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Abstract

This paper analyzes the dynamic behavior of day-ahead spot prices in the German electricity spot market due to positive structural shocks in wind and solar power. It uses a dynamic structural vector autoregressive model to estimate the related structural impulse response functions. The estimates suggest that wind power shocks have a more prolonged negative effect on spot prices than solar power shocks. These may be explained by significant autocorrelations of wind power for larger lags. The total negative merit order effect of a solar power shock, however, is larger. One reason might be that solar power shocks coincide with demand peaks. Past empirical results show differences in the total average negative merit order effects. The inherently dynamic nature of wind and solar power could explain these differences because the dynamics, which are ignored by past studies on the subject using static ordinary least squares estimations, could be transferred to the merit order effects.

Keywords:
Electricity Market, Spot Prices, Wind and Solar Power Dynamics, Structural Vector Autoregressive Model, Structural Impulse Response Functions

JEL Classification: Q42, Q41, C32, C51

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1. Introduction

This paper empirically analyzes the dynamic effects of important variables in the European Energy Exchange (EEX) day-ahead spot market for power. The main aim is to obtain a better understanding of how a wind or solar power shock on a given day affects future spot prices.

Electricity from renewable sources has become increasingly attractive in recent years because it produces no CO_2 emissions and can help to reduce dependence on fossil fuel imports. Moreover, in contrast to nuclear power, renewables entail no danger of serious environmental accidents. In recent years, there has been a rise in the level of renewable generating capacity in Germany. This is in part the result of the German energy transition (introduced by the governments feed-in law of 1991 and formlated in further detail in the Renewable Energy Act (EEG) of 2000), which places a strong focus on renewable energies. In 2013, renewables accounted for 23.9% of the total German electricity supply. The most important renewable energy source was wind power with a share of 35.8% in the total supply of renewables. A smaller but also significant share (20%) belonged to solar power (BDEW (2014)). According to the EEG 2.0 of 2014, the share of renewables in the electricity supply will have to rise to 40-45% by 2025 and to 55-60% by 2035. Following Gelabert et al. (2011), there has been a debate on how increased renewable capacity will affect electricity prices, and whether the competitiveness of large energy consumers will suffer as a result.

The analysis of dynamic effects over time, such as that of an unforeseen shock in wind power production on spot prices, sheds light on the debate over the duration and persistence of merit order effects (cf. Würzburg et al. (2013)).[2] Moreover, as further discussed, the dynamic behavior of the spot price due to shocks in wind or solar power is of special interest to power end users.

So far, most research has focused on the average effect of renewables on the spot price for power, but not on the short-term persistence of that effect. With respect to the theoretical literature, Jensen and Skytte (2002) found, using a microeconomic model, that power prices will fall in a power market if the amount of renewables rises. This negative merit order effect is due to the relation between the low marginal costs of renewables and the higher marginal costs of fossil fuels (e.g., coal or gas). If the use of renewables rises, the supply function of the power market – the merit order curve – shifts to

[2] In this paper, however, persistence over time refers to a period of a few days.

the right. Thus, production types with higher marginal costs are forced out of the market and a lower equilibrium price is reached. A model with residual demand can be used alternatively to obtain the same result. Germanys EEG, particularly because of the priority placed on wind and solar power feed-in, produces negative merit order effects. Here, the residual demand for all production types except renewables in the market will shift to the left, and the new equilibrium price will be lower. Amundsen and Mortensen (2001) as well as Fischer (2006) also found, using microeconomic models, negative merit order effects and therefore lower prices as a result of increased subsidized renewables.

In the empirical literature, Gelabert et al. (2011) investigated the merit order effects of renewables including wind and solar power as well as cogeneration on the spot price for six years in the Spanish day-ahead spot market using ordinary least squares (OLS). They found an average negative merit order effect when the use of renewables or cogeneration increased. Cludius et al. (2013) conducted several different linear regressions (time periods: January 2008 to June 2012, July 2010 to June 2012). They found negative merit order effects of wind and solar power for Germany. Würzburg et al. (2013) identified an average negative effect of predicted wind and solar power on the day-ahead spot price for Germany and Austria by using OLS (time period: July 2010 to June 2012). Böckers et al. (2013) found a negative merit order effect of wind, but surprisingly a positive effect of solar in the Spanish wholesale electricity market over a time period of five years using a structural vector autoregressive model. Maciejowska (2014) found negative merit order effects of wind in the United Kingdom (UK) electricity market over a time period of two years using a structural vector autoregressive model. In addition, other researchers have reported empirical average negative effects of wind power specifically, and of renewables generally, on electricity prices in European markets (e.g., Jonsson et al. (2010) for Denmark). Finally, several researchers have found negative merit order effects of renewables on electricity prices using electricity simulation models (e.g., Sensfuß et al. (2008) for Germany and Miera et al. (2008) for Spain).

So far, most of the empirical models (and all of the models that analyze the German electricity market empirically) have investigated merit order effects using OLS. However, OLS models do not take into account the time dependency of wind and solar power, and they ignore interdependencies between the variables on spot markets. Such interdependencies may violate the ceteris paribus condition of OLS models. For example, if there is a positive shock in wind power production causing wind power to rise, the spot price falls due to the negative merit order effect. However, conventional power sources such as coal, gas, oil, lignite, and uranium might not stay constant but fall as well because the larger wind power feed-in might have to be compensated if there is no change in load. If the dynamic structures of wind and solar power as well as the interdependencies between the variables are not taken into account, estimated OLS coefficients could be biased because the ignored dynamic structures and interdependencies may remain in the residuals. In this case, explanatory variables will be correlated with the residuals, leading to inconsistent estimators (Baltagi (2002)).

Therefore, in this paper, a structural vector autoregressive (SVAR) model is estimated as well. An SVAR is an appropriate dynamic econometric method because the related structural impulse response functions (SIRFs) reveal the (unbiased) dynamic behavior of spot prices due to shocks in wind or solar power on a given day. The SVAR attempts to identify the dynamic interrelationships between the variables on spot markets over days and thereby also between spot prices and wind power and solar power, respectively. A dynamic structure is needed because of the inherently dynamic behavior of wind and solar power, which might be transferred to the system as a whole. Furthermore, SVAR models are able to produce significant estimates even in the presence of interdependencies between variables.

