Short-term dynamics of day-ahead and intraday electricity prices

Journal Article

Author(s):
Wolff, Georg; Feuerriegel, Stefan

Publication date:
2017-11

Permanent link:
https://doi.org/10.3929/ethz-b-000183298

Originally published in:
International Journal of Energy Sector Management 11(4), https://doi.org/10.1108/IJESM-05-2016-0009

Short-term dynamics of day-ahead and intraday electricity prices

Abstract

Purpose

Since the liberalization of electricity markets in the European Union, prices are subject to market dynamics. Hence, understanding the short-term drivers of electricity prices is of major interest to electricity companies and policy-makers. Accordingly, this paper studies movements of prices in the combined German and Austrian electricity market.

Approach

We estimate an autoregressive model with exogenous variables (ARX) in a two-step procedure. We first de-seasonalize both time series, which inherently feature seasonality, and, in a second step, measure the influence of all model variables on the two dependent variables, i. e. the day-ahead and intraday EPEX prices.

Findings

Our results reveal that the short-term market is largely driven by seasonality, consumer demand and short-term feed-ins from renewable energy sources. As a contribution to the existing body of literature, this paper specifically compares the price movements in day-ahead and intraday markets. In intraday markets, the influences of renewable energies are much stronger than in day-ahead markets, i. e. by 24.12 % for wind and 116.82 % for solar infeeds.

Originality

Knowledge on the price setting mechanism in the intraday market is particularly scarce. This paper contributes to existing research on this topic by deriving drivers

in the intraday market and then contrasting them to the day-ahead market. A more thorough understanding is especially crucial all stakeholders, who can use this knowledge to optimize their bidding strategies. Furthermore, our findings suggest policy implications for a more stable and efficient electricity market.
Keywords: Electricity, price modeling, renewable energies, external drivers, weather influence, time series analysis, autoregressive model

---

1. Introduction

Liberalized electricity markets have been fostered worldwide by policy-makers since the end of the 20th century. The European Union has played a leading role in liberalizing its electricity market and enforcing an integrated European market across national boundaries (Jamasb and Pollitt, 2005), the starting point of which was the European Directive[1] on the liberalization of national electricity markets in 1996 (Ellersdorfer, 2009).

Nowadays, participants in the electricity sector can trade electricity on the spot market. For example, the German and Austrian spot market is organized by the European Power Energy Exchange (EPEX), which is a joint venture between the European Energy Exchange (EEX) and the French Powernext.[2] This has triggered a fundamental change: though the largest share of electricity is traded in over-the-counter transactions, trading in the intraday and day-ahead markets has become prevalent. For instance, the electricity volume of the EPEX day-ahead spot market has increased by roughly 300 % in the last ten years. This amounts to a daily day-ahead trading volume of 750,559 MWh as of December 31, 2014.[3]

Such a dynamic spot market and the limitations of electricity storage lead to unique market conditions with highly volatile electricity prices (e. g. Bierbrauer et al., 2007, Deng and Oren, 2006, Weron, 2007). In addition, external variables, such as fuel prices and economic factors, can influence the electricity spot price (e. g. Gelabert et al., 2011, Paraschiv et al., 2014, Paschen, 2016). Electricity traders thus form their price expectations based on fundamental, as well as external, factors. Understanding these drivers of electricity prices can be of great help to various stakeholders. Based on this information, electricity traders can improve their bidding strategies and find new investment opportunities. Furthermore, policy-makers benefit as they are able to verify that policy incentives, such as the preferential treatment of renewables, are yielding the expected societal and environmental results (Menanteau et al., 2003).

A crucial component of the electricity price is its price-setting mechanism, i. e. the *merit order*. In the merit order system, power plants are activated in order, beginning with those that entail the lowest marginal costs (Ellersdorfer, 2009). Power plants with higher marginal costs are then connected to the grid step-by-step until the electricity demand is satisfied. Figure 1 illustrates the marginal costs of the system through the so-called merit order curve.

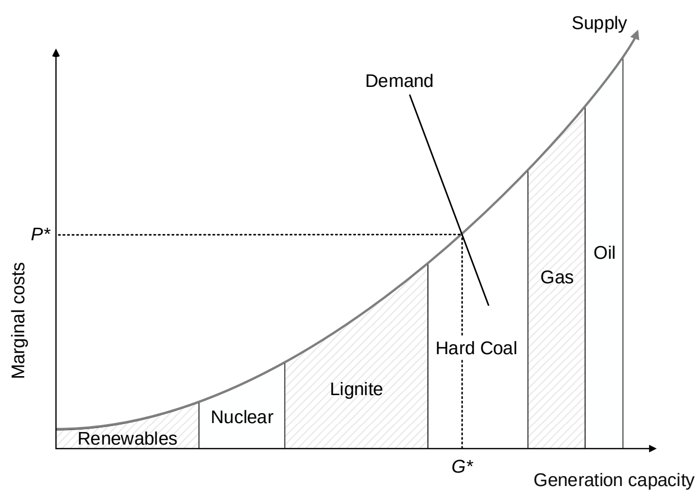


Figure 1: Merit order curve describes price setting mechanism in spot markets (source: own illustration, adapted from Sensfuss et al. (2008)).

Based on the merit order curve, we observe that the electricity price is highly dependent on the power plants involved – such as coal-fired power plants, gas-steam power plants or wind farms – while, at the same time, consumer demand changes from hour to hour. Therefore, many different factors on the demand side, as well as the supply side, influence the electricity price. We group these factors as follows:

1. **Seasonality.** The price of electricity depends on several seasonal considerations. On the one hand, seasonality can originate from climate conditions, such as temperature, and the hours of daylight (Weron, 2007). On the other hand, different consumption levels, e. g. between working days and the weekend, are an additional source of fluctuations. This results in the electricity price having hourly, daily, weekly and yearly seasonal patterns.
2. **Supply side.** On the supply side, the infeed from renewable energies can have a strong impact on the electricity price. Electricity from renewable sources, such as photovoltaic plants and wind farms, is given preferential treatment in the German electricity market in order to promote investment in environmentally-friendly technologies. In addition to this special treatment, renewable energy power plants can produce electricity with almost zero marginal cost per additional unit of electricity (Sensfuss et al., 2008).
3. **Demand side.** Electricity consumption, representing the demand side, may play an important role as a price driver. If electricity consumption increases, it is necessary to generate additional electricity from backup power plants. In regard to the merit order system, this results in an increased share of infeeds from power plants with higher marginal costs, such as coal-fired power plants.
4. **Fuel prices.** The price of electricity also reflects production costs, which depend, among other things, on the corresponding fuel prices, such as the cost of coal and natural gas.
5. **Economic factors.** Further economic factors, such as the exchange rate, can increase generation costs for power plant operators. For instance, fuels are frequently traded in U. S. dollars and, hence, they are subject to the highly volatile exchange rate.

