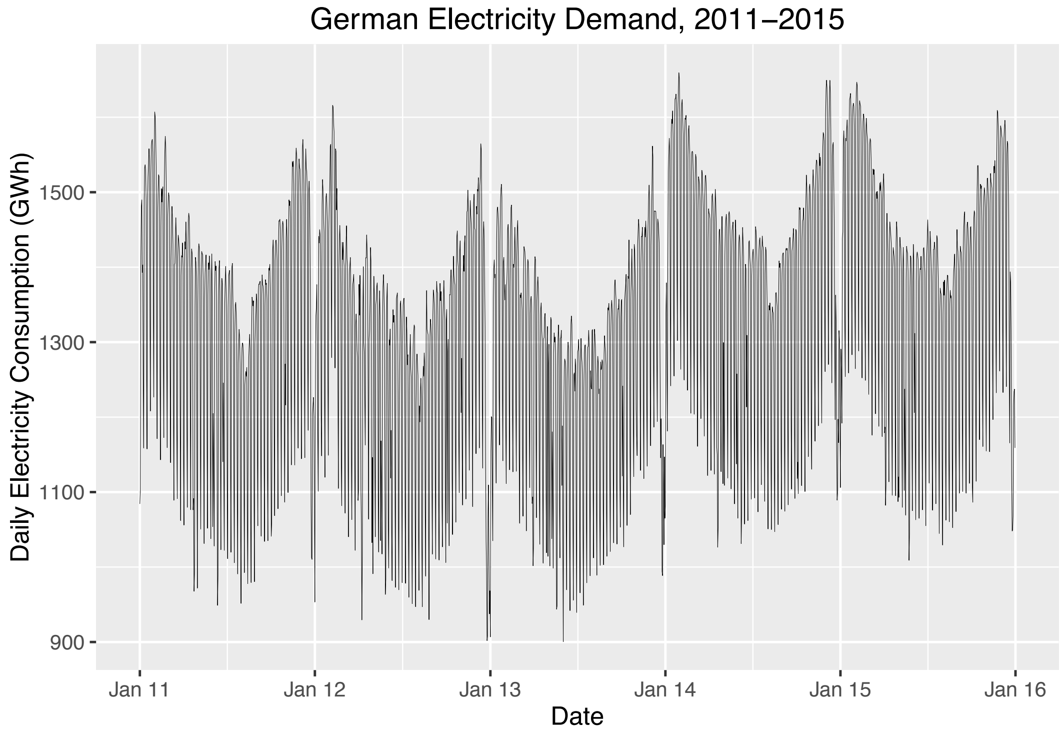

Figure 1: Data provided by ENTSO-E, accessible on www.entsoe.eu

at the end of December serving as a stark example [2].

Figure 2 demonstrates the effect the current weekday has on the demand for electricity. Following a bell-shaped curve from Mondays to Fridays, the electricity consumption decreases significantly on Saturdays and continues on downwards to reach its weekly low point on Sundays. This effect is mainly due to the business-leisure structure of the typical German week, Mondays to Fridays being business days and Saturdays and Sundays generally being days off (the latter even as a government mandated holiday).

Having identified these three seasonalities (monthly, weekly and holiday-specific) we can represent the demand for electricity at time point t, D_t, by splitting it into a deterministic part Δ_t and a stochastic part Σ_t, the former being determined by the above mentioned factors the latter being due to unsystematic disturbances in demand

$$D_t := \Delta_t + \Sigma_t$$

[2] At this point should be noted that there are also a number of regional holidays which are only observed in few of Germany's federal states. Most of them are due to a historic protestant-catholic divide from north to south (Some of them can however also be traced back to the state mandated atheism of the former German Democratic Republic (GDR), which nowadays compromises the eastern half of the German state.). To reduce unnecessary complexity only statewide holidays are considered in the following.

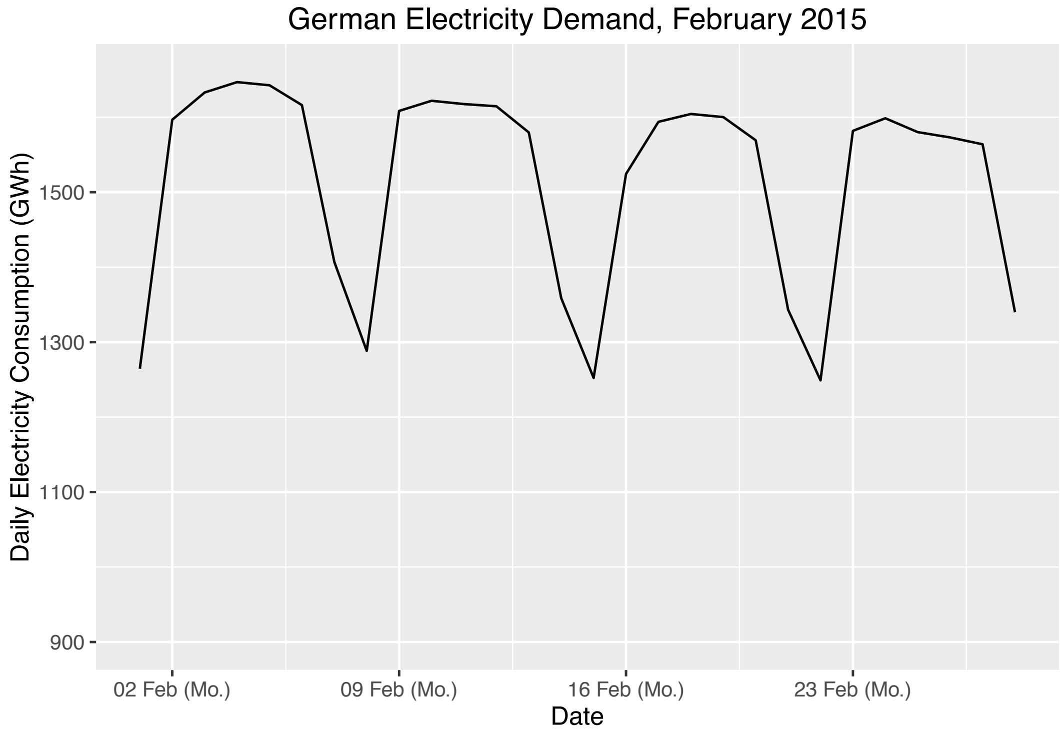

Figure 2: Data provided by ENTSO-E, accessible on www.entsoe.eu

Following Ketterer (2014), Würzburg et al. (2013) and others, the seasonal cycle Δ_t can be approximated by a linear function of consumption on monthly and weekly dummies, and a single holiday-specific dummy ($m_{i,t}$, $w_{i,t}$ and h_t respectively). Furthermore an additional trend variable t can be included in the linear function, meant to capture time trending effects such as technological progress and a long-term change in the aggregate demand for electricity

$$\Delta_t := \sum_{i=1}^{12} \alpha_i m_{i,t} + \sum_{j=1}^{7} \beta_j w_{j,t} + \gamma h_t + \delta t$$

Keeping this stylized representation of the demand for electricity in the back of our mind, we continue by looking at how it is supplied.

2.2 Electricity Supply

Historically power demand in Germany has been mainly met by fossil fuels, coal-generated and nuclear power standing out among them, with renewable forms of power production playing only a minor role (see Figure 3). Since the early 2000's however, several shifts have taken place in the German political landscape towards increasing popular support for expanding the percentage of renewables in the German energy mix and gradually phasing out