Wind and solar power production are time-dependent: Their current values depend on their past values. Daily intertemporal dependencies can be identified by autocorrelations of wind and solar power at several time lags (days). If stormy weather and therefore a surge in wind power occurs on one day, there still may be significantly increased wind power on the following day due, for example, to a storms continuing effects. Hasche (2010) reports that most of the wind parks and wind power generation across Germany are positively correlated, suggesting that wind power dynamics are indeed relevant for Germany as a whole. Although there has been no research on autocorrelated wind power in Germany, such dynamic relationships have been identified on the west coast of Canada, where Brett and Tuller (1991) found autocorrelations of wind speeds and, therefore, of wind power.

Solar power depends on the behavior of solar irradiance. Thus, the amount of solar irradiance on one day could influence the amount a day later. These dynamics are included in persistence models, a kind of benchmark model that is used to forecast solar irradiance (including daily time steps). Lorenz et al. (2009), for example, compared persistence models with other forecast models using data from several radiometric stations, which were located in Southern Germany, among others. Therefore, German solar power generation may be influenced by the dynamic behavior of solar irradiance. Moreover, Safi et al. (2002) identified autocorrelations in daily solar radiation at a radiometric station in Marrakesh, Morocco, while Boland (1995) found autoregressive processes for the residuals in daily solar radiation at several locations distributed over large parts of Australia. The latter findings indicate that the dynamic structure of solar irradiance could also be present in a larger geographic area as a whole.

Wind and solar power depend on stochastically changing weather conditions. Since their fluctuations are directly related to weather variability (von Bremen (2010)), wind and solar power in Germany would be influenced by stochastic shocks.

The results of the present study show that dynamic negative merit order effects due to both wind and solar power are existent, and that the effects of wind power on spot prices are more persistent over time than those of solar (two days for wind and one for solar). The longer duration of the effects of wind power could be explained by significant autocorrelations of wind power for larger lags. Moreover, solar power effects have larger negative magnitudes. The estimates show a total average negative effect in the range of -2.4 up to -2.15 €/MWh caused by solar power and in the range of -1.7 up to -1.6 €/MWh caused by wind power on spot prices. The larger magnitudes for solar power might be because solar power coincides with demand peaks, resulting in a steeper merit order curve. When comparing past German empirical results, Würzburg et al. (2013) did not find this expected difference when using OLS. Furthermore, lower magnitudes of the total average negative merit order effects (OLS) of wind and solar power are found in the range of 0.7 up to 1.4 €/MWh. OLS estimates might be overstated if wind and solar power dynamics are transferred to the merit order effects. The SVAR analysis itself (with consistent estimates) might be able to take into account these larger magnitudes, particularly by including dynamic relationships.

This paper is structured as follows. Section 2 presents the data and the estimation methodology. Section 3 presents the results and section 4 some sensitivity analyses. Section 5 gives concluding remarks.

2. Data and model

2.1. Data

Six variables are included in the dataset: total wind power production $wind_t$ (GW), total solar power production $solar_t$ (GW), net total load $load_t$ (GW), net exports $net\_exports_t$ (GW), overall conventional power production $conventional_t$ (GW), and the European Power Exchange (EPEX) day-ahead spot price for power $price_t$ (€/MWh). It is assumed that these are the most important variables for describing and explaining the relationships and mechanisms of the day-ahead spot market. Realized values for all power variables are used rather than forecasts. The latter might contradict the choice of a linear estimation model because renewable forecasts are highly non-linear (see Lorenz et al. (2009)). Hourly and quarter-hourly time points are converted into daily average values in order to smooth out temporary and exceptional events over the course of a day.

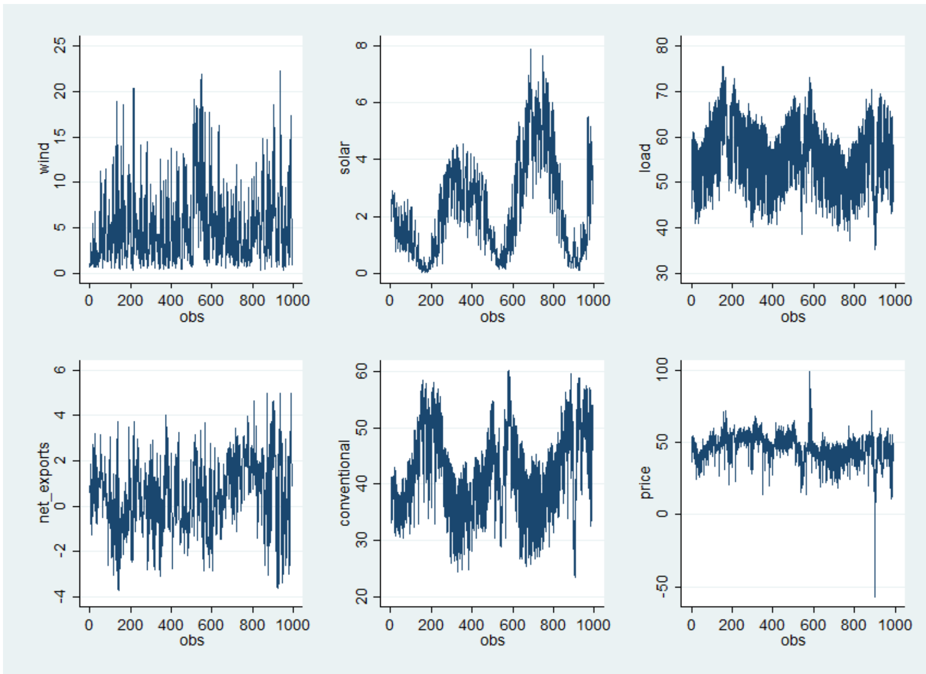
Exact data sources (web links) for all variables are given in Appendix A. Wind and solar power data are taken from the four German Transmission System Operators (TSOs) Amprion, TenneT, 50Hertz, TransnetBW, and from the EEX-Transparency platform (EEX-T). Original data is average German power feed-in (MW) per 15 minutes. Data sources are mixed due to data gaps on specific days from specific sources. Total load data is taken from the European Network of TSOs for Electricity (ENTSOE-E). Original data is average German total demand for power (MW) per hour. Net total load is total load (from 91% extrapolated to 100%) minus network losses and net exports. Network losses are assumed to be 4% of total load, which is the average of most recent yearly data (years 2009-2011, no daily data available). Net exports data are taken from German TSOs and Creos S.A., the TSO of Luxembourg. Original data is average German cross-border load flows of power per 15 minutes. Net exports refers to exports minus imports and includes cross-border load flows between Germany and Poland, Denmark, Netherlands, France, Austria, Switzerland, Czech Republic, and Luxemburg. Flows between Germany and Sweden are not available. Data sources are mixed due to data gaps on specific days from specific sources. Overall conventional power data is taken from EEX-T. Original data are average German power feed-in (MW) per hour. Conventional power includes lignite, coal, gas, oil, uranium, pump storage, seasonal storage, and furnace gas. Conventional power only covers data on power generators with an installed capacity of at least 100 MW per block-unit power station; further data (e.g., biogas) are not available. The sum of load and net exports is not equal to the sum of wind, solar, and conventional power because of excluded network losses and missing conventional power data. Spot price data are taken from EEX (bilateral contract data are not available). Original hourly data are the spot prices (€/MWh) for each of the 24 hours of the following day determined by supply and demand at the EEX.