This paper contributes to an understanding of EPEX electricity prices by modeling the short-term dynamics. While many studies have addressed merely the day-ahead market, we also consider the intraday market and explicitly take the important step of comparing the two.

The remainder of the paper is structured as follows. Section 2 provides an overview of related work on modeling electricity prices. This serves as a foundation for Section 3, in which we present our approach to modeling the EPEX electricity price. The corresponding results in Section 4 compare the day-ahead and intraday electricity prices. Finally, in Section 5, we summarize our findings and present policy implications.

2. Related work on modeling electricity prices

This section first presents related works regarding the choice of the underlying model. Second, we address seasonality and, finally, we discuss the driving factors – namely, consumption, renewable energies, fuel prices, emission rights and economic variables.

2.1. Model choice

Various statistical techniques are used to analyze electricity price movements. Related works predominantly focus on price forecasting, in which autoregressive moving average ARMA(N,M) models are commonly utilized. The autoregressive (AR) component includes N past values to explain the current price, while the second component accounts for the moving average (MA) of M foregoing noise terms. Incorporating exogenous factors into ARMA models further improves the forecast (e. g. Contreras et al., 2003, Ludwig et al., 2015).

As an alternative, vector autoregressive (VAR) models investigate the influence of several variables simultaneously (Lütkepohl, 2007) and typically treat variables as endogenous. Several works analyze the impact of external variables on the electricity price through VAR models or their variants, e. g. structural VAR models or the vector error correction model (VECM). For example, Bello and Reneses (2013), Freitas and da Silva (2015) and Muñoz and Dickey (2009) use cointegration techniques to study the Spanish market; Mohammadi (2009) and Mjelde and Bessler (2009) consider the U. S. market; and Thoenes (2011), as well as Paschen (2016), analyzes the day-ahead EEX price.

2.2. Seasonality

Electricity prices reflect seasonal characteristics of various duration (Weron, 2007). Electricity prices usually decrease at night (when demand is low) and peak during the daytime (when consumption is high). Daily seasonality may arise, among other things, from higher industrial production and demand levels during weekdays as compared to weekends. Monthly seasonality may originate, for example, from different weather conditions, such as windy or hot periods during the year. We refer to Knittel and Roberts (2005) for deeper insight into the stylized facts of electricity prices.

2.3. Driving factors of electricity prices

All of the aforementioned studies address the impact of different factors on electricity prices. We thus detail potential drivers in the following section.

Demand side: electricity consumption

In an efficient market, electricity consumption positively affects the price of electricity. Accordingly, previous works often take into account electricity consumption or the grid load. For example, Bello and Reneses (2013), Clò et al. (2015) and Gelabert et al. (2011) consider the load as an explanatory variable, while other studies incorporate the expected load (e. g. Paraschiv et al., 2014, Würzburg et al., 2013).

Supply side: infeed of renewable energies

Renewable energy sources can considerably influence the price of electricity due to their low marginal costs. Hence, many references take the feed-in from renewable energy sources into account. For instance, the feed-ins of photovoltaic plants and wind farms make up a large share of German renewable electricity production and are consequently of predominant interest (BMWi, 2017).

Würzburg et al. (2013) estimate several model specifications with, inter alia, a joint variable, as well as the expected wind and solar production. Both specifications yield the same result: a significantly negative effect of renewables on the electricity price in the short-run. In the case of wind power, the same relationship is found when using the actual production data (Cutler et al., 2011, Gelabert et al., 2011). This is in contrast to the long-term relationship, where Bello and Reneses (2013) provide evidence of a positive relationship; the authors attribute this finding to market participants who bid offensively over a span of time to restore losses from periods with high feed-ins from wind power. Further studies, such as Ketterer (2014), Paraschiv et al. (2014) and Würzburg et al. (2013), incorporate the expected wind production instead of the ex post figures. The argument behind this approach is that, for day-ahead markets, producers and consumers form their decisions based on the expected generation.

In the case of solar power, Bello and Reneses (2013), Clò et al. (2015) and Gelabert et al. (2011) find that solar production has a significantly negative impact on the price of electricity. Paraschiv et al. (2014) and Würzburg et al. (2013) consider expected solar production and also establish a negative relationship. All in all, renewables should have – empirically and theoretically – a negative impact on the short-term electricity price. When comparing wind and solar power, Paschen (2016) reports a more prolonged negative effect of wind power shocks compared to solar power.

Fuel prices

Coal-fired power plants account for 45 % of total German electricity production (BMWi, 2017) and, therefore, the coal price may be a reasonable cost driver for electricity prices. Paraschiv et al. (2014) find a significantly positive short-term impact.

However, most studies utilize a long-term model to estimate the influence of the coal price on electricity prices, albeit with diverging outcomes: there is evidence of a positive effect (e. g. Bello and Reneses, 2013, Fell et al., 2010, Freitas and da Silva, 2015), as well as a negative effect (Mohammadi, 2009), whereas others cannot see any significant effect (Ferkingstad et al., 2011, Mjelde and Bessler, 2009).

The gas price reveals similar differences between the short-term and long-term influence. In the short-run, Würzburg et al. (2013), Paraschiv et al. (2014) and Woo et al. (2011) provide evidence of a significant positive impact, whereas Freitas and da Silva (2015) see no response to a shock in the price of gas. A year-by-year evaluation suggests that this effect is highly dependent on the period under consideration (Clò et al., 2015). The authors find a positive effect only for certain years (e. g. 2006, 2007, 2011 and 2013). In long-term analysis, previous works have measured that a 1 % change in the gas price results in a 0.68 % increase (Bunn and Fezzi, 2009) or a 0.39 % increase (Freitas and da Silva, 2015) in the price of electricity over an extended period of time. Hence, electricity prices seem to reflect changes in the gas price predominantly in the long run (e. g. Fell et al., 2010, Thoenes, 2011).

Several studies suggest that the price of oil influences the price of electricity since oil-fired power plants serve as backups (e. g. Paraschiv et al., 2014, Gelabert et al., 2011). Erni (2012) argues that the oil price affects the transportation costs of coal-fired power plants. However, Mohammadi (2009) does not find a significant effect, though Paraschiv et al. (2014) establish a positive relationship between the price of oil and electricity. Ferkingstad et al. (2011) observe a weakly exogenous positive impact, similar to Mjelde and Bessler (2009) and Bello and Reneses (2013). In Germany, oil-fired power plants meet only one percent of the electricity demand (BMWi, 2017) and the price of oil might thus reveal a negligible influence.