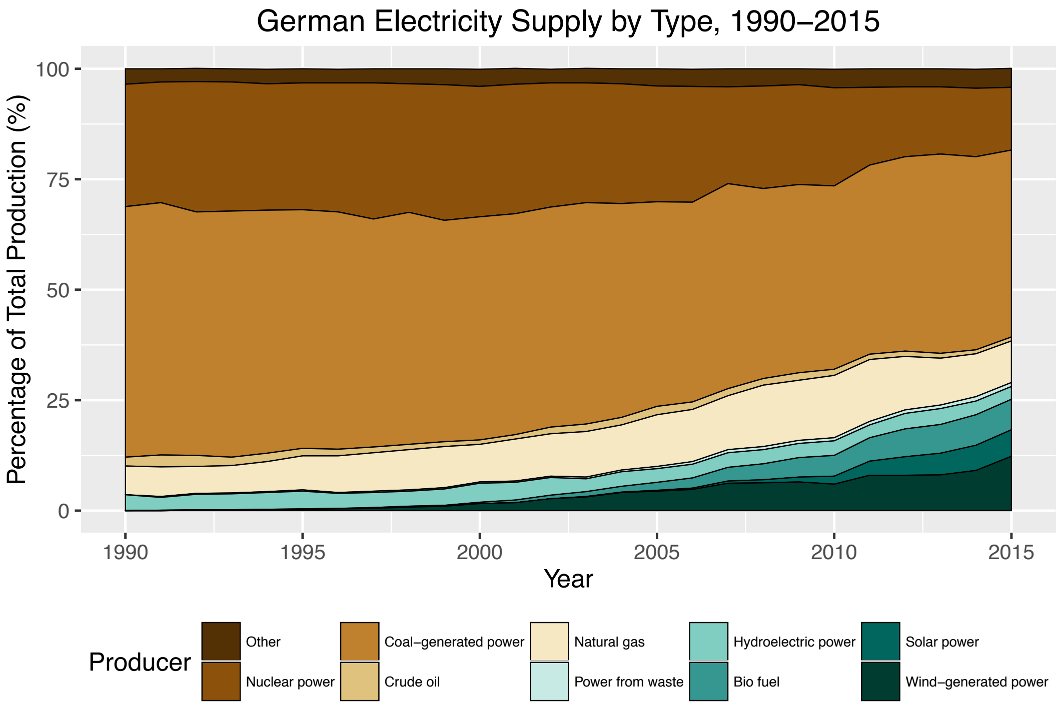

Figure 3: Data provided by AG Energiebilanzen, accessible on www.ag-energiebilanzen.de

nuclear power production. Originally a policy position only supported by the German Green Party, it became more widespread following public awareness of global climate change in the late 2000's and the malfunctioning of a Japanese nuclear power plant off the coast of Fukushima in 2011 (Wolling and Arlt 2014). From then onwards, renewables have consistently managed to increase their share in the German energy mix, accounting for over 25% of all power generated in Germany in 2015.

A special characteristic of the market for electricity, which sets it apart from most other commodity markets, is the inability to store power efficiently over long periods of time on a large scale [3]. Furthermore, to ensure the stability of the power grid no more electricity is allowed to be fed into the transmission network than is currently being taken out of it. Therefore the supply of electricity needs to roughly equal its demand at any point in time. A considerably complex task recalling the fluctuating nature of electricity demand we saw in Section 2.1.

It follows that in order to be able to meet the strongly varying demand we saw in Section 2.1, the available forms of energy production need to be balanced in such a way that they are able to flexibly adjust their output to the current level of demand, ideally in a cost-effective manner. To do so, the different forms of energy production depicted in Figure 3 are separated

[3]Notable exceptions include hydroelectric dams, which are for example extensively used in Norway due to the unique geographic features of the country.

Energy Producer	Marginal Costs in €/MWh	Production Tier
Solar power	≈ 0	Base Load
Wind-generated power	≈ 0	
Hydroelectric power	≈ 0	
Nuclear power	6-8	
Coal-generated power	15-45	Medium Load
Natural gas	45-110	Peak Load
Crude oil	110-200	
Bio fuel	110-200	

Table 1: Ranking of electricity production types by marginal costs, Data provided by Cludius et al. (2014)

into three distinct tiers, which are utilized according to their individual strengths: those in a lower tier supplying "base load", with low variable costs per MWh but high initial fixed costs, those in a middle tier supplying "medium load", with moderate variable and fixed costs, and those in a highest tier supplying "peak load", with high variable costs but low fixed costs (Nicolosi and Fürsch 2009).

Due to the nature of the cost structures of the tiers outlined above, a inherent trade off between the flexibility of a plant and its production costs becomes apparent. Inflexible base load plants are utilized around the clock to supply a constant demand for electricity, thereby justifying their high initial fixed costs through extensive use of their low variable costs. Medium load plants on the other hand service seasonally determined medium to high demand with reasonably priced electricity. Finally, peak load plants flexibly service short periods of exceptionally high demand, however doing so at a very high variable cost (Nicolosi 2010; v.Roon and Huck 2010).

Reordering the major forms of energy production presented in Figure 3 into these three categories, we get Table 1. This ranking of the forms of energy production by marginal costs is also known as the "merit order", with the cheapest forms of production getting ranked before the more expensive.

As mentioned in the introduction, renewables fall into the category of base load plants due to their practically non-existent marginal costs [4]. What separates them from other base load plants however, such as nuclear power plants, is that they cannot reliably produce a constant supply of electricity around the clock, but rather are dependent on hard to forecast external factors such as the weather. This leads to renewables adding a considerable amount of uncertainty to the supply of electricity available the next day, which in turn needs to be balanced out by an increased use of reliable and flexible methods of energy production, to be able to meet demand: medium and peak load plants. This is especially true for energy

[4] Most renewables like solar power or wind energy lack any sort of fuel-costs and only have negligible upkeep and maintenance costs per MWh.

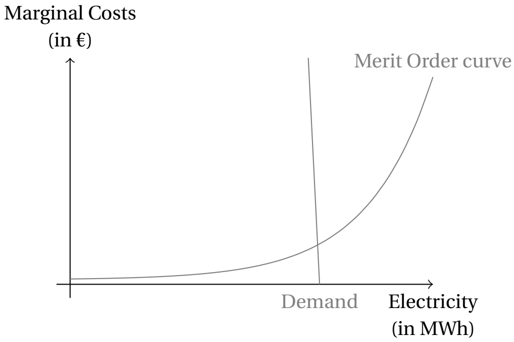

Figure 4: Stylized merit order and demand curves

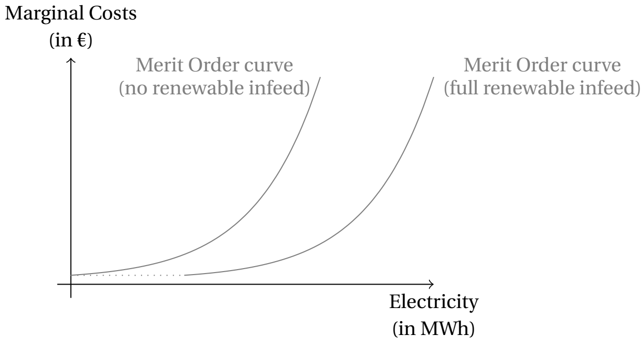

Figure 5: Stylized merit order curve with renewables

generated by wind turbines, as wind itself follows no strong seasonal pattern, as opposed to sunshine or currents and tides. The following analysis will therefore be mainly centered around the effect the increasing replacement of nuclear power with wind turbines has had on electricity prices in Germany.

Having discussed supply and demand, we now turn to the place where they meet and prices are determined: the marketplace.

2.3 The European Energy Exchange

One of the largest in Europe, the German power market is split into a largely unregulated over-the-counter market (OTC-market), on which roughly three quarters of all energy volume is traded, and the European Energy Exchange in Leipzig (EEX), on which among other commodities electricity is traded on a day-ahead spot market [5]. Prices on the EEX are settled at hourly rates, which are in turn aggregated into daily averages for peak and non-peak hours by the PHELIX-index (Nicolosi 2010). These hourly prices can be seen as an important benchmark for the price of electricity on the OTC-market, as they provide an easy arbitrage opportunity in case of strong deviations in pricing. It can therefore be assumed that prices agreed upon on the EEX and those agreed upon on the OTC-market for a given amount of electricity to a certain time are reasonably close to each other.

On the EEX, sellers of electricity anonymously bid the quantity they are able to produce the next day at its marginal cost into the market. Sorting these bids by their marginal costs gives us the merit order curve we are already familiar with from Table 1. Buyers in turn bid into the market the quantity of electricity they are willing to consume the next day at a given price, whereby the quantity they require is usually very inelastic (consumers will demand the same amount of energy on a given day, irrelevant of price). Following basic economics, mar-

[5]This means prices are agreed upon a day in advance, e.g. prices for a Tuesday are settled on the preceding Monday.

ket clearance occurs at the intersection of the demand and the supply curves, with all sellers receiving and all buyers paying the marginal cost necessary to produce the last MWh sold on the cleared market (Benhmad and Percebois 2016; v.Roon and Huck 2010). This process is also illustrated in Figure 4.

In order to incentivize increased investment into renewables in Germany, power produced by them is guaranteed a minimal price by the "Erneuerbare Energien Gesetz" [6] (EEG), which is subsidized by a tax on non-commercial electricity consumption known as the "Erneuerbare Energien Gesetz-Umlage" [7] (EEG-Umlage) (§19 EEG). For the owners of renewable power plants this means that they always have an incentive to feed into the market the full amount of energy they produce, as they either receive a state guaranteed minimal price or an even higher market clearing price determined on the EEX.