The number of observations is 993 days and the total time period is from July 1, 2010 to March 30, 2013. This period was chosen because of the significant wind and solar power feed-in that occurred in it, as shown in table 1 and figure 1 (descriptive statistics and time series of the variables). The effects of wind and solar on the spot price are therefore expected to be relevant during this period. The means of the variables are nearly the same as in Cludius et al. (2013) because of nearly the same dataset and time period. Average wind power is twice the average solar power due to the higher wind capacity or more suitable weather conditions at most of the time points investigated. However, wind volatility is also 3 times higher. There is also significantly high demand volatility. Most of the demand is met by conventional power because of its very high share in total production. The remaining extreme price events do not influence the SVAR analysis below.

Looking at figure 1, a significant increase in solar power is observable as a result of increased capacity. For wind, solar, conventional power, and load, there are seasonal elements in the time series. A significantly higher solar feed-in during the summer months is apparent. In contrast, wind power tends to spike in winter months, when load also tends to be higher, due to, for example, a higher demand by end users for electric powered light. Most of this demand is met by conventional power. Therefore, seasonal patterns are similar and differences are due to fluctuations in wind and solar power (priority feed-in). Non-stationarity and autocorrelation problems regarding these seasonal elements in the time series are dealt with conventionally by taking first differences. Furthermore, the lag structure in the SVAR is chosen such that autocorrelation disappears (see section 2.3).

From 2010 to November 2012, wind capacity was higher than solar capacity. However, solar subsidies has brought about substantially increased growth in solar capacity, leading to higher solar capacity in 2013. Table 2 shows wind and solar capacity for the relevant years (data sources are given in Appendix A).

Table 3 shows cross-correlations of the variables. Most cross-correlations are significantly different from zero. This indicates the possibility of interde-



X-axis: Days, Y-axis: Power feed-in/demand (quantity variables) (GW), spot price for power (€/MWh).

Figure 1: Time series of variables in SVAR

Variable	Obs	Mean	Std. Dev.	Min	Max
wind (GW)	993	5.077	4.128	.277	22.311
solar (GW)	993	2.285	1.711	.034	7.885
load (GW)	993	57.355	7.911	35.107	75.598
net_exports (GW)	993	.415	1.63	-3.719	4.995
conventional (GW)	993	42.726	7.89	23.45	60.249
price (€/MWh)	993	46.577	11.167	-56.87	98.982

Table 1: Descriptive statistics

Date	15.11.2010	16.11.2011	16.11.2012	18.11.2013
Wind capacity (GW)	25.96	27.55	30.04	32.45
Solar capacity (GW)	10.64	19.76	28.19	34.85

Source: EEX-T

Table 2: Wind and solar capacity

pendencies between variables. Price correlations have the expected signs. Correlations with wind and solar power are negative due to merit order effects. The correlation with load is positive due to the slope of the merit order curve. The correlation with overall conventional supply is positive, indicating that power increases for high marginal cost technologies lead to price increases. An increase in net exports indicates a decrease in the spot price in the German power market because of higher power outflows.

Variables	wind	solar	load	net_exports	conventional	price
wind	1.000					
solar	-0.246	1.000				
load	-0.092	-0.324	1.000			
net_exports	0.476	0.218	-0.587	1.000		
conventional	-0.213	-0.387	0.829	-0.462	1.000	
price	-0.432	-0.124	0.733	-0.566	0.622	1.000

Table 3: Cross-correlations of variables

2.2. The model

Estimation is based on SVAR techniques described in Hamilton (1994) and Lütkepohl (2006). The following SVAR model for the variables (collected in the vector $\mathbf{x}_t$) is estimated:

$$\mathbf{A}_0\,\mathbf{x}_t = \mathbf{A}_0\,\mathbf{c} + \mathbf{A}_0 \times \left[\sum_{\tau=1}^{p} \mathbf{A}_\tau\,\mathbf{x}_{t-\tau} + \mathbf{B}\,\mathbf{e}_t\right]. \tag{1}$$

$\mathbf{A}_0$ is the coefficient matrix of the direct instantaneous effects between the variables and $\mathbf{B}$ between the structural shocks and the shocks in the underlying vector autoregressive (VAR) model. $\mathbf{A}_\tau$ are coefficient matrices with respect to the past time lags up to the maximum lag p, $\mathbf{c}$ is a vector of constants and $\mathbf{e}_t$ is a vector of the structural shocks in the SVAR in each equation. The underlying VAR is the reduced form of the SVAR. Therefore, the shocks in the VAR and the SVAR are related as follows: $\mathbf{u}_t = \mathbf{A}_0^{-1}\mathbf{B}\mathbf{e}_t$ with $\mathbf{u}_t$ as a vector of the shocks in the underlying VAR.