Economic factors

Since most commodities are traded in U. S. dollars (USD), the exchange rate may also be a relevant factor. Several studies find evidence of a relationship between the exchange rate and commodity prices. Akram (2009) finds that a weaker dollar is associated with higher commodity prices. Chen and Chen (2007) and Zhang et al. (2008) provide evidence of a relationship between the oil price and exchange rates, while Muñoz and Dickey (2009) analyze a cointegration relationship between the electricity price, the oil price and the USD/euro exchange rate.

3. Materials and Methods

This section presents our datasets and the statistical approach to modeling short-term electricity price movements. An overview of all variables under consideration is given in Table 1, while the corresponding descriptive statistics are listed in Table 2.

3.1. Model variables: electricity price and exogenous drivers

In the model, we include the hourly infeeds from wind and solar power as proxies for infeeds from renewables, since renewable energies had a total share of 25.8 % of German electricity production in 2014 (BMWi, 2017). We take the actual values of the infeeds from renewables and the grid load, thus avoiding the potential estimation bias from using forecasts. Nevertheless, Erni (2012) finds a very high correlation between the expected and the real wind infeed. We omitted the generated electricity volume from other power sources, such as coal or nuclear power, since these correlate with the overall demand that is already encoded in the load variable. In addition, we incorporate feed-ins from renewable energy sources, as well as fuel costs for electricity generation represented by the prices for coal, gas and oil. We include the USD/euro exchange rate in our subsequent analysis to control for exchange rate effects pertaining to commodity trading. In the day-ahead model, the fuel prices, as well as the economic factors, enter the model as lagged variables, since the day-ahead price is set one day in advance.

Insert Table 1 about here

3.1.1. *Descriptive statistics*

Figure 2 illustrates the hourly day-ahead spot price at EPEX with its corresponding distribution from January 1, 2010 to December 31, 2014. We observe a high volatility with significant positive and negative price peaks and also an indication of seasonality.

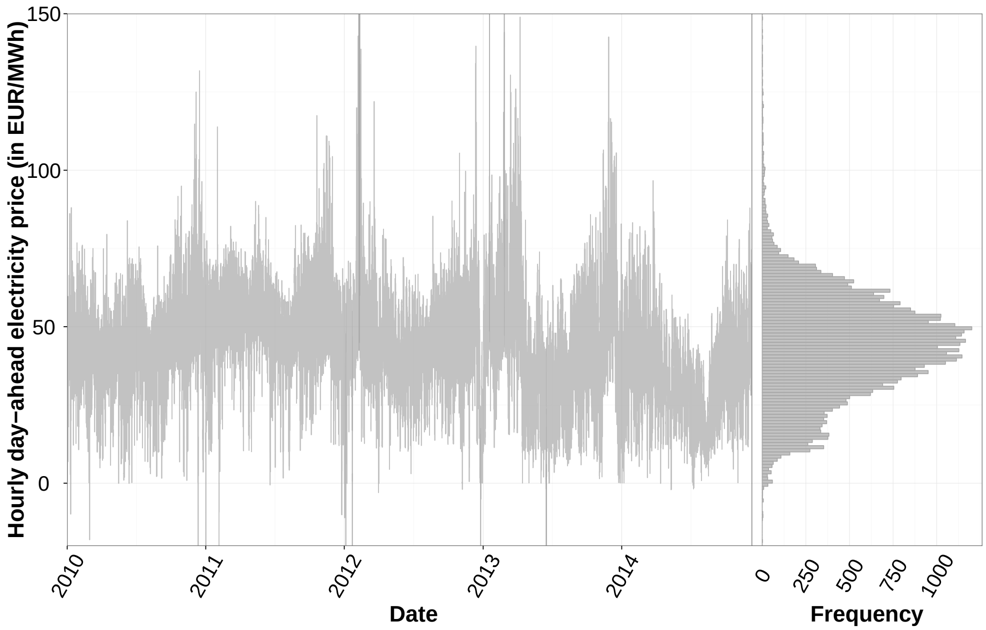


Figure 2: Time series (left) and corresponding histogram (right) of the hourly day-ahead electricity spot price at the EPEX (cropped to the range of −20€ /MWh to 150€ /MWh).

According to Table 2, the mean day-ahead spot price accounts for 43.32€ /MWh, with a price range from −200€ /MWh to 210€ /MWh. The distribution shows a skewness of −0.12 and a kurtosis of 5.52, resulting into a fairly normal distribution. In contrast, the intraday spot price accounts for a mean price of 42.37€ /MWh, which is lower by 0.95€ /MWh. The intraday spot price ranges from −270.11€ /MWh to 272.95€ /MWh, featuring higher price peaks. As a result, one can also find a higher kurtosis of 9.60, whereas the skewness remains similar. When comparing day-ahead and intraday prices, we see a statistically significant correlation coefficient of 0.8032.

Insert Table 2 about here

3.1.2. Stationarity

Stationary time series represent a necessary condition for a robust estimation and ensure the absence of a spurious regression (Wooldridge, 2012). Accordingly, Table 3 reports the results of the augmented Dickey-Fuller test. We find stationary time series in levels for both electricity prices, wind infeed, solar infeed and the natural gas price. The prices for coal and crude oil, as well as the exchange rate, are integrated of order one. We transform these into stationary time series by taking the first differences.

Insert Table 3 about here

3.2. Methodology

In order to investigate drivers of electricity prices, we estimate autoregressive models with exogenous variables (ARX) in a two-step procedure as follows (Wooldridge, 2012): the first step de-seasonalizes the time series, which inherently feature seasonality namely, both electricity prices, solar infeed, wind infeed and electricity consumption. In the second step, we measure the influence of all model variables on the de-seasonalized electricity prices.

3.2.1. Step 1: de-seasonalizing electricity prices

Accounting for seasonality is a crucial step when analyzing electricity spot prices (Weron, 2007). The two common approaches are (i) transformations, such as the wavelet transformation or spectral decomposition, and (ii) the use of dummy variables for each periodic time interval, such as hour, day or month. We follow the latter approach and include hourly, daily and monthly dummies plus a trend t. We add lags of 24 hours, 48 hours and 168 hours to account for the recurring patterns (Weron, 2007). Accordingly, we estimate

$$P_t = \gamma_t t + \xi_1 P_{t-24} + \xi_2 P_{t-48} + \xi_3 P_{t-168} + h_t D_{t,\text{hour}} + w_t D_{t,\text{weekday}} + m_t D_{t,\text{month}} + \tilde{P}_t, \tag{1}$$

with electricity price P_t, error term $\tilde{P}_t$, binary dummy variables D_{hour}, D_{weekday}, as well as D_{month}, and free parameters γ_t, ξ_1, ξ_2, ξ_3, h_t, w_t and m_t. The residual $\tilde{P}_t$ gives the de-seasonalized electricity price, which we utilize in the following step.