Furthermore, renewables play a special role in determining the market clearing price itself. Under current legislation they are fed into the market at zero marginal costs, thereby shifting the merit order curve outwards as seen in Figure 5 (§11 EEG). This so called "merit order effect" has lead to an overall falling price of electricity as the same demand can be met at a lower cost. The effect has however also made the price itself more volatile, as it has become more dependent on an increasing amount of energy that is unreliably fed into the market. A negative side effect of the increased use of renewables has therefore also been the increased accumulation of days with unusually high or low prices, mainly due to temporal scarcity or oversaturation of the market with power produced by renewables [8].

As already seen in Figure 3, the combination of these incentives has over the years lead to a strong increase in the portion of power generated by wind energy relative to the total amount of electricity consumed in Germany. It can therefore be expected that all the positive and negative consequences of the "merit order effect" will increase in magnitude, if there is no change in current policy.

Summarizing, it follows that the price of electricity depends on two important factors: variations in demand, as discussed in Section 2.1, and variations in supply, as discussed in this section and Section 2.2. Strong variations in prices from one day to another, as depicted in Figure 6, can therefore be seen as signals that indicate strong movements in one or both factors.

As the main focus of this thesis lies on identifying the effect the increased usage of wind turbines for power generation has on electricity prices in Germany, we will try to isolate this supply-side effect from any demand-side effects by deseasonalizing the data in the following section. After that we give a brief introduction to the models we use to asses the range of this effect in Section 4, and present the results of estimating these models in Section 5.

[6] Law for Renewable Energy

[7] Renewable Energy Redistribution Scheme

[8] In some cases prices even ventured into negative territory. Further discussions on the mechanisms behind negative electricity prices in Germany, and policy recommendations to combat them can be found in Götz et al. (2014).

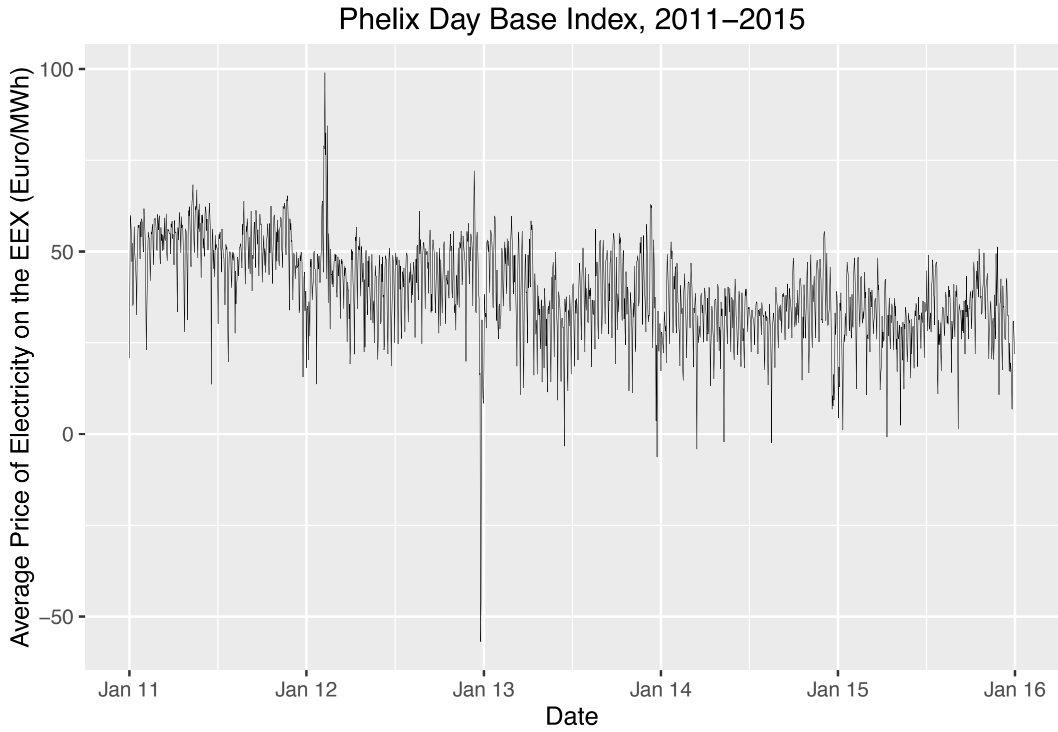

Figure 6: Data provided by Bloomberg, daily data accessible on www.eex.com

3 Data

3.1 Raw Data Sets

In total data on three variables was gathered to estimate the models we will introduce in the following Sections: The daily load of electricity consumed in Germany downloaded from the website of the European Network of Transmission System Operators for Electricity (ENTSO-E), the day-ahead forecast of electricity generated by wind in Germany downloaded from the websites of the German transmission system operators (TSOs) Amprion, TransnetBW, Tennet TSO and 50Hertz, and the average daily price agreed upon on the EEX (Phelix Day Base) downloaded from Bloomberg.

Furthermore, following Jónsson et al. (2010) we calculate a "wind-penetration index" WP_t, defined as

$$WP_t := \frac{V_t}{D_t}$$

with V_t being the forecasted amount of electricity generated by wind, and D_t being the market clearing load of electricity. The index allows us to identify days in which electricity produced by wind energy makes up a proportionally large amount of the total electricity pro-

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Consumption (GWh)	900.5	1205	1360	1328	1443	1659
Forecasted Wind Power (GWh)	10.74	58.72	107.7	145.9	192.7	750.9
Phelix Day Base Index (€/MWh)	-56.87	31.33	38.72	39.18	48.4	98.98
Wind-Penetration Index	0.00792	0.04443	0.08066	0.1106	0.1455	0.5913

Table 2: Summary statistics of the electricity consumption, the forecasted amount of wind-generated electricity, the Phelix day base index, and the wind-penetration index, for Germany from 2011-01-01 to 2015-12-31

duced, thereby heavily "penetrating" the market. By using such an index we can more easily compare market situations from day to day, as the same absolute amount of electricity produced by wind energy may make up a large portion of the market on low demand days and only a small portion on high demand days [9].

3.2 Deseasonalized Prices

As discussed in Section 2.1 the demand for electricity follows strong seasonal patterns. Due to the fact that the electricity market is cleared daily and demand itself is highly inelastic, these seasonalities are in part directly transferred to the prices agreed upon on the EEX-market. As our focus lies on examining supply-side effects, namely the effect of the varying supply of wind generated electricity on the market, it is therefore necessary to deseasonalize the prices from deterministic demand-side effects. This allows us to isolate movements in prices that are solely due to movements in supply (Bierbrauer et al. 2004; Ketterer 2014; Veraart 2016).

Several different ways to deseasonalize price data are common in the literature, with Bierbrauer et al. (2004) and Veraart (2016) removing a combination of sinusoidal functions to the data, Weron et al. (2004) choosing a wavelet decomposition technique, and Ketterer (2014) removing a series of weekday and month specific dummies from the data, which are estimated by a robust OLS-regression. We go with the latter approach, as it is in line with the description of demand seasonalities in Section 2.1 and although being less complex yields similar results as the aforementioned techniques. The price of electricity, price_t, can therefore be expressed as

$$\text{price}_t = \mu + \sum_{i=1}^{11} \alpha_i m_{i,t} + \sum_{j=1}^{6} \beta_j w_{j,t} + \gamma h_t + \delta t + \pi_t \qquad (1)$$

with $m_{i,t}$, $w_{j,t}$, h_t, and t defined as in Section 2.1, α_i, β_j, γ, and δ as month, weekday, holiday and time-specific coefficients respectively, μ as a baseline reference category specifying

[9] We use the forecasted amount of electricity produced by wind energy as opposed to the actual amount generated, as the forecast is the relevant information which is acted upon when determining the market-clearing price on the day-ahead market.