Each variable is assumed to be endogenous because of possible interdependencies between the variables or dynamic dependencies of the variables themselves over time. As stated in the introduction, values for wind and solar

power on a given day can be seen as dependent on their values on previous days. These variables are therefore modeled endogenously, in contrast to the approach taken by Böckers et al. (2013). The data reveals that the average of net exports is positive, meaning that this variable can be seen as foreign demand for domestic power because exports are larger than imports on average (see table 1). It is common to model demand variables as nearly price inelastic (see Gelabert et al. (2011) on the Spanish electricity market). For example, most private power customers have fixed power contracts. In Böckers et al. (2013), demand is modeled exogenously. However, price elasticity could be present, if, for example, energy-intensive companies with more flexible contracts reacted to a price increase. Furthermore, table 3 shows that spot prices are significantly correlated with load and net exports. Moreover, the structural impulse response function in figure B.7 in Appendix B indicates that load depends on its own values on previous days. Table B.18 in Appendix B shows that for most significance levels, load cannot be seen as exogenous when applying the score test of Wooldridge (1995) and the regression-based F test of Hausman (1978) for exogeneity (load is endogenously modeled as dependent on its own past daily values). Therefore, demand variables are also modeled as endogenous.
In section 4, time dummies, modeled as exogenous variables, are additionally taken into account in the SVAR as a sensitivity analysis.
The variables in the model can be seen as possibly influenced by stochastic shocks. The dependency of wind and solar power on the weather has already been discussed in the introduction. Another example is the possibility of a stochastic shock in the oil price influencing the spot price, overall conventional production, as well as imports and therefore also net exports. Despite these considerations, if one variable is not influenced by a shock and if the estimated coefficients of the SVAR are consistent, the related coefficients will not be significant and therefore will not bias the other results.
Specifically, the structure of the SVAR model is presented in equations 2 - 5:

$$\mathbf{A}_0\,\mathbf{x}_t = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_{21,0} & 1 & 0 & 0 & 0 & 0 \\ a_{31,0} & a_{32,0} & 1 & 0 & 0 & 0.001 \\ a_{41,0} & a_{42,0} & a_{43,0} & 1 & 0 & 0.001 \\ a_{51,0} & a_{52,0} & a_{53,0} & a_{54,0} & 1 & -0.05 \\ a_{61,0} & a_{62,0} & a_{63,0} & a_{64,0} & a_{65,0} & 1 \end{pmatrix} \times \begin{pmatrix} wind_t \\ solar_t \\ load_t \\ net\_exports_t \\ conventional_t \\ price_t \end{pmatrix}. \tag{2}$$

$$\mathbf{A}_0\,\mathbf{c} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_{21,0} & 1 & 0 & 0 & 0 & 0 \\ a_{31,0} & a_{32,0} & 1 & 0 & 0 & 0.001 \\ a_{41,0} & a_{42,0} & a_{43,0} & 1 & 0 & 0.001 \\ a_{51,0} & a_{52,0} & a_{53,0} & a_{54,0} & 1 & -0.05 \\ a_{61,0} & a_{62,0} & a_{63,0} & a_{64,0} & a_{65,0} & 1 \end{pmatrix} \times \begin{pmatrix} c_{wind,t} \\ c_{solar,t} \\ c_{load,t} \\ c_{net\_exports,t} \\ c_{conventional,t} \\ c_{price,t} \end{pmatrix}. \tag{3}$$

$$\mathbf{A}_\tau\,\mathbf{x}_{t-\tau} = \begin{pmatrix} a_{11,\tau} & a_{12,\tau} & a_{13,\tau} & a_{14,\tau} & a_{15,\tau} & a_{16,\tau} \\ a_{21,\tau} & a_{22,\tau} & a_{23,\tau} & a_{24,\tau} & a_{25,\tau} & a_{26,\tau} \\ a_{31,\tau} & a_{32,\tau} & a_{33,\tau} & a_{34,\tau} & a_{35,\tau} & a_{36,\tau} \\ a_{41,\tau} & a_{42,\tau} & a_{43,\tau} & a_{44,\tau} & a_{45,\tau} & a_{46,\tau} \\ a_{51,\tau} & a_{52,\tau} & a_{53,\tau} & a_{54,\tau} & a_{55,\tau} & a_{56,\tau} \\ a_{61,\tau} & a_{62,\tau} & a_{63,\tau} & a_{64,\tau} & a_{65,\tau} & a_{66,\tau} \end{pmatrix} \times \begin{pmatrix} wind_{t-\tau} \\ solar_{t-\tau} \\ load_{t-\tau} \\ net\_exports_{t-\tau} \\ conventional_{t-\tau} \\ price_{t-\tau} \end{pmatrix}. \tag{4}$$

$$\mathbf{B}\,\mathbf{e}_t = \begin{pmatrix} b_{11,0} & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{22,0} & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{33,0} & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{44,0} & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{55,0} & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{66,0} \end{pmatrix} \times \begin{pmatrix} e_{wind,t} \\ e_{solar,t} \\ e_{load,t} \\ e_{net\_exports,t} \\ e_{conventional,t} \\ e_{price,t} \end{pmatrix}. \tag{5}$$