3.2.2. Step 2: processing de-seaonalized electricity prices using regression techniques

Here, we analyze the impact of external variables by running regressions on de-seasonalized day-ahead and intraday electricity prices via

$$\begin{aligned}\tilde{P}_{A,t} = \beta_1 Wind_t + \beta_2 PV_t + \beta_3 Load_t + \beta_4 Wind_t \cdot PV_t \\ + \beta_5 \Delta Coal_{t-1} + \beta_6 Gas_{t-1} + \beta_7 \Delta Oil_{t-1} \\ + \beta_8 \Delta FX_{t-1} + \varepsilon_{A,t},\end{aligned} \tag{2}$$

$$\begin{aligned}\tilde{P}_{I,t} = \beta_1 Wind_t + \beta_2 PV_t + \beta_3 Load_t + \beta_4 Wind_t \cdot PV_t \\ + \beta_5 \Delta Coal_t + \beta_6 Gas_t + \beta_7 \Delta Oil_t \\ + \beta_8 \Delta FX_t + \varepsilon_{I,t}\end{aligned} \tag{3}$$

with the de-seasonalized day-ahead spot price $\tilde{P}_{A,t}$ and de-seasonalized intraday spot price $\tilde{P}_{I,t}$, coefficients β_i and error terms $\varepsilon_{A,t}$ and $\varepsilon_{I,t}$. We include an interaction term between wind and solar feed-ins and utilize the difference operator Δ to obtain stationary time series based on the results from the Augmented Dickey-Fuller test.

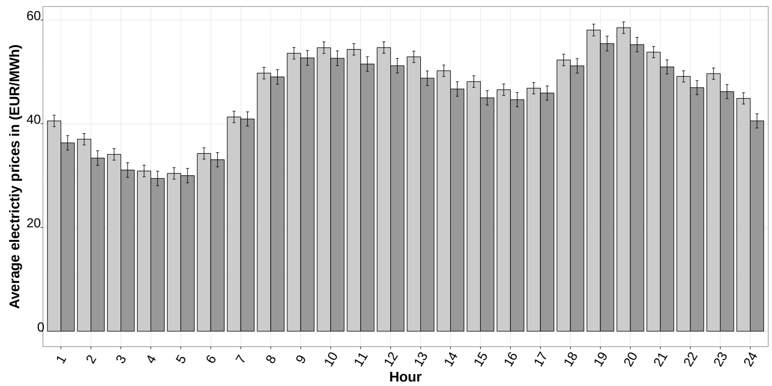
4. Evaluation

This section presents the results of the de-seasonalization procedure. We investigate the influence of external factors on the EPEX electricity prices and compare the results across the day-ahead and intraday markets.

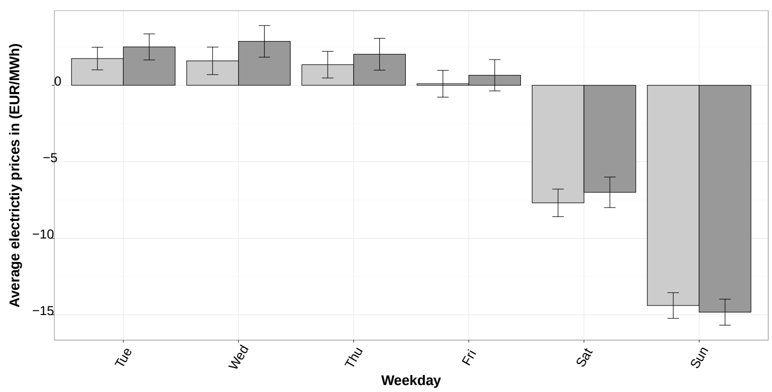
4.1. Seasonal components of EPEX electricity prices

Due to the extensive scope of the full regression results of the de-seasonalization process, we show only the goodness-of-fit measure – the adjusted R^2. When studying the adjusted R^2, we see that pure seasonal influences already explain a large proportion of the variance. The adjusted R^2 of 0.964 is slightly higher for day-ahead prices than the value 0.894 for the intraday market; allowing the latter to have a larger proportion of its variance explained by non-seasonal influences. We note that all standard errors are corrected for autocorrelations and heteroskedasticity; we later also provide robustness checks to ensure that our results are not confounded.

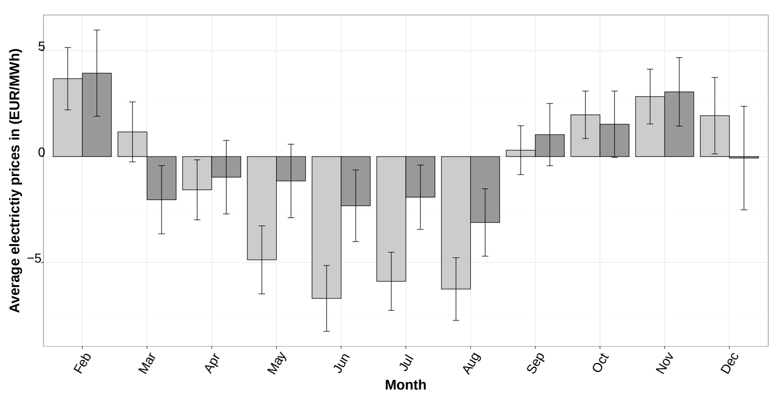
In addition, we visualize all seasonal components, i. e. hourly, daily and monthly dummies, without lags in Figure 3 and compare the day-ahead and intraday prices.[4] The plots show a clear pattern as follows: the intraday price is higher on average than that in the day-ahead market. The lowest average price throughout the day occurs during the trading block from 4–5 a. m. for both the day-ahead and the intraday markets, whereas it peaks during the block from 7–8 p. m. in both markets; see upper panel in Figure 3. Furthermore, we observe that electricity prices remain fairly constant during weekdays, but drop significantly over the weekend (middle panel). The lower panel illustrates monthly changes in electricity prices, using figures from January as a point of reference. Consistent with previous findings, prices are lower during the summer due to more hours of sunshine and less need for heating.