	Coefficent	95%-Confidence Interval	p-value
Intercept	52.54	[50.89, 54.19]	< 0.0001***
February	4.45	[2.61, 6.29]	< 0.0001***
March	0.35	[-1.45, 2.14]	0.70
April	0.92	[-0.89, 2.72]	0.32
May	-0.47	[-2.27, 1.33]	0.61
June	-1.55	[-3.36, 0.26]	0.094
July	0.39	[-1.41, 2.18]	0.67
August	1.03	[-0.77, 2.83]	0.26
September	4.33	[2.51, 6.14]	< 0.0001***
October	5.56	[3.75, 7.36]	< 0.0001***
November	5.68	[3.86, 7.50]	< 0.0001***
December	0.41	[-1.40, 2.21]	0.66
Tuesday	1.15	[-0.23, 2.53]	0.10
Wednesday	1.64	[0.26, 3.02]	0.02*
Thursday	1.53	[0.15, 2.91]	0.03*
Friday	0.32	[-1.07, 1.70]	0.65
Saturday	-7.43	[-8.81, -6.05]	< 0.0001***
Sunday	-14.26	[-15.64, -12.88]	< 0.0001***
Holiday	-16.83	[-19.25, -14.40]	< 0.0001***
Time	-0.013	[-0.01, -0.01]	< 0.0001***

Table 3: OLS regression-output of the Phelix day base on seasonal variables. Reference category is a hypothetical Monday in January 2011 which is not a state holiday.
Significance codes: *** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05
Multiple R^2: 0.5876, **Adjusted** R^2: 0.5832

the price on a given weekday in a given month [10], and finally π_t as the deseasonalized price.

As stated above estimations for the coefficients and the intercept are calculated by an OLS-regression, whose results are presented in Table 3. As expected, the data shows a seasonal increase in prices during the winter months and on weekdays, and a decrease in prices during summer, on the weekends, on holidays and in general over time [11].

In the next step, the deseasonalized prices, π_t, were obtained by removing all seasonal components from the raw price data. This amounts to using the residuals of the OLS-regression reported in Table 3. A plot of π_t can be found in Figure 7.

As π_t will be used as the dependent variable in two models we will describe in Section 4.3, both of which will propose a first-order autoregressive process in one of their regimes (AR(1)-process) it should be worthwhile to check the variable for its autocorrelation structure. This

[10] In further estimations a Monday in January

[11] Notable exceptions to this trend include July, August, and December, which are major holiday months in Germany

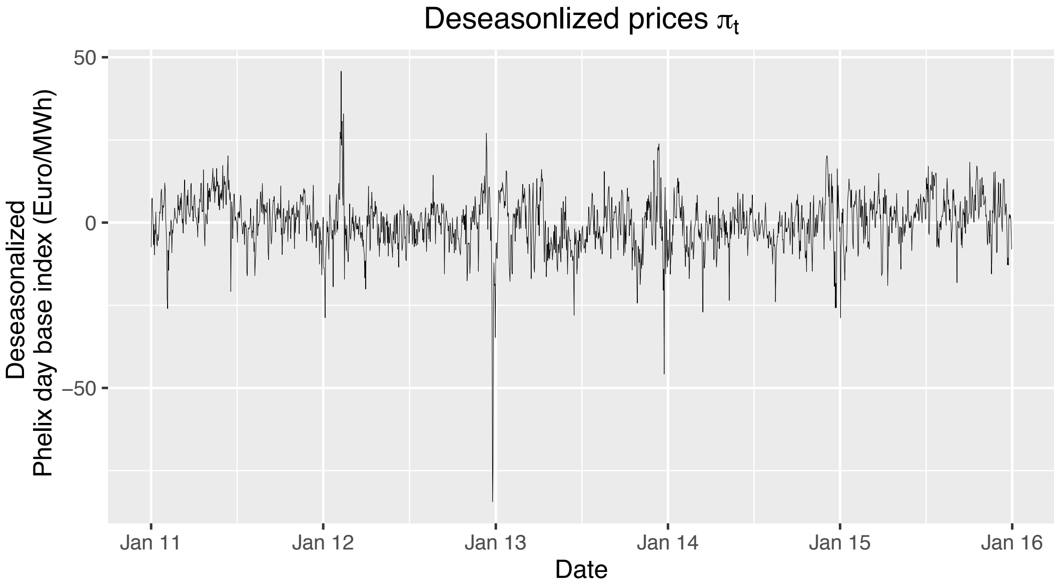

Figure 7: Deseasonalized Phelix Day Base Index, 2011-2015

is done graphically via an Autocorrelation Plot (ACF-Plot) and an Partial Autocorrelation Plot (PACF-Plot), both depicted in Figure 8. In both plots the blue dashed lines correspond to the 95%-confidence interval of an insignificant amount of autocorrelation in the variable with values of itself lagged by the amount of days given on the x-axis. Multiple transgressions of the interval given by both lines can be seen as a reliable sign of an autocorrelative structure present in the data.

We can immediately see in the ACF plot, that a significant amount of autocorrelationis is present in the data with prices as far back as nearly two weeks beeing significantly correlated with the deseasonalized price today. Furthermore, in the PACF plot we can see that the majority of the autocorrelation is present in the first lag of the variable. A further Augmented Dickey-Fuller Test (ADF-Test) confirms that the deseasonalized prices follow a stationary process (p-value < 0.01).

Given the specification of the models we will discribe in the following section these results are encouraging, as they confirm that the use of a stationary AR(1)-process to describe the structure of the deseasonalized prices is appropriate [12].

[12] We are aware that autoregressive processes of a higher order might provide a better fit to the data. As however the focus of this thesis lies on improving an already existing model which uses a AR(1) process by augmenting it with time-varying switching probabilities, we refrain from fitting a higher order process.

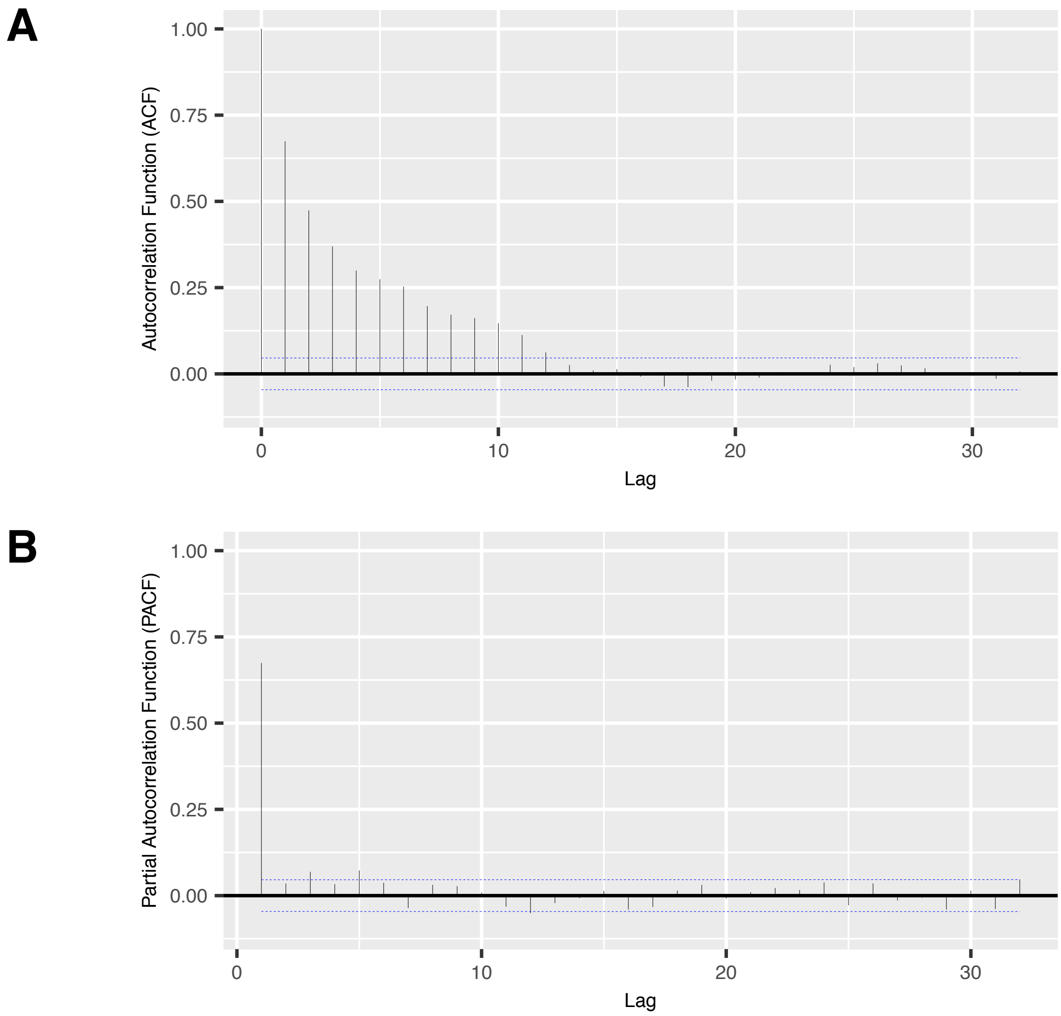

Figure 8: Autocorrelation Plot (A) and Partial Autocorrelation Plot (B) for the deseasonalized Phelix day base index π_t