By using an SVAR, a priori restrictions based on economic theory are imposed on $\mathbf{A}_0$ and on $\mathbf{B}$ in order to achieve identification of the model. After specifying an SVAR with six endogenous variables and their related estimation equations, 51 restrictions are left for the direct instantaneous effects between the variables (see equation 2)[3] and between the shocks (see equation 5). By assuming that the VAR shocks only depend on the structural shocks of the same variable, $\mathbf{B}$ becomes a diagonal matrix because all off-diagonal elements are set to zero. This transformation is usually carried out in order to scale the variances of the structural shocks to unity. Moreover, it is obvious that each variable is dependent on the other variables in the respective equation. Therefore, all diagonal elements in $\mathbf{A}_0$ are set to one. The last 15 restrictions refer to several instantaneous effects between the variables in $\mathbf{A}_0$, which have to be chosen a priori. To my knowledge, there is unfortunately no energy economic theory describing interrelations of the stated variables. Thus, the following assumptions similar to the ones in Maciejowska (2014)

[3]Elements are negative instantaneous effects because $\mathbf{A}_0$ is (also) on the left-hand side in equation 1.

are given.
In an SVAR, the most endogenous variable has to be ordered last and the least endogenous variable has to be ordered first. Therefore, wind and solar power are ordered first and load follows. The spot price is ordered last because it depends on all other variables. Wind as well as solar power production are only dependent on themselves due to the priority feed-in, and load is only affected by the spot price and itself. Load is not perfectly but nearly inelastic to the spot price, and therefore a number near but not equal to zero (-0.001) is chosen.[4] The price effect on net exports (foreign demand for domestic power) is chosen to be the same as on load, and net exports can be seen as independent of conventional supply. Moreover, conventional supply is more endogenous than load and net exports. There exists the possibility of market power, meaning that the effect of the price on conventional power is not zero but positive. After running several OLS regressions with different specifications (varying control variables, time dummy structure, robust standard errors) and using conventional supply as the dependent variable, the average of the marginal average price effects is chosen as a proxy (0.05). Regressions are given in table B.8 in Appendix B. A perfect recursive (Cholesky) structure of the variables (another option to achieve identification) does not fit the specific relationships between the variables. However, the stated restrictions are similar to a Cholesky structure.
The shocks in both models are assumed to be vector white noise with zero mean, that is, mutually independent and identically distributed:

$$\mathbf{u}_t \sim (\mathbf{0}, \mathbf{S}_u)\ ,\ \mathbf{e}_t \sim (\mathbf{0}, \mathbf{I}_6)\ ,\ \mathbf{S}_u = \mathbf{A}_0^{-1}\mathbf{B}\mathbf{B}'(\mathbf{A}_0^{-1})'. \tag{6}$$

$\mathbf{S}_u$ is the variance-covariance matrix (VCM) of the shocks in the underlying VAR, and the VCM of the structural shocks in the SVAR is the identity matrix. Therefore, each structural shock has unit variance and there is no instantaneous correlation of the shocks. If these restrictions hold, causal interpretation of the effects in the SVAR is possible because the structural shocks are serially and mutually uncorrelated (which is not the case for the shocks in the VAR).
The maximum likelihood estimates of the SVAR coefficients as well as of the coefficients of the following interpretation tools are consistent if the SVAR is identified and stationary. Furthermore, both shocks have to be vector white

[4] In section 4, larger negative values in the SVAR are also chosen as a sensitivity analysis.

noise, and in particular, there can be no vector autocorrelation of the shocks (Lütkepohl (2006)). Maximization of the log-likelihood function of the model is achieved using the scoring method (Harvey (1990) and Amisano and Giannini (1997)).
Tools for presenting and interpreting the results are structural impulse response functions (SIRFs) and structural forecast error variance decompositions (SFEVDs). In this paper, SIRFs measure the marginal effects of a one standard deviation increase in the structural shock of wind or solar power at time t on the spot price at time $t+s$ for all $s = 0, ...$ up to the maximum time horizon, holding everything else constant:

$$\frac{\partial price_{t+s}}{\partial e_{j,t}} = m^{(s)}_{price,j} \quad , \quad j = wind, solar. \tag{7}$$

$m^{(s)}_{price,j}$ are moving average (MA) coefficients of the stationary process $\mathbf{x}_t$. This paper deals with the causal effects on the spot price as a result of positive structural shocks in wind and solar power production over time. The causal effects can therefore be described as average dynamic changes in the spot price due to structural shocks in wind and solar power production at different points in time, or rather, on different days.[5] In order to be able to compare the effects of a one-unit (1 GW) shock in wind and solar power, the estimated effects of the SIRFs will be divided by the standard deviations of wind and solar power such that the related shocks equal 1 GW.
In this context, SFEVDs measure the fraction of the total forecast error variance of the spot price that is attributable to a shock in wind or solar power. In other words, SFEVDs present the importance of a structural shock in wind and solar power in explaining the fluctuation of the spot price.

2.3. Preliminary analysis

All variables are tested for unit roots using the augmented test of Dickey and Fuller (1979) (cf. table B.12 in Appendix B). Wind power, load, net exports, as well as spot prices are stationary in levels. Solar power and conventional power are not stationary in levels, but their first differences are (notation: *variable_d*). In order to avoid non-stationarity problems, the last two vari-

[5]Considering additionally figure B.7 in Appendix B, the SIRF presents dynamic changes in load caused by a structural shock in the same variable.

ables are in first differences and all other variables are in levels.[6]

Solar power and conventional power may be cointegrated because they are stationary in first differences (integrated of order 1). If this is the case, a vector error correction model (VECM) instead of a VAR should be implemented in order to include long-run relationships due to cointegration. Therefore, solar and conventional power are tested for cointegration by using the trace test and the maximum-eigenvalue test of Johansen (1995) (see table B.13 in Appendix B). Both tests suggest no cointegration for the 1% and 5% significance levels. Therefore, no cointegration between solar and conventional power is expected.