(a) Hourly seasonality: average hourly prices.



(b) Daily seasonality: average daily price differences compared to Monday as a reference.



(c) Monthly seasonality: average weekly price differences compared to January as a reference.

Figure 3: The above plots show the seasonal components of electriticy prices. For this purpose, we present dummy coefficients from our autoregressive mode for both the day-ahead (light gray) and intraday (dark gray) markets. Black intervals denote standard errors. The dummies for Monday and January are omitted as these serve strictly as references. For this visualization, we estimate the model only with the seasonal components.

4.2. Drivers of the EPEX day-ahead electricity price

We estimate four different model specifications to investigate the movements of the day-ahead electricity price. All models utilize the de-seasonalized day-ahead spot price as the dependent variable. The results are provided in Table 4. Model (A) evaluates the influence of merely the demand and supply side. It also incorporates an interaction term of wind and solar feed-ins to control for additional non-linear effects. Models (B) and (C) additionally include fuel prices and exchange rates to account for the costs of electricity generation.

In the first place, we find only stationary residuals and thus can confirm that we are not analyzing a spurious regression. We find autocorrelation of the residuals by using the Durbin-Watson test. Performing the Breusch-Pagan test indicates heteroscedastic residuals. To adjust the test values for autocorrelation and heteroscedasticity, we apply the Newey-West procedure (Wooldridge, 2012). Hence, we report the t-statistics, which are robust to heteroscedasticity and serial correlation, in the subsequent evaluation.

Insert Table 4 about here

As expected, feed-ins from renewable energy sources reveal a statistically significant negative impact on the day-ahead electricity price. Increasing wind infeed by one standard deviation results in a price decrease of -0.369 standard deviations in the day-ahead electricity price; solar infeeds reduce the day-ahead electricity price by -0.107 standard deviations. Furthermore, we include an interaction term between wind and solar feed-ins to account for additional non-linear effects, but which turns out to be statistically non-significant at the 5 % significance level. Therefore, we exclude the interaction from our final model, in which we still observe that a rise in electricity load by one standard deviation increases the electricity price by 0.404 standard deviations. The goodness-of-fit, i. e. the adjusted R^2, numbers around 0.3. While this value seems low at first, we must keep in mind that most fluctuations originate from seasonal patterns, which have already been removed. Finally, we combine the R^2 values of both estimation steps from the ARX model to compute the total explained variance. This amounts to 97.49 %, leaving unknown fluctuations only a marginal space.

In addition, we find that fuel prices have no statistically significant influence on the price of electricity. Therefore, adding fuel prices does not improve the explanatory power of the model. The same holds true for the USD/euro exchange rate.

Finally, we compare the different models in Table 4 in terms of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The former suggests including non-significant variables, whereas the latter puts a stronger penalty on additional regressors. It attains the lowest value for the final model and thus advocates this model choice. The corresponding F-tests (adjusted for significance levels from the Newey-West correction) suggest that the regressors have a combined influence on the dependent variable.

4.3. Drivers of the EPEX intraday electricity price

We now analyze factors influencing the intraday electricity price. We follow the previous estimation procedure and include a sub-sample analysis, due to expansion of the market to Austria. In 2010 and 2011, the EPEX intraday market covered only the German electricity production. In the years from 2012 to 2014, the EPEX intraday market additionally encompassed electricity supply from Austria. The results are shown in Table 5.

Insert Table 5 about here

Similar to previous results, feed-ins from renewable energy sources have a statistically significant negative impact on the intraday electricity price. A one standard deviation increase in wind infeed results in a price decrease of −0.458 standard deviations, while solar infeeds have a smaller influence of −0.232 standard deviations. Consumer demand is positively related to price of electricity with a coefficient of

0.333. The adjusted R^2 numbers 0.359 and is thus slightly higher than for the day-ahead market. The total explained variance from both estimation steps accounts for 95.84 %.

Evidently, there are no major changes in the impact of the underlying variables on the intraday electricity price. However, the effects of solar infeed are much higher in the second period, from 2012 to 2014, compared to the first period under consideration. Interestingly, we find non-linear effects between 2010 and 2011, which we do not find in the sample ranging from 2010 to 2014. In contrast, in the second period, the oil price affects the intraday electricity price. Fuel prices yield the same results as for the day-ahead market: we hardy find any significant coefficients for coal, gas and oil price. We thus conclude that fuel prices do not substantially contribute to the overall explanatory power of the model. We find the same results for the exchange rate. In summary, we find that the market modification does not considerably alter the price dynamics.

We finally compare the BIC for the complete period, where the lowest value stems from the final model. We find a similar pattern for the F-tests: these again provide statistical evidence that the regressors have a combined influence on the intraday electricity price. As in the previous case, the highest test statistic can be found for the final model.

4.4. Comparison of the day-ahead and intraday market

This section compares the results from the day-ahead and the intraday markets. We find similarities, as well as differences, as follows (see Table 6):

1. **Supply and demand side.** The response of the intraday electricity price to changes of renewable feed-ins is 24.12 % higher than for the day-ahead market. In contrast, changes in electricity consumption produce a weaker response in the intraday market. This indicates that the intraday market is less driven by unexpected changes in demand, but is used more to balance surprises in power generation from weather-dependent resources.

2. **Fuel prices.** Interestingly, fuel prices do not contribute to the explanatory power of the model in either the day-ahead or the intraday market. Accordingly, fuel prices can only be a minor cost driver for the electricity generation, whereas a larger proportion is spent on the running costs for standby, maintenance and operation.
3. **Economic factors.** The results of the day-ahead and intraday markets are similar with regard to the economic factors. Economic factors have no substantial impact on electricity prices in the period under consideration.
4. **Total explained variance.** We see that the day-ahead market reveals a slightly higher total explained variance. This serves as an indication that intraday markets are either driven by other, unknown factors or else subject to speculations to a larger extent.

Insert Table 6 about here

4.5. Discussion

Our research paper specifically addresses the intraday market. According to Section 2, we see that previous research has largely neglected this market and we thus cannot specifically compare our results to existing literature.

Overall, our empirical evidence reveals a strong impact of the demand and supply side on the short-term electricity price. In both markets, we find evidence of the negative impacts of renewable infeeds, as well as the positive impact of consumption levels, on electricity prices; each of them is statistically highly significant. These results are in line with established theory, as well as previous research (e. g. Bello and Reneses, 2013, Gelabert et al., 2011, Paschen, 2016). The more pronounced influence within the intraday market can be partially explained by the almost immutable demand, while regulations require most of the feed-ins from renewable energy sources to be accommodated by the market.