4 Model Building

4.1 A brief Introduction to Markov-Switching Models

An elegant way to model variables which undergo distinct episodes of varying behavior was introduced by Hamilton in 1989, with the introduction of the Markov-Switching model (MS-model) into the field of econometrics (J. D. Hamilton 1994). The main idea of MS-models can be summarized as specifying a set of regimes $S = \{1, 2, ..., s\}$, under which a variable y_t follows a distinctively different underlying process $f_{s_t}(Z_t;\theta)$, determined by some independent variables Z_t and a vector of parameters θ, and specified by the regime $s_t \in S$ it is under at time point t, e.g.

$$y_t = \begin{cases} f_1(Z_t;\theta) & \text{if } s_t = 1 \\ f_2(Z_t;\theta) & \text{if } s_t = 2 \\ \dots & \\ f_s(Z_t;\theta) & \text{if } s_t = n \end{cases}$$

Switches between these s different regimes from one time point to the next are governed by a $s \times s$ matrix $\mathbf{P}$,

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1s} \\ p_{21} & p_{22} & \cdots & p_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ p_{s1} & p_{s2} & \cdots & p_{ss} \end{pmatrix}$$

which describes a Markov-chain modeling the transition mechanism between them. In the matrix, p_{ij} specifies the probability to transition from regime i to j and therefore corresponds to $P(s_t = j|s_{t-1} = i)$ [13].

As the underlying process of the regimes and their respective switching probabilities, which govern the composition of y_t, is usually unobservable, maximum-likelihood estimations are most commonly used to approximate the vector of parameters θ used to specify the regime-specific processes and the probabilities of transitioning between them [14].

[13] It should be noted that the sum of each row of the matrix must be equal to unity, as

$$\sum_{j=1}^{S} p_{ij} = \sum_{j=1}^{S} P(s_t = j|s_{t-1} = i) = 1$$

This property will help us in making coming parameter estimations more parsimonious. For example in the case of two regimes, by rearrangement it can immediately be seen that $p_{12} = 1 - p_{11}$ and $p_{21} = 1 - p_{22}$.

[14] For an exact derivation of the log-likelihood function optimized to estimate θ see Hamilton (1994).

4.2 Integrating time-varying Probabilities

The success with which MS-models were met with by the academic community after their introduction motivated further research into refining their mechanics. One of these innovations was the introduction of time-varying probabilities by Diebold et al. (1994). Up to then, most MS-models had focused on correctly specifying the regimes through which they were switching, leaving switching probabilities constant over time as Hamilton had done in his original paper. Diebold et al. (1994) broke with this constraint, providing a framework allowing the probabilities which govern the switches between the different regimes to vary over time. In the case of two regimes they specified the matrix **P** at time point t, P_t, as

$$P_t = \begin{pmatrix} p_t^{11} & 1-p_t^{11} \\ 1-p_t^{22} & p_t^{22} \end{pmatrix} = \begin{pmatrix} \frac{e^{x_t\beta_1}}{1+e^{x_t\beta_1}} & 1-\frac{e^{x_t\beta_1}}{1+e^{x_t\beta_1}} \\ 1-\frac{e^{x_t\beta_2}}{1+e^{x_t\beta_2}} & \frac{e^{x_t\beta_2}}{1+e^{x_t\beta_2}} \end{pmatrix} = \begin{pmatrix} \frac{e^{x_t\beta_1}}{1+e^{x_t\beta_1}} & \frac{1}{1+e^{x_t\beta_1}} \\ \frac{1}{1+e^{x_t\beta_2}} & \frac{e^{x_t\beta_2}}{1+e^{x_t\beta_2}} \end{pmatrix}$$

with x_t being a $1 \times n+1$ vector of n independent, time-varying variables at time point t, with unity added as the first element, and β_i, $i \in \{1,2\}$, being a $n+1 \times 1$ vector of unknown parameters, appended to θ during the estimation of the model [15].

This approach allows the Matrix **P** to vary over time as a series of matrices P_t, which are in turn dependent on the the time varying vector of variables x_t.

Considering the special case of using only a single dummy variable d_t as a time-varying variable to determine P_t, making $x_t = (1, d_t)'$, Diebold et al.'s approach further simplifies to

$$P_t = \begin{pmatrix} \frac{e^{x_t\beta_1}}{1+e^{x_t\beta_1}} & \frac{1}{1+e^{x_t\beta_1}} \\ \frac{1}{1+e^{x_t\beta_2}} & \frac{e^{x_t\beta_2}}{1+e^{x_t\beta_2}} \end{pmatrix} = \begin{pmatrix} \frac{e^{\beta_{10}+\beta_{11}d_t}}{1+e^{\beta_{10}+\beta_{11}d_t}} & \frac{1}{1+e^{\beta_{10}+\beta_{11}d_t}} \\ \frac{1}{1+e^{\beta_{20}+\beta_{21}d_t}} & \frac{e^{\beta_{20}+\beta_{21}d_t}}{1+e^{\beta_{20}+\beta_{21}d_t}} \end{pmatrix}$$

which in turn can be written as

$$P^0 = \begin{pmatrix} \frac{e^{\beta_{10}+\beta_{11}0}}{1+e^{\beta_{10}+\beta_{11}0}} & \frac{1}{1+e^{\beta_{10}+\beta_{11}0}} \\ \frac{1}{1+e^{\beta_{20}+\beta_{21}0}} & \frac{e^{\beta_{20}+\beta_{21}0}}{1+e^{\beta_{20}+\beta_{21}0}} \end{pmatrix} = \begin{pmatrix} \frac{e^{\beta_{10}}}{1+e^{\beta_{10}}} & \frac{1}{1+e^{\beta_{10}}} \\ \frac{1}{1+e^{\beta_{20}}} & \frac{e^{\beta_{20}}}{1+e^{\beta_{20}}} \end{pmatrix} := \begin{pmatrix} p_{11}^0 & p_{12}^0 \\ p_{21}^0 & p_{22}^0 \end{pmatrix}$$

for $d_t = 0$, and

[15]Although obvious, it may be helpful to see that the condition that the row entries of the Matrix P_t add up to unity is upheld, as for row i

$$p_t^{i1} + p_t^{i2} = \frac{e^{x_t\beta_i}}{1+e^{x_t\beta_i}} + \frac{1}{1+e^{x_t\beta_i}} = \frac{1+e^{x_t\beta_i}}{1+e^{x_t\beta_i}} = 1, i \in \{1,2\}$$

$$P^1 = \begin{pmatrix} \frac{e^{\beta_{10}+\beta_{11}1}}{1+e^{\beta_{10}+\beta_{11}1}} & \frac{1}{1+e^{\beta_{10}+\beta_{11}1}} \\ \frac{1}{1+e^{\beta_{20}+\beta_{21}1}} & \frac{e^{\beta_{20}+\beta_{21}1}}{1+e^{\beta_{20}+\beta_{21}1}} \end{pmatrix} = \begin{pmatrix} \frac{e^{\beta_{10}+\beta_{11}}}{1+e^{\beta_{10}+\beta_{11}}} & \frac{1}{1+e^{\beta_{10}+\beta_{11}}} \\ \frac{1}{1+e^{\beta_{20}+\beta_{21}}} & \frac{e^{\beta_{20}+\beta_{21}}}{1+e^{\beta_{20}+\beta_{21}}} \end{pmatrix} := \begin{pmatrix} p_{11}^1 & p_{12}^1 \\ p_{21}^1 & p_{22}^1 \end{pmatrix}$$

for $d_t = 1$.

Therefore by substituting the elements p_{11} and p_{22} in the parameter vector θ by appending $\beta = (\beta_{10}, \beta_{11}, \beta_{20}, \beta_{21})$, a formerly time-constant MS-model with two regimes can be augmented with time-varying switching probabilities dependent on only a single independent dummy variable.

4.3 Modeling Electricity Prices subject to changing Regimes

Since their introduction MS-models have been used to characterize the behavior of a number of different variables, among them GDP-growth, foreign exchange rates and CO_2-certificates (Benschop and Cabrera 2014; J. Hamilton 1990).

