Energy Economics 75 (2018) 150–162

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

The effect of wind and solar power forecasts on day-ahead and intraday electricity prices in Germany

Marc Gürtler, Thomas Paulsen *

Braunschweig Institute of Technology, Department of Finance, Abt-Jerusalem-Str. 7, 38106 Braunschweig, Germany

ARTICLE INFO

Article history:
Received 1 January 2018
Received in revised form 3 July 2018
Accepted 5 July 2018
Available online xxxx

JEL classification:
C33
C59
Q20
Q41

Keywords:
Merit-order effect
Renewable energy sources
Wind
Solar
Ramping costs
Forecasting errors

ABSTRACT

This study analyzes the effects of wind and solar power generation forecasts on electricity prices. Converse to the existing empirical literature in this area, we apply a panel data analysis to control for endogeneity due to unobserved heterogeneity. We use a dataset with 24 daily observations of day-ahead and intraday prices from 2010 to 2016, and we apply a fixed effects regression under consideration of robust Driscoll-Kraay standard errors. A noteworthy element of the regression model is the simulation-based design of a variable indicating the power generation technology that is price-determining at a certain point in time. In this context, we differentiate between the fuel types coal, gas, and others, to model the nonlinear price behavior for a varying demand. For 2016, we find price dampening effects of both wind and solar power of approximately 0.6 €/MWh per additional GWh of feed-in. Along with the rapidly increasing shares of wind and solar power of the total power generation during the last years, their price dampening effect has declined since 2013, due to a drop in fuel prices. Another finding is that a reduction in forecasting errors on the power generation from wind and solar, and smoothing of the cyclical demand would lead to a decreased price volatility.

1. Introduction

In recent years, European electricity markets have undergone rapid change, due to the increasing share of power generation from renewable energy sources (RES). RES have gradually replaced power generation from conventional power plants using coal, gas, lignite, or nuclear energy. This development has a distinct effect on electricity prices, and has already forced traditional market participants to revise their business models.

Germany plays a pioneering role in the transition towards a sustainable power supply with installed capacities of wind power of 45 gigawatts (GW) and of photovoltaic (PV) of 39 GW. In total, renewables (incl. biomass, hydro and waste) account for 29% of the gross electricity generation in Germany.[1]

By law, the feed-ins of wind and solar power – which are produced at marginal costs of zero – are prioritized over other sources. Since the demand for electricity is quasi inelastic, this causes considerable changes on the supply side and leads to decreasing prices. This is because conventional power plants with higher marginal costs are squeezed out of the market. This is called the merit-order effect (MOE). The MOE has been extensively studied in the recent literature (see e.g., Sensfuß et al. (2008)). Generally, several simulation studies and regression analyses have found a substantial price dampening effect of renewable energy sources (RES). For their empirical analyses of the German market, Würzburg et al. (2013) and Cludius et al. (2014) for example, apply pooled OLS (ordinary least squares) regressions with Newey & West (1987) standard errors. Others, such as Ketterer (2014) and Benhmad and Percebois (2016), employ time series models (in these cases, GARCH, or generalized autoregressive conditional heteroscedasticity).

In contrast to the existing empirical literature in this area, in the present study we apply a panel data analysis. The advantage of panel data analysis against standard pooled regression is the avoidance of an omitted variables bias caused by unobserved heterogeneity (part of the error term) that is constant over time. More specifically, we apply the so-called fixed effects model according to which heterogeneity is removed by the "within transformation".[2] We construct two panel

* Corresponding author.
E-mail addresses: marc.guertler@tu-braunschweig.de (M. Gürtler), t.paulsen@tu-braunschweig.de (T. Paulsen).

[1] Values have been published officially in the lists of power plants for the year 2016 of the BNetzA and by AG Energiebilanzen (2017).

[2] In addition to a fixed effects model, it is also possible to apply a so-called random effects model according to which the regression is only partly corrected for unobserved heterogeneity. Without going deeper into the specific advantages of the random effects model, it will be shown below that the fixed effects model is more suitable for the present study.

https://doi.org/10.1016/j.eneco.2018.07.006

datasets with day-ahead prices and intraday prices as dependent variables. These datasets cover 24 observations each day, from 2010 to 2016. We apply a fixed effects regression where we apply standard errors of Driscoll and Kraay (1998), which are robust to heteroscedasticity, autocorrelation and cross-sectional dependence of the residuals. The model structure allows us to identify time dependent effects in the results. Applying the fixed effects regression implies that price levels within each hour of a day reveal their own specific effects.

A noteworthy element of the regression model is the simulation-based design of a variable indicating the power generation technology that is price-determining at a certain point in time. This marginal power generation capacity is just required to exactly meet the current demand. Taking the power generation technology into consideration allows us a deeper perspective into the MOE, as we assume nonlinear price-load-relationships. For the analysis, we differentiate between the fuel types coal, gas, and others.

Besides studying the MOE, we quantify price changes due to power plant ramping, as well as price changes due to forecasting errors on wind and solar power generation. Ramping costs are costs which are incurred by varying operation capacities of power plants due to a lower efficiency of the power generation combined with higher operational costs. As the balance of demand and supply needs to be offset at each point in time, flexibility in the power generation is required to cope with a cyclical demand for electricity. Contrasting with other studies, we do not only account for the current change of the demand, but we also assume that the residual demand (forecast) in subsequent periods of the same day affects current prices. Additionally, the hypothesis continues that very short (non-)utilization periods of power generation capacities and steep demand increases or decreases incur additional generation costs, which reflects in the market in the form of higher prices. The identification of these measures is analytically based on Hansen's (1999) threshold regression.