Evidently, fuel prices do not contribute to the explanatory power of short-term price dynamics. However, this relationship changes when studying the long-term relationship. In case of the coal price, our literature review in Section 2 identifies only one study with a short-term model, which identifies a significant positive impact (Paraschiv et al., 2014), while one can see a positive, negative or even no relationship in the long run (Bello and Reneses, 2013, Ferkingstad et al., 2011, Mohammadi, 2009). The price of gas reveals similar differences between the short-term and long-term influence. In the long run, references provide evidence of either a positive or no measurable influence (Freitas and da Silva, 2015, Würzburg et al., 2013). In regard to the long term, previous works have measured that a 1 % change in the gas price results in a 0.68 % increase (Bunn and Fezzi, 2009) or a 0.39 % increase (Freitas and da Silva, 2015) in the price of electricity over an extended period of time.

5. Conclusion and policy implications

5.1. Summary

Since the liberalization of the electricity market in Europe, and especially Germany, prices are set by market participants and, hence, subject to various influences. Understanding the short-term dynamics is of great interest to consumers, electricity traders and policy-makers. Knowledge concerning the price setting mechanism in the intraday market is particularly scarce. As a remedy, this paper contributes to recent literature by comparing the price drivers in both the EPEX day-ahead and intraday electricity markets. We utilize an autoregressive model to study seasonality, as well as the exogenous variables. Our findings suggest that the predominant factors with regard to short-term dynamics are based on the supply and demand side. On the supply side, we find that infeeds from wind farms negatively affect the intraday electricity price by 24.12 % more than in the day-ahead market, while photovoltaic infeeds have a stronger (negative) impact by 116.82 %. On the demand side, the influence of electricity consumption on the electricity price is 17.77 % less in intraday markets than in day-ahead markets.

5.2. *Policy implications*

Based on our findings, we derive the following policy implications.

- **Implication 1:** In short-term electricity markets, fuel prices do not affect electricity prices. Hence, policy-makers can disregard fuel prices in short-term markets when seeking to improve market efficiency through new market regulations.

- **Implication 2:** Electricity generation from renewable electricity sources has low marginal costs. Accordingly, larger feed-ins from wind or solar power reduces the price of electricity. Although this might serve to increase the penetration of renewables, policy-makers must also consider the necessary investment costs and potential side effects in terms of grid stabilization.

- **Implication 3:** Policy-makers are able to reduce electricity prices when they ensure a secure supply and matching demand. Therefore, different levers can help reduce electricity prices. For example, policy-makers can offer incentives to increase energy storage capacity or augment the prevalence of demand-side management.

5.3. *Outlook*

In future work, we see the potential for advances in the following directions. First, a long-term analysis of fuel prices may help to understand the influence of fuel prices on electricity futures. Second, including the merit order effects could contribute to our understanding of the short-term dynamics of electricity prices.

References

Akram, Q.F., 2009. Commodity prices, interest rates and the dollar. Energy Economics 31, 838–851.

Bello, A., Reneses, J., 2013. Electricity price forecasting in the Spanish market using cointegration techniques, in: 33rd Annual International Symposium on Forecasting (ISF 2013). Forecasting with Big Data. Seoul, Korea: ISF Electronic Proceedings, pp. 1–7.

Bierbrauer, M., Menn, C., Rachev, S.T., Trück, S., 2007. Spot and derivative pricing in the EEX power market. Journal of Banking & Finance 31, 3462–3485.

BMWi, 2017. Website. URL: `http://www.bmwi.de/DE/Themen/Energie/Erneuerbare-Energien/erneuerbare-energien-auf-einen-blick.html`. Visited on 2017-01-10.

Bunn, D., Fezzi, C., 2009. Interaction of European carbon trading and energy prices. Journal of Energy Markets 2, 53–69.

Chen, S.S., Chen, H.C., 2007. Oil prices and real exchange rates. Energy Economics 29, 390–404.

Clò, S., Cataldi, A., Zoppoli, P., 2015. The merit-order effect in the Italian power market: The impact of solar and wind generation on national wholesale electricity prices. Energy Policy 77, 79–88.

Contreras, J., Espinola, R., Nogales, F.J., Conejo, A.J., 2003. ARIMA models to predict next-day electricity prices. IEEE Transactions on Power Systems 18, 1014–1020.

Cutler, N.J., Boerema, N.D., MacGill, I.F., Outhred, H.R., 2011. High penetration wind generation impacts on spot prices in the Australian national electricity market. Energy Policy 39, 5939–5949.

Deng, S., Oren, S.S., 2006. Electricity derivatives and risk management. Energy 31, 940–953.

Ellersdorfer, I., 2009. Marktmachtpotenziale im deutschen Elektrizitätssektor: Analysen für den Großhandelsmarkt mit einem spieltheoretischen Modell. 1st ed., Springer, Oldenburg, Germany.

Erni, D., 2012. Day-Ahead Electricity Spot Prices-Fundamental Modelling and the Role of Expected Wind Electricity Infeed at the European Energy Exchange. Ph.D. thesis. University of St. Gallen.

Fell, H., et al., 2010. EU-ETS and Nordic electricity: A CVAR analysis. Energy Journal 31, 1–25.

Ferkingstad, E., Løland, A., Wilhelmsen, M., 2011. Causal modeling and inference for electricity markets. Energy Economics 33, 404–412.

Freitas, C.J.P., da Silva, P.P., 2015. European Union emissions trading scheme impact on the Spanish electricity price during phase II and phase III implementation. Utilities Policy 33, 54–62.

Gelabert, L., Labandeira, X., Linares, P., 2011. An ex-post analysis of the effect of renewables and cogeneration on Spanish electricity prices. Energy Economics 33, 59–65.

Jamasb, T., Pollitt, M., 2005. Electricity market reform in the European Union: Review of progress toward liberalization & integration. Energy Journal , 11–41.

Ketterer, J.C., 2014. The impact of wind power generation on the electricity price in Germany. Energy Economics 44, 270–280.

Knittel, C.R., Roberts, M.R., 2005. An empirical examination of restructured electricity prices. Energy Economics 27, 791–817.

Ludwig, N., Feuerriegel, S., Neumann, D., 2015. Putting big data analytics to work: Feature selection for forecasting electricity prices using the LASSO and random forests. Journal of Decision Systems 24, 19–36.

Lütkepohl, H., 2007. New introduction to multiple time series analysis. Springer, Berlin, Germany.