As mentioned in the Introduction, Bierbrauer et al. (2004) proposed fitting deseasonalized log-prices gathered from the Nordic power market (NordPool) by a number of two-regime MS-model, thereby being able to capture the "jumpy" behavior of the price process observed over time. All of their models consist of a so called "base regime", characterized by a mean reverting Ornstein-Uhlenbeck process (OU-process), and a so called "jump regime", characterized by a random draw from a number of different probability distributions. Their most basic model with a Gaussian distribution serving as a jump regime is accordingly defined as

$$\log(\pi_t) = \begin{cases} \log(\pi_{1,t}) \text{ where } \mathrm{d}\pi_{1,t} = (c_1 - \beta_1 \log(\pi_t))\,\mathrm{d}t + \sigma_1\,\mathrm{d}B_t & \text{if } s_t = 1 \text{ (base regime)} \\ \log(\pi_{2,t}) \text{ where } \log(\pi_{2,t}) \sim N(\mu_2, \sigma_2^2) & \text{if } s_t = 2 \text{ (jump regime)} \end{cases}$$

with $\mathrm{d}\pi_t$ as the change in the deseasonalized price at period t, $\mathrm{d}B_t$ as increments of a random Brownian motion, $(c_1 - \beta_1 \log(\pi_t))$ as an incremental temporal drift towards the mean c_1, σ_1 as the volatility contained in regime 1 and $\log(\pi_{2,t}) \sim N(\mu_2, \sigma_2^2)$ as a draw from a random variable with mean μ_2 and standard deviation σ_2 following a Gaussian distribution.

Discretizing the continuous OU-process by the Euler–Maruyama method into an easier to estimate first order autoregressive process (AR(1)-process), yields the to some more familiar model

$$\log(\pi_t) = \begin{cases} \log(\pi_{1,t}) \text{ where } \log(\pi_{1,t}) = \phi_0 + \phi_1 \log(\pi_{t-1}) + \epsilon_t & \text{if } s_t = 1 \text{ (base regime)} \\ \log(\pi_{2,t}) \text{ where } \log(\pi_{2,t}) \sim N(\mu_2, \sigma_2^2) & \text{if } s_t = 2 \text{ (jump regime)} \end{cases}$$

with ϕ_0 as a constant parameter, ϕ_1 a mean regressive parameter, and $\epsilon_t \sim N(0, \sigma_1^2)$ as Gaussian white noise with standard deviation σ_1.

In both cases, the probabilities of switching between the two regimes are characterized by the 2×2 matrix P, such that

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{pmatrix}$$

with the probabilities p_{ii} defined as in section 4.1.

With this relatively simple model, Bierbrauer et al. were able to describe the basic functioning of electricity prices on publicly traded markets. Published in 2004 their model however did not take into account two important facts: The possibility of negative prices agreed upon on the market and the added volatility in the market due to an ever larger strongly varying supply of wind generated power.

To combat the first restriction, we propose using raw deseasonalized prices instead of log-prices as the dependent variable. Accordingly, we rewrite the model as

$$\pi_t = \begin{cases} \pi_{1,t} \text{ where } \pi_{1,t} = \phi_0 + \phi_1 \pi_{t-1} + \epsilon_t & \text{if } s_t = 1 \text{ (base regime)} \\ \\ \pi_{2,t} \text{ where } \pi_{2,t} \sim N(\mu_2, \sigma_2^2) & \text{if } s_t = 2 \text{ (jump regime)} \end{cases}$$

with all parameters defined as above. To combat the second restriction, we propose letting switching probabilities in the model vary dependent on the amount of wind generation fed into the market. As similarly done in Veraart (2016) we make switches between the base and the jump regimes dependent on a version of the wind-penetration index WP_t dichotomized along the 75%-Quantile, defined as

$$d_t := \begin{cases} 0 & \text{if } WP_t \leq Q_{0.75}(WP_t) \\ \\ 1 & \text{if } WP_t \geq Q_{0.75}(WP_t) \end{cases}$$

and replace the time-constant matrix $\mathbf{P}$ by P_t, such that

$$P_t = \begin{pmatrix} p_t^{11} & 1 - p_t^{11} \\ 1 - p_t^{22} & p_t^{22} \end{pmatrix} = \begin{pmatrix} \frac{e^{\beta_{10} + \beta_{11} d_t}}{1 + e^{\beta_{10} + \beta_{11} d_t}} & \frac{1}{1 + e^{\beta_{10} + \beta_{11} d_t}} \\ \frac{1}{1 + e^{\beta_{20} + \beta_{21} d_t}} & \frac{e^{\beta_{20} + \beta_{21} d_t}}{1 + e^{\beta_{20} + \beta_{21} d_t}} \end{pmatrix} = \begin{cases} \begin{pmatrix} \frac{e^{\beta_{10}}}{1 + e^{\beta_{10}}} & \frac{1}{1 + e^{\beta_{10}}} \\ \frac{1}{1 + e^{\beta_{20}}} & \frac{e^{\beta_{20}}}{1 + e^{\beta_{20}}} \end{pmatrix} & \text{if } d_t = 0 \\ \begin{pmatrix} \frac{e^{\beta_{10} + \beta_{11}}}{1 + e^{\beta_{10} + \beta_{11}}} & \frac{1}{1 + e^{\beta_{10} + \beta_{11}}} \\ \frac{1}{1 + e^{\beta_{20} + \beta_{21}}} & \frac{e^{\beta_{20} + \beta_{21}}}{1 + e^{\beta_{20} + \beta_{21}}} \end{pmatrix} & \text{if } d_t = 1 \end{cases}$$

As can be seen in Table 2 the cut off point for the wind-penetration dummy d_t, the 3rd quantile of the wind-penetration index (also known as $Q_{0.75}$), is about 14.5%, showing that 25% of all days in the data set experience a higher amount of wind-penetration. For our new model this augmentation with time-varying switching probabilities means that switches between the base and jump regimes on days with a wind-penetration lower than 14.5% are governed by the entries of a different matrix than switches on days experiencing a higher wind-penetration. This stands in contrast to the constant switching probabilities used in Bierbrauer et al.'s conventional model.

In the next section we will estimate a version of Bierbrauer et al.'s discretized model with constant switching probabilities and a version of the same model with time-varying switching probabilities (called constant MS-model and time-varying MS-model respectively in the following). In both models the deseasonalized prices from the EEX as calculated in Subsection 3.2 will be used as the dependent variable, with the dichotomized wind-penetration index used as described in this subsection as an independent variable in the time-varying MS-model. After that we conclude by comparing the estimates of both models with one another and discussing their results.

5 Estimation Results

5.1 Parameter Estimations

The results presented in Table 4 were obtained by numerically maximizing the model specific log-likelihood function, $\log(L(\theta)) = l(\theta)$, of both the MS-Model with constant and the MS-Model with time-varying switching probabilities, with regard to their corresponding vector of parameters θ [16] set to a number of constraints [17]. All estimations were performed in the statistical programming language *R*, with a wrapper on the *optim* package being used to numerically maximize given the log-likelihood function under constraints.

We can see that according to the estimated parameters, both models switch through overall similar regimes, with slight differences between the mean of the AR(1)-process in the base regime and pronounced differences between the standard deviations of the Gaussian distribution in the jump regime. In both models the estimated constant of the autoregressive process, ϕ_0, in the base regime is centered relatively close to 0, with the estimated stationary AR(1) parameter ϕ_1 corresponding to a value close to 0.66 and the standard deviation

[16] In the case of the constant MS-model
$\theta_{\text{constant}} = (\phi_0, \mu_2, \phi_1, \sigma_1, \sigma_2, p_{11}, p_{22})$
and in the case of the time-varying MS-model
$\theta_{\text{varying}} = (\phi_0, \mu_2, \phi_1, \sigma_1, \sigma_2, \beta_{10}, \beta_{11}, \beta_{20}, \beta_{21})$

[17] Both models were constrained by
$\sigma_i \geq 0,\ i \in \{1,2\}$,
with the additional constraints
$0 \leq p_{ii} \leq 1,\ i \in \{1,2\}$
added for the constant model.

	Two-Regime Markov-Switching Model with constant Switching Probabilities	Two-Regime Markov-Switching Model with time-varying Switching Probabilities
ϕ_0	0.14	0.94
μ_2	-8.35	-8.81
ϕ_1	0.67	0.64
σ_1	4.93	4.65
σ_2	21.45	9.43
p_{11}	0.99	
p_{22}	0.72	
β_{10}		25.51
β_{11}		-24.77
β_{20}		-2.31
β_{21}		25.26
p^0_{11}		1.00
p^0_{22}		0.09
p^1_{11}		0.68
p^1_{22}		1.00

Table 4: Estimation results for the vectors of parameters θ_{constant} and θ_{varying}

of the Gaussian white noise σ_1 estimated to be at about 4.5. Although somewhat different when it comes to their dispersion, the Gaussian distributions specifying the jump regime in both models also seem to follow similar patterns, with μ_2, the estimated expected downwards jump of π_t when in the jump regime corresponding to a value of about -8.5 in both models.