Despite their name, electricity spot markets are in fact day-ahead markets, meaning that the pricing is based on available forecasts of demand and supply. Consequently, prices may be affected by forecast errors. Residual quantities need to be traded in the subsequent intraday market. Focusing on the forecasting errors of RES, this effect on prices has been studied by von Roon and Wagner (2009), Hagemann (2015) and Kiesel and Paraschiv (2017), but has not yet been studied in relation to the MOE in general. This is where this study raises the research issue of whether the price effects due to forecasting errors are significantly different compared to the MOE. To address these additional issues, we extend the regression model by incorporating the forecasting errors and ramping parameters.

This study is organized as follows: Section 2 provides an overview of existing research literature on the price effects of power generation from RES, power plant ramping and forecasting errors of wind and solar power. In Section 3, the regression model and the characteristics of the dataset are described. This includes the construction of indicator variables to identify the price-determining power plant technology and variables capturing ramping effects. In Section 4, we present the empirical results of the analysis. This section is subdivided to separately answer the three raised research issues, and includes several robustness checks of the findings. Finally, Section 5 concludes the analysis.

2. Literature review

2.1. Merit-order effect

A wide range of literature exists on the effects of RES on electricity prices. In general, findings are very consistent regarding the conclusion that an increase of power generation from RES results in decreasing electricity prices.

A comprehensive literature overview on the price effects of RES is given by Würzburg et al. (2013). Similarly, Table 1 summarizes the literature on the quantification of the MOE, focusing on the German market. The presented effects have not necessarily been reported in the respective sources. Several of the effect sizes have been normalized to receive the effect as per €/MWh per additional GWh of feed-ins from RES.[3] The applied models can be categorized into either simulation-based or regression models, but in more recent studies, regression models are more common. The MOE quantifications reflect the total price effect of RES, the wind-induced effect or the solar-induced effect. Wind and solar are of specific interest due to their fluctuating power generation and their large growth rates during the recent years.

Table 1 shows that the MOE has been quantified in a range from 0.55 to 2.67 €/MWh per additional GWh from RES. Especially, the effects of the very recent regression models of Würzburg et al. (2013), Cludius et al. (2014), Benhmad and Percebois (2016) and Paschen (2016) are very consistent in their magnitude at approximately 1 €/MWh.[4] Several authors assume the MOE to be constant over time. Of those, who analyze longer periods than just a single year, Rathmann (2007), vbw (2011), Würzburg et al. (2013), Ketterer (2014), Benhmad and Percebois (2016) and Paschen (2016) do not try to identify time dependent effects of the MOE.

For their regression analyses, for example, Würzburg et al. (2013) and Cludius et al. (2014) apply pooled OLS (ordinary least squares) with Newey-West standard errors. Others, such as Ketterer (2014) and Benhmad and Percebois (2016) employ a time series model (in these cases, GARCH). The ingenuity of this study is that, in contrast to common literature, a fixed effects panel regression is applied on electricity price modeling.

Few studies have tried to simultaneously extract different price effects of feed-ins of either wind or PV. Würzburg et al. (2013) do not find evidence indicating significant differences between the two power sources. However, the authors mention that effects of PV might be greater if they had used hourly data instead of daily average values. Cludius et al. (2014) state that the PV-induced MOE is larger than the effect of wind. Paschen (2016) also finds a higher solar-induced MOE than a wind MOE.

Due to high wind shares, the Spanish market is also of interest in the current research. Saenz de Miera et al. (2008), Gil et al. (2012), and Azofra et al. (2014) all confirm the price dampening effects of wind power. Gelabert et al. (2011) finds profound effects of RES in general. Focusing on the Italian market, Clò et al. (2015) also find empirical evidence of the MOE. An additional result of that study is that the total price dampening effects by solar power are stronger than those by wind power. The authors argue that this results from the higher market share of solar power.

On the Danish power market (with a generally very high wind penetration), Jónsson et al. (2010) find price effects of up to 40% (depending on the level of wind penetration). O'Mahoney and Denny (2011) and Di Cosmo and Magaluzzi Valeri (2012) (both Ireland), and Nieuwenhout and Brand (2011) and Mulder and Scholtens (2013) (both based out of the Netherlands), also identify lower electricity prices due to increased wind power generation on other markets.

Outside Europe, Nicholson et al. (2010) and Woo et al. (2011) find lower prices due to wind power generation in Texas, USA. Forrest and MacGill (2013) and McConnel et al. (2013) provide evidence on the MOE for wind and PV, respectively, in Australia.

[3] The effect sizes are calculated by dividing the total effects by the average RES feed-ins per year. It should be noted that effects are regarded to be linear in this summarized representation. This corresponds to the *common measure* ratio of Würzburg et al. (2013), but with slightly deviating values.

[4] In the case of Paschen (2016), if we take into consideration only the instantaneous effect (omitting the impact of RES feed-ins on future power prices), the price effects are 0.82 €/MWh (wind) and 1.17 €/MWh (solar). These values are different compared to the values reported in Table 1.