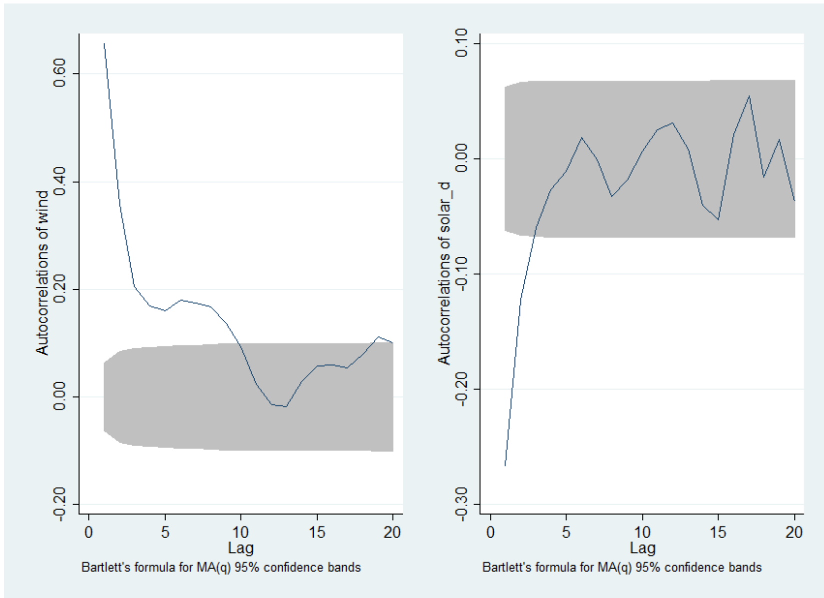
There are high autocorrelations of wind power for the first three lags and a rapid decline within this period. Afterwards, autocorrelations are much smaller and significantly different from zero up to the tenth lag. Figure 2 shows the respective lags and autocorrelations. Given the significant lags, the pattern is roughly similar to those of autocorrelated wind speeds in Brett and Tuller (1991), where the autocorrelations are only high for the first day.[7]

Moreover figure 2 shows the autocorrelations of solar power in first differences. Autocorrelations of solar in levels vary over time because of the non-stationarity. There are also significant but smaller (negative) autocorrelations for the first two lags, and afterwards they are not significantly different from zero. Despite the different locations and weather conditions, these autocorrelations for lag 1 or lag 2 are also consistent with past evidence, as cited, for example, in Safi et al. (2002).

The lags of the underlying VAR have to be chosen such that there is no mutual autocorrelation of the shocks. Several selection criteria (AIC, SBIC, FPE, HQIC) suggest a number of maximum lags between 7 and 8 (see table B.14 in Appendix B). However, there still exists mutual autocorrelation. By considering several VARs with alternative numbers of maximum lags, an underlying VAR with 14 lags as well as the seventeenth lag (excluding lags 15 and 16) reveals no mutual autocorrelation of the shocks. The Lagrange-

[6]Considering the time series in figure 1, conventional power may contain a slight time trend. The related tests indicate non-stationarity for most significance levels. Solar power clearly contains a time trend, and related tests show non-stationarity. Their first differences are stationary. With regard to load, unit root tests indicate stationarity for almost any significance levels (with or without trend).

[7]However, the patterns in Brett and Tuller (1991) are for individual wind stations in Canada. Moreover, their autocorrelations do not disappear up to two months.



X-axis: Lags (days), Y-axis: Autocorrelations

Figure 2: Autocorrelations of wind (left graphic) and solar power (right graphic)

Multiplier test for autocorrelation of Johansen (1995) is used (see table B.15 in Appendix B). Therefore, the residuals can be seen as vector white noise. The lag structure may be due to autocorrelated weekly load data up to 2-2.5 weeks. However, by choosing the stated lags, residual autocorrelation in the model disappears.

Finally, the specific SVAR is estimated, that is, the stated underlying VAR combined with the given a priori short-run restrictions of the instantaneous effects in $\mathbf{A}_0$ and $\mathbf{B}$. The structural shocks in this SVAR are not mutually autocorrelated because there is no mutual autocorrelation of the stated VAR shocks, and $\mathbf{e}_t = \mathbf{B}^{-1}\mathbf{A}_0\mathbf{u}_t$ holds. Moreover, the SVAR is exactly identified and stationary. Therefore, estimated coefficients in the model are consistent. Checking for identification of the SVAR is done using the method of Amisano and Giannini (1997). The SVAR is stationary if the modulus of each eigenvalue of the companion matrix of the underlying VAR is less than one (Hamilton (1994) and Lütkepohl (2006), see table B.16 in Appendix B). The residuals of the VAR and SVAR are tested to be not normally distributed using the method of Lütkepohl (2006) (see table B.17 in Appendix B). Therefore, consistent standard errors and confidence intervals of the fol-

lowing SIRFs and SFEVDs are created by using the bootstrapping method for the residuals of Lütkepohl (2006). Convergence of estimations is achieved from 1000 replications. This method does not require a specific distribution assumption for the residuals. The confidence probability for each confidence interval (CI) of the point estimates is 95% as usual. The maximum time horizon for the SIRFs is 18 days in order to use all available information up to the seventeenth lag of the underlying VAR.
There could be a problem of multicollinearity because overall demand and supply of the spot market at each point in time is included in the model. However, there is no perfect multicollinearity because network losses are excluded, and data on conventional power is incomplete due to data-specific restrictions. In order to investigate quasi-multicollinearity, table B.9 in Appendix B shows the symmetric correlation matrix including cross-correlations of stationary variables. Following Verbeek (2008) quasi-multicollinearity is very unlikely to be a problem with respect to the data and the stated variables because the modulus of each cross-correlation does not exceed 0.8.[8]
By using average hourly data, nearly the same values as in Cludius et al. (2013) are obtained. Specifically, an OLS regression with the spot price as the dependent variable and load, wind and solar power as explanatory variables (including time dummies and robust standard errors) over nearly the same time period with nearly the same dataset leads to nearly the same negative merit order effects on average (around -1 €/MWh for wind and solar). This is a proof of the validity of the data (see table B.11 in Appendix B). Moreover, Table B.10 in Appendix B shows daily OLS estimates for merit order effects due to wind and solar power. Although the effect of solar power is smaller, the estimates are quite similar to Würzburg et al. (2013) and Cludius et al. (2013). The smaller effect of solar power may be due to some differences in empirical analysis. In contrast to Würzburg et al. (2013) and Cludius et al. (2013) most variables are in levels (not first differences) and the time period is about 9 months longer. With respect to Würzburg et al. (2013), no forecasts are chosen as stated in section 2.1.