Menanteau, P., Finon, D., Lamy, M.L., 2003. Prices versus quantities: Choosing policies for promoting the development of renewable energy. Energy Policy 31, 799 – 812.

Mjelde, J.W., Bessler, D.A., 2009. Market integration among electricity markets and their major fuel source markets. Energy Economics 31, 482–491.

Mohammadi, H., 2009. Electricity prices and fuel costs: Long-run relations and short-run dynamics. Energy Economics 31, 503–509.

Muñoz, M.P., Dickey, D.A., 2009. Are electricity prices affected by the US dollar to Euro exchange rate? The Spanish case. Energy Economics 31, 857–866.

Paraschiv, F., Erni, D., Pietsch, R., 2014. The impact of renewable energies on EEX day-ahead electricity prices. Energy Policy 73, 196–210.

Paschen, M., 2016. Dynamic analysis of the German day-ahead electricity spot market. Energy Economics 59, 118 – 128.

Sensfuss, F., Ragwitz, M., Genoese, M., 2008. The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36, 3086–3094.

Thoenes, S., 2011. Understanding the determinants of electricity prices and the impact of the German Nuclear Moratorium in 2011. EWI Working paper .

Weron, R., 2007. Modeling and forecasting electricity loads and prices: A statistical approach. volume 403. John Wiley & Sons, Chichester, England.

Woo, C.K., Horowitz, I., Moore, J., Pacheco, A., 2011. The impact of wind generation on the electricity spot-market price level and variance: The Texas experience. Energy Policy 39, 3939–3944.

Wooldridge, J., 2012. Introductory econometrics: A modern approach. 5th. ed., Cengage Learning, Mansion, USA.

Würzburg, K., Labandeira, X., Linares, P., 2013. Renewable generation and electricity prices: Taking stock and new evidence for Germany and Austria. Energy Economics 40, 159–171.

Zhang, Y.J., Fan, Y., Tsai, H.T., Wei, Y.M., 2008. Spillover effect of US dollar exchange rate on oil prices. Journal of Policy Modeling 30, 973–991.

Notes

[1]Directive 96/92/EC concerning common rules for the internal market of electricity.

[2]Note: The prices at the EPEX and EEX are identical. In the following, we make use of the terminus EPEX.

[3]Retrieved on February 02, 2017 from `https://www.eex.com/en/market-data/power/spot-market/auction\#!/2014/12/31`.

[4]Here, the dummies for Monday and January serve as point of reference in the regression and are thus excluded to allow a unique solution of the estimation procedure.

Variable, unit	Symbol	Frequency	Description	Data source
DEPENDENT VARIABLES				
Day-ahead spot price, € /MWh	P_A	Hourly	Day-ahead auction electricity price with delivery in Germany and Austria. The auction price is set at 12:00 a.m. for each hour of the next day	European Power Exchange (EPEX)
Intraday spot price, € /MWh	P_I	Hourly	Continuous intraday electricity price with delivery in Germany and (partially) Austria. Trading is possible up to 30 min before delivery	European Power Exchange (EPEX)
EXOGENOUS VARIABLES				
Wind infeed, MW	*Wind*	Hourly	Aggregated total wind infeed from the four transmission system operators (TransnetBW, Tennet, Amprion, 50Hertz) in Germany	EEX Transparency
Solar infeed, MW	*PV*	Hourly	Aggregated total photovoltaic infeed from the four transmission system operators (TransnetBW, Tennet, Amprion, 50Hertz) in Germany	EEX Transparency
Load, MW	*Load*	Hourly	Total hourly electricity consumption in Germany	ENTSO-E
Coal price, USD/t	*Coal*	Daily	Credit Suisse Commodity Benchmark for coal API 2 spot return price index at the Amsterdam-Rotterdam-Antwerp Hub	Thomson Reuters Datastream
Gas price, € /MWh	*Gas*	Daily	Setting price of natural gas first near future at the virtual gas trading hub Title Transfer Facility (TTF)	Thomson Reuters Datastream
Oil price, USD/bbl	*Oil*	Daily	Brent crude oil spot price in USD per barrel	Thomson Reuters Datastream
Foreign exchange rate, USD/euro	*FX*	Daily	Closing price of U. S. dollar to euro exchange rate	Thomson Reuters Datastream

Table 1: Overview of variables that are taken into account in the subsequent analysis.

Variable	Symbol	Unit	Mean	Median	Min.	Max.	Std. dev.	Skew.	Kurt.	Frequency
Day-ahead spot price	P_A	€ /MWh	43.32	44.01	−200.00	210.00	16.66	−0.12	5.52	Hourly
Intraday spot price	P_I	€ /MWh	42.37	42.01	−270.11	272.95	17.99	−0.12	9.60	Hourly
Wind infeed	*Wind*	MW	20623.08	14742.20	115.00	118212.40	18704.10	1.60	2.72	Hourly
Solar infeed	*PV*	MW	10627.31	251.70	0.00	96281.90	18116.31	2.00	3.47	Hourly
Load	*Load*	MW	55003.04	54911.00	29201.00	79884.00	10139.15	−0.04	−1.05	Hourly
Coal price	*Coal*	USD	92.87	90.14	64.38	132.01	17.13	0.64	−0.74	Daily
Gas price	*Gas*	€ /MWh	22.60	23.20	10.40	38.50	4.17	−0.34	0.80	Daily
Oil price	*Oil*	USD/bbl	102.09	108.01	58.69	126.62	14.85	−0.85	−0.32	Daily
Foreign exchange rate	*FX*	USD/euro	1.33	1.33	1.19	1.49	0.06	0.08	−0.38	Daily

Table 2: Descriptive statistics of day-ahead and intraday spot price, as well as all exogenous variables, from January 1, 2010 to December 31, 2014.