Turning to the switching probabilities between the rather similar set of jump and base regimes in both models, we can observe significant differences.

In the constant model, a period in which the price was determined by the base regime is followed by a period in which the price is again determined by the base regime by a probability of over 99% ($p_{11} = P(s_t = 1|s_{t-1} = 1) \geq 0.99$). This was also true for the time varying model, under the condition that the period being switched into is not one experiencing a high penetration of wind energy in the market ($p^0_{11} = P(s_t = 1|s_{t-1} = 1, d_t = 0) \approx 1$). Conversely, if the following period is experiencing a high wind-penetration in the market the probability of staying in the base regime drops considerably to a value of about 68% ($p^1_{11} = P(s_t = 1|s_{t-1} = 1, d_t = 1) \approx 0.68$), making the switch into the peak pricing regime during such a time much more likely ($p^1_{12} = P(s_t = 2|s_{t-1} = 1, d_t = 1) = 1 - p^1_{11} \approx 0.32$).

A more complex picture emerges when looking at the probability of staying in the jump regime in two consecutive periods. In the constant model this probability, p_{22}, was estimated as being at around 72%, ($p_{22} = P(s_t = 2|s_{t-1} = 2) \approx 0.72$) leaving a probability of 28% of reverting back to the base regime after a period in the jump regime. In the time-varying model however the probability of staying in the jump regime varies drastically depending on the wind-penetration the market experiences on the day of the switch. Given the market experiences a very high wind energy penetration, the probability of staying in the jump regime was given by a value roughly equal to 100%, making a switch into into the base regime highly improbable, whereas given no high wind-penetration the same probability changes to a vastly different 9%, leaving a 91% chance of reverting into the base regime ($p^1_{22} = P(s_t = 2|s_{t-1} = 2, d_t = 0) \approx 0.09$, $p^2_{22} = P(s_t = 2|s_{t-1} = 2, d_t = 1) \approx 1$).

Summing up the results seem to imply, that during time points in which the market is forecasted to experience a high amount of wind-penetration, a switch into and a remainder in the highly volatile jump regime becomes drastically more likely. Looking back at the estimated parameters this implies that during periods of high wind-penetration prices drop significantly as they are more likely to be determined by the jump regime, a proposition that is in line with the theoretical considerations developed in Subsection 2.3.

The opposite can be said about time points in which the market is forecasted not to experience a high wind-penetration. On such days switches into the jump regime were estimated to be highly unlikely, with reversions out of the jump regime back into the base regime being much more likely. Furthermore the probability of staying in the base regime was estimated to be close to unity, implying that a switch into the jump regime was extremely unlikely. This fits the ideas outlined in Subsection 2.3, as on such days the market experience a relative scarcity of supply which in turn drives prices up.

5.2 Comparing Model Fits

Comparing both models to each other, it seems as if the wind-penetration index proves to be a reasonably good filter for differentiating between time points in which a switch in regimes is highly probable and those in which it is not. It follows that during time points in which the market is forecasted to experience a high penetration of wind energy the prices for electricity are very likely to drop significantly due to being determined by the jump regime, whereas during times of low wind-penetration such price drops are considerably more unlikely.

Tabulating in-sample goodness-of-fit criteria of both models next to each other, we see that the time-varying model also manages to provide a better overall fit to the sampled data (Table 5). The first two columns show the results of a Kolmogorov-Smirnov Test (KS Test), which uses the largest distance between the probability distribution function proposed by the respective model and the distribution function of the empirical data as a test statistic to measure if both distributions are equal. The results and their corresponding p-values confirm to a significant degree (p-value > 0.05), that for both models the null hypothesis that the simulated data and the sampled empirical data follow the same distribution function cannot

	KS Test-Statistic	KS p-value	AIC
Model with constant Switching Probabilities	0.0291	0.095	11370
Model with time-varying Switching Probabilities	0.0289	0.099	11312

Table 5: Goodness of fit test-statistics for the model with constant switching probabilities and the model with time-varying switching probabilities
Abbreviations: KS Test = Kolmogorov-Smirnov Test, AIC = Akaike Information Criterion
Note: Critical values were calculated for 1825 observations

be falsified. Furthermore, the Akaike Information Criterion (AIC) shown in the third column of Table 5 gives a comparison of the adjusted log-likelihood values of both models, whereby the adjustment is made relative to the number of parameters estimated in the model. We can see that here too the time-varying model provides a better fit to the sampled data (lower AIC values signify a better fit). As both models only differ in their estimation by two parameters, it can be assumed that the sizable difference in the log-likelihood value of both models is mainly due to the better fit of the time-varying model.

In Figure 9 we see Quantile-Quantile Plots (QQ-plots) for the distribution of deseasonalized prices proposed by both the estimated constant MS-model and the time-varying MS-models plotted against the distribution of the empirical data. We see that the constant MS-model overall provides a good fit, but fails to take into account the fat negative tail of the distribution of the deseasonalized prices. In the plot next to it we see that the time-varying MS-model picks up on this weakness, providing a much better fit to large negative values due to its flexible switching probabilities. Figure 10 further illustrates this point, showing how the density distribution proposed by the constant MS-model underrepresents large negative values, which are however taken into account by the distribution proposed by the time-varying MS-model.

Summing up, the advantages of the time-varying MS-model are most probably best illustrated in Figure 11. Examining a plot of deseasonalized prices with time points of high wind-penetration shaded red, we notice that major price drops from one day to the next nearly always coincide with a high wind-penetration on that day. Plotting the smoothed probabilities of being in the jump regime in both models next to it, we see that the time-varying model is much better at factoring in the short-term probability of switching into the jump regime on such days [18]. This seems straightforward, as the switching probabilities of the time-varying model are determined by the current wind-penetration. Nevertheless this approach seems to provide a real benefit to modeling electricity prices, as by factoring in wind-penetration it is able to reliably differentiate the time points in which a switch into the jump regime is likely from those in which it is not.

[18] Smoothed probabilities were calculated as described in Hamilton (1994).

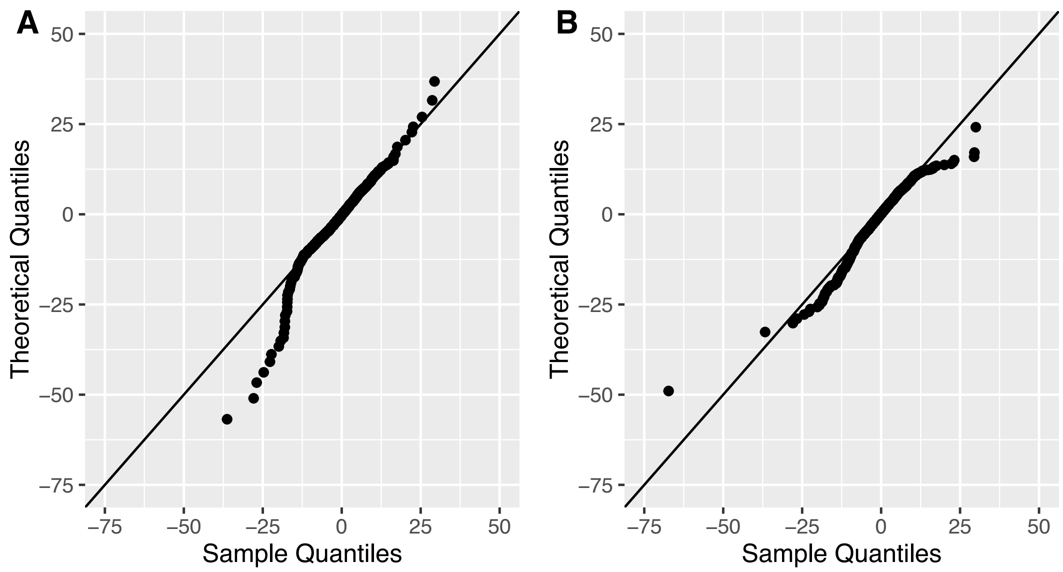

Figure 9: Quantile-Quantile Plots for the theoretical distribution of π_t proposed by (A) the model with constant switching probabilities and (B) the model with time-varying switching probabilities (dots) against the empirical distribution of the sample (line)