[8]In the SVAR model, all variables are dependent in one equation, and thus all variables are explanatory in the remaining equations. Therefore, the stated threshold must hold for all cross-correlations.

3. Results

Figures 3 and 4 show the SIRFs for a positive shock of one standard deviation in wind and solar power. Spot prices are decreasing over time due to shocks in wind and solar power. The effects can be seen as different negative merit order effects on the day of the shock and on the days subsequent to the shock. The directions of the effects are in line with past theoretical and empirical research on (average) negative merit order effects. The persistence of a wind power shock is longer: The spot price decreases constantly over two days, which is twice the duration of a solar power shock (one day). For comparing the magnitudes of the effects of 1 GW wind and solar power shocks, the effects are divided by the standard deviations of wind and solar power as stated in section 2.2. Table 4 shows the related effects on the significant instantaneous day and on significant future days as well as the aggregated effects.[9]

Step,day	impulse: Wind	impulse: Solar_d
0	-.81591189	-1.1635381
1	-.5769002	-1.2171447
2	-.31220399	0
Aggregated effect	-1.7050161	-2.3806828
975 observations in SVAR		

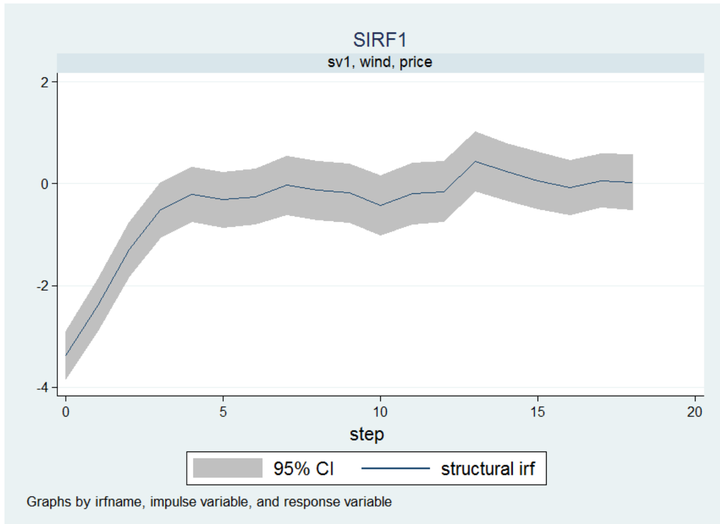
SIRFs: Effects of 1 GW wind/solar power shock on spot price (€/MWh)

Table 4: SIRFs: One-unit shock wind and solar power on spot price

The negative merit order effects of a solar power shock are larger on each significant day (the largest effect is one day later, at about -1.2 €/MWh) the effects of a wind power shock (largest effect is the instantaneous effect, about -0.8 €/MWh). Moreover, when the dynamic effects of wind and solar power are added together, the results show a total average negative effect of -2.4 €/MWh for solar power and of -1.7 €/MWh for wind power on the spot price.

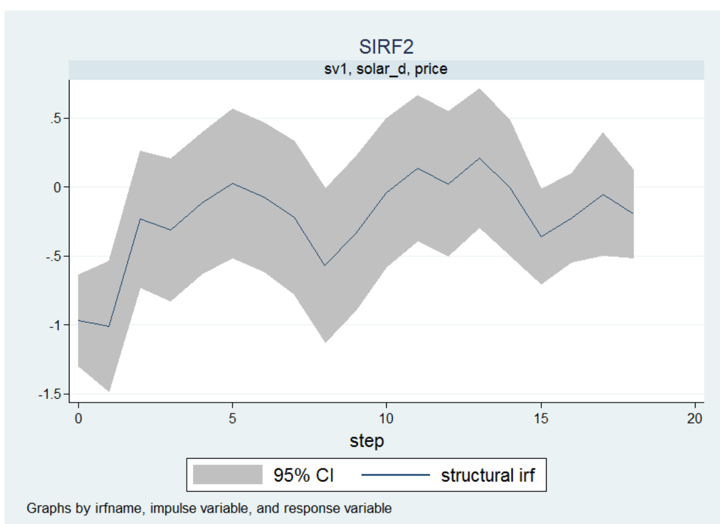
Considering figure 2, the high autocorrelations of wind power for the first three lags and the gradual decline during this time period could explain the dynamic negative effects of wind power on the spot price for the time period

[9]The significance of the effects does not change because the bootstrapped standard errors and confidence intervals will be transformed linearly and, therefore, confidence intervals will not change signs.



X-axis: Days, Y-axis: Marginal effects (€/MWh), below title: Name of technical file (irfname). 975 observations in SVAR.

Figure 3: Effects of wind power shock on spot price



X-axis: Days, Y-axis: Marginal effects (€/MWh), below title: Name of technical file (irfname). 975 observations in SVAR.

Figure 4: Effects of solar power shock on spot price

subsequent to a shock. Because the results only show significant autocorrelations of solar power in differences for the first two lags and since these also decline gradually, this dynamic structure is also a possible explanation for the dynamic effects of solar power on the spot price. In this sense, the dynamic structures of wind power as well as solar power are transferred to the merit order effects on the spot price. Dynamic effects of wind power may persist longer over time because of the longer persistence of autocorrelated wind speeds. In contrast to wind power, solar power coincides with demand peaks. Thus, the merit order curve is steeper when solar is fed into the grid and, therefore, the magnitude of the total negative merit order effect of solar power should be larger.

The negative aggregated effects found here are slightly higher than those reported by Würzburg et al. (2013) and Cludius et al. (2013) (static average OLS merit order effects of wind and solar power of about -1 €/MWh). Neither of these papers reported any differences in the effects of wind and solar power on average. Moreover, by taking electricity simulation models into account as well, the present paper finds merit order effects for Germany in the range of those reported in past research (from -2.5 to -0.5 €/MWh) as presented in Würzburg et al. (2013).