Variable	Deterministic trend	Lags	Test value	Critical values		
				1 %	5 %	10 %
Day-ahead spot price	Drift, trend	0	−42.47	−3.96	−2.88	−2.57
Day-ahead spot price (de-seasonalized)	None	0	−60.64	−2.58	−1.95	−1.62
Intraday spot price	Drift, trend	0	−42.95	−3.96	−3.41	−3.12
Intraday spot price (de-seasonalized)	None	0	−179.33	−2.58	−1.95	−1.62
Wind infeed	Drift	0	−11.85	−3.43	−2.86	−2.57
Wind infeed (de-seasonalized)	None	0	−84.86	−2.58	−1.95	−1.62
Solar infeed	Constant, trend	0	−31.27	−3.96	−3.41	−2.57
Solar infeed (de-seasonalized)	None	0	−60.31	−2.58	−1.95	−1.62
Load	Drift	0	−27.27	−3.43	−2.86	−2.57
Load (de-seasonalized)	None	0	−110.10	−2.58	−1.95	−1.62
Gas price	Drift	0	−3.84	−3.43	−2.86	−2.57
Coal price	Drift, trend	0	−1.86	−3.96	−3.41	−3.12
ΔCoal price	None	0	−23.10	−2.58	−1.95	−1.62
Oil price	trend	0	0.43	−3.96	−3.41	−3.12
ΔOil price	None	0	−9.72	−2.58	−1.95	−1.62
Foreign exchange rate	Drift	0	−2.33	−3.43	−2.86	−2.57
ΔForeign exchange rate	None	0	−25.35	−2.58	−1.95	−1.62

Note: varying the lag length results into the same outcomes

Table 3: Augmented Dickey-Fuller tests indicate that most time series are stationary. Only prices for coal and crude oil, as well as the exchange rate, are integrated of order one. Details on de-seasonalization are provided in Section 3.2.

	Dependent variable: hourly EPEX day-ahead electricity price (de-seasonalized)			
	(A)	(B)	(C)	Final model
Infeed: $Wind_t$	-0.369^{***}	-0.369^{***}	-0.369^{***}	-0.368^{***}
	(-21.944)	(-20.745)	(-20.758)	(-21.947)
Infeed: PV_t	-0.107^{***}	-0.107^{***}	-0.107^{***}	-0.107^{***}
	(-9.768)	(-9.848)	(-9.834)	(-9.832)
$Load_t$	0.404^{***}	0.405^{***}	0.404^{***}	0.404^{***}
	(23.557)	(23.134)	(23.136)	(23.565)
Interaction: $Wind_t \cdot PV_t$	-0.004	-0.003	-0.003	
	(-0.374)	(-0.269)	(-0.274)	
$\Delta Coal_{t-1}$		-0.010	-0.012	
		(-0.909)	(-0.995)	
Gas_{t-1}		0.017	0.017	
		(1.058)	(1.056)	
ΔOil_{t-1}		0.004	0.004	
		(0.328)	(0.304)	
ΔFX_{t-1}			0.007	
			(0.546)	
Observations	43655	43655	43655	43655
Adjusted R^2	0.304	0.305	0.305	0.304
AIC (in 1000)	298.001	297.982	297.981	298.000
BIC (in 1000)	298.044	298.051	298.059	298.035
F-statistic	1039.10	1025.30	1028.10	1038.50

Statistical significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standardized OLS coefficients (due to different units); robust t-statistics in parentheses

Table 4: Estimated coefficients (and corresponding robust t-statistics) of ARX models reveal those variables that influence the day-ahead electricity price.

	Dependent variable: hourly EPEX intraday electricity price (de-seasonalized)									
	Years 2010–2014				Years 2010–2011			Years 2012–2014		
	(A)	(B)	(C)	Final model	(E)	(F)	Final model	(G)	(H)	Final model
Infeed: $Wind_t$	-0.458^{***}	-0.458^{***}	-0.458^{***}	-0.458^{***}	-0.454^{***}	-0.454^{***}	-0.454^{***}	-0.455^{***}	-0.455^{***}	-0.456^{***}
	(−28.154)	(−28.633)	(−28.626)	(−28.181)	(−13.606)	(−13.312)	(−13.606)	(−27.043)	(−25.555)	(−27.226)
Infeed: PV_t	-0.232^{***}	-0.232^{***}	-0.232^{***}	-0.232^{***}	-0.114^{***}	-0.115^{***}	-0.114^{***}	-0.280^{***}	-0.279^{***}	-0.280^{***}
	(−20.308)	(−18.955)	(−18.918)	(−20.448)	(−9.271)	(−9.761)	(−9.271)	(−18.143)	(−14.096)	(−18.327)
$Load_t$	0.333^{***}	0.333^{***}	0.333^{***}	0.333^{***}	0.307^{***}	0.306^{***}	0.307^{***}	0.352^{***}	0.352^{***}	0.352^{***}
	(20.852)	(20.151)	(20.135)	(20.815)	(12.962)	(14.736)	(12.962)	(16.652)	(15.764)	(16.612)
Interaction: $Wind_t \cdot PV_t$	−0.001	0.001	0.001		-0.038^{**}	-0.035^{**}	-0.038^{**}	0.010	0.011	
	(−0.074)	(0.064)	(0.058)		(−2.086)	(−2.023)	(−2.086)	(0.848)	(0.725)	
$\Delta Coal_t$		−0.010	−0.012			−0.016			−0.011	
		(−0.760)	(−0.868)			(−0.683)			(−0.547)	
Gas_t		0.017	0.017			0.034			0.007	
		(1.269)	(1.266)			(1.459)			(0.403)	
ΔOil_t		0.009	0.009			−0.020			0.008	
		(0.696)	(0.668)			(−0.789)			(0.630)	
ΔFX_t			0.009			0.025			−0.014	
			(0.648)			(1.284)			(−0.975)	
Observations	43655	43655	43655	43655	17352	17352	17352	26135	26135	26135
Adjusted R^2	0.359	0.359	0.359	0.359	0.283	0.285	0.283	0.407	0.407	0.407
AIC (in 1000)	319.660	319.634	319.632	319.658	127.854	127.814	127.854	190.367	190.352	190.352
BIC (in 1000)	319.704	319.704	319.710	319.693	127.893	127.884	127.893	190.407	190.425	190.352
F-statistic	1162.50	1188.10	1200.20	1161.00	350.21	499.28	350.21	923.39	911.19	932.37

Statistical significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standardized OLS coefficients (due to different units); robust t-statistics in parentheses

Table 5: Estimated coefficients (and corresponding robust t-statistics) of ARX models reveal those variables that influence the intraday electricity price. The time frames are varied across the regressions, since the intraday market served only Germany until the end of 2011 and, additionally covered Austria from the year 2012 onwards.

	Day-ahead price	Intraday price	Relative difference
Influence of wind infeed	-0.369^{***}	-0.458^{***}	+24.12 %
Influence of solar infeed	-0.107^{***}	-0.232^{***}	+116.82 %
Influence of load	0.404^{***}	0.333^{***}	−17.57 %
Adjusted R^2 of step 2 model	0.305	0.359	+17.70 %
Total explained variance	97.94 %	95.84 %	−2.14 %

Statistical significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standardized OLS coefficients (due to different units) with robust p-values

Table 6: Comparison of the impact of the main drivers based on previous ARX models for the day-ahead and intraday markets. The results originate from the full sample covering 2010–2014.