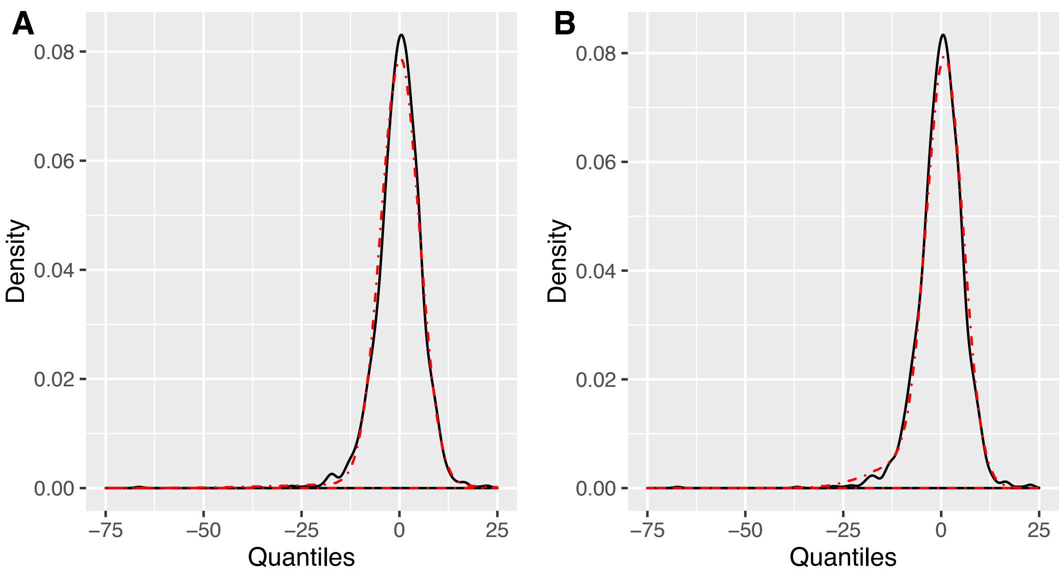

Figure 10: Kernel-Density Plots for the theoretical distribution of π_t proposed by (A) the model with constant switching probabilities and (B) the model with time-varying switching probabilities (red dashed line) against the empirical distribution of the sample (black solid line)

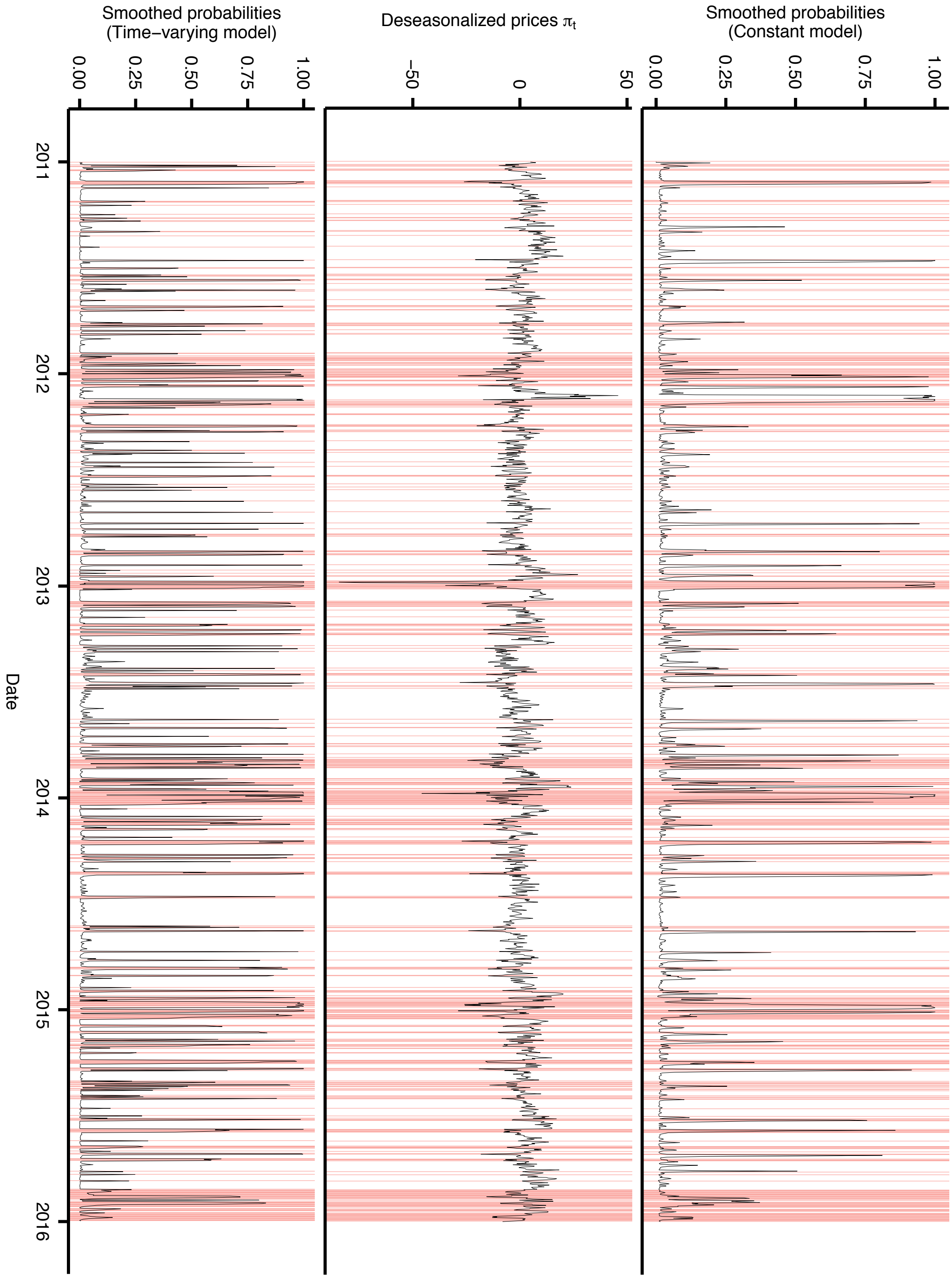

Figure 11: Smoothed probabilities of being in the jump regime from 2011-01-01 to 2015-12-31 plotted against the deseasonalized prices. Red shaded areas mark time points in which the market experiences high wind-penetration as characterized by the wind-penetration index.

6 Conclusion

The aim of this thesis was to asses the impact the increasing use of wind energy to produce electricity has had on the price of electricity in Germany. We were able to conclusively show that the fluctuating nature of electricity generated by wind has had a strong effect on electricity prices in Germany under the current market system, leading to an increase of days with extremely low prices.

Overall it can be said that due to their low to non-existent marginal costs wind turbines have not only managed to push power prices down over the last decade, but have at the same time made the price itself increasingly more volatile. This development has been bad news for conventional base load power producers which have to take these prices, as their business model relies on being able to constantly supply the market with electricity. As with the expanded use of wind energy time points with exceptionally low prices have become more common, this business model has also become increasingly more unsustainable. Considering that wind generated power and other renewables currently cannot reliably supply electricity around the clock, they cannot function as perfect substitutes for conventional forms of power production. Pushing these conventional power producers from the market too rapidly therefore goes against the public interest, as without replacing them adequately it undermines the current supply security Germany enjoys [19].

It is therefore necessary to take up policy measures aimed to combat the negative side effects of the increased use of wind energy. Such policy measures could be manifold and aimed at different parts of the electricity market: changing the design of the market itself, reforming the EEG to better incentivize investments into more reliable and financially sustainable forms of energy production, and stimulating increased research into methods of power storage and distribution.

Summing up, the German government's decision to transition from conventional to renewable sources of power production has set considerable challenges to all market participants. A lot has already been done in the past and present to meet them, with the EEX introducing the trading of futures with wind generated power as an underlying in October 2016 and the German government planning to restructure the current subsidization scheme for renewables in the coming year with the "EEG-Novelle 2017". Nonetheless plenty of further research on how to sustainably integrate the growing number of renewable power producers into the market is necessary, to guarantee the success of the German "Energiewende".

[19] Be it through political pressure as in the case of nuclear power or economic pressure as in the case of coal-fired plants.

Appendix

Declaration of Academic Honesty

I, Manuel P. Mezger, hereby declare that I have not previously submitted the present work for other examinations. I wrote this work independently. All sources, including sources from the Internet, that I have reproduced in either an unaltered or modified form (particularly sources for texts, graphs, tables and images), have been acknowledged by me as such.

I understand that violations of these principles will result in proceedings regarding deception or attempted deception.

Manuel P. Mezger

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