Similar daily OLS estimates of the merit order effects for wind and solar power, such as those in Würzburg et al. (2013) and Cludius et al. (2013), are discussed in section 2.3. Following Baltagi (2002), OLS estimates (without lagged explanatory variables) may be overstated because wind or solar power and OLS residuals may be positively contemporaneously correlated. Positive correlation should be present when parts of the residuals are lagged values of explanatory variables. Furthermore, applying SVAR techniques changes the relation of a merit order effect of wind and solar power. OLS indicates that the negative effect of wind power on the spot price is slightly higher. In contrast, SVAR estimates (and SIRFs) suggest a higher negative effect of solar power. When using an SVAR, Böckers et al. (2013) also found a negative merit order effect of wind power, but a positive effect of solar power for Spain. The latter stands in contrast to previous theoretical as well as empirical findings. Possibly, the contrary results reported by Böckers et al. (2013) are driven by modeling wind and solar production in their SVAR as exogenous (and, therefore, ignoring wind and solar power dynamics).

After the SIRFs, Structural Forecast Error Variance Decompositions are calculated. Table 5 shows the respective SFEVDs and their standard errors.

A structural shock in wind power accounts for 27-28% of the variance up

step,day	SFEVD-wind	standard error	SFEVD-solar_d	standard error
0	0	0	0	0
1	0.272142	0.032765	0.022428	0.008394
2	0.280252	0.035310	0.032248	0.012173
975 observations in SVAR				

Table 5: SFEVDs wind and solar power

to the second day and a structural shock in solar power accounts for 2-3% up to the first day. This means that a shock in wind power contribute a larger share to the variance of error made in forecasting the spot price than a shock in solar power. Therefore, wind power shocks are more important in explaining the fluctuation of the spot price. A possible explanation is that such shocks tend to occur more often and therefore influence the spot price more often. Moreover, wind capacity exceeds solar capacity for most of the investigated time period. However, the effects are not large in magnitude due to the relatively flat merit order curve (e.g., at night). A significant share of the variance is also explained by solar power shocks, despite their lesser importance.

4. Sensitivity analysis

Sensitivity analysis is done by using alternative a-priori short-run restrictions in $\mathbf{A}_0$ without changing the variable ordering. There is no theoretical reason to use a different order. Starting with an exact Cholesky structure, the instantaneous effect of the spot price on conventional power is varied in the interval $[0.01; 0.2]$ with steps of 0.01, and in the interval $[0.2; 0.8]$ with steps of 0.1. The instantaneous effect of the spot price on load is varied in the interval $[-0.009; 0]$ with steps of 0.001. The instantaneous effect of the spot price on net exports is varied in the interval $[-0.04; 0]$ with steps of 0.005. The instantaneous effect of conventional power on net exports is varied in the interval $[-0.005; 0.005]$ with steps of 0.001, and in the interval $[0.01; 0.05]$ with steps of 0.01. For some variations, estimation is not possible because the related log-likelihood function of the SVAR is not concave. Taking into account all remaining alternatives, the SVAR results do not change.
As a further sensitivity analysis, time dummies as exogenous variables are included in the SVAR in order to control additionally for seasonal elements in

the endogenous variables.[10] There are six weekly dummies (monday is base category), 11 monthly dummies (January is base category) and three yearly dummies (year 2010 is the base category) in the SVAR and all calculations are repeated. Table 6 shows the effects due to a 1 GW shock in wind and solar power on the significant instantaneous day and on significant future days as well as the aggregated effects.

Step,day	impulse: Wind	impulse: Solar_d
0	-.79948813	-1.0208895
1	-.52680048	-1.1245361
2	-.27183255	0
Aggregated effect	-1.5981212	-2.1454256
971 observations in SVAR		

SIRFs: Effects of 1 GW wind/solar power shock on spot price (€/MWh)

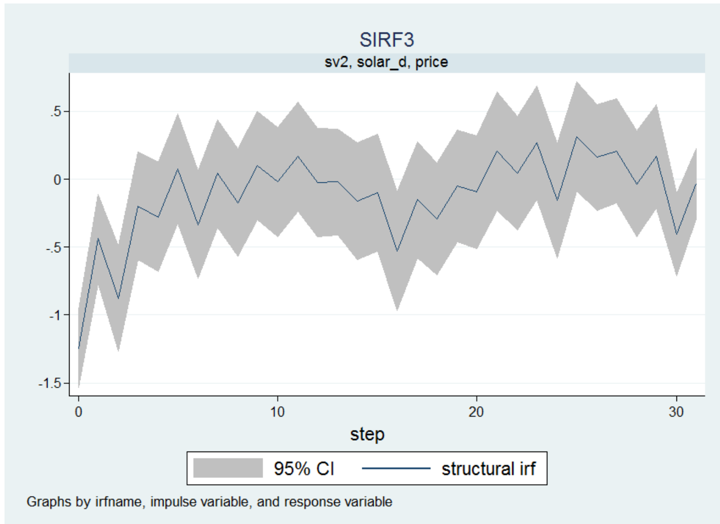
Table 6: SIRFs: One-unit shock wind and solar power on spot price (time dummies in SVAR included)

The basic patterns and the time periods of the dynamic effects in the SIRFs remain unchanged. The magnitudes of the negative dynamic effects as well as of the aggregated effects are slightly lower for both shocks. However, the negative effects of a solar power shock are still significantly higher, as in section 3. Furthermore, the aggregated effects of both shocks have still a larger magnitude than the OLS effects in Würzburg et al. (2013) and Cludius et al. (2013).

Taking average daily values may bias the results because solar power feed-in occurs only during the day, and most of the wind power feed-in occurs at night. Therefore, each day is separated into average daytime values (from 6 a.m. to 6 p.m.) and nighttime values (from 6 p.m. to 6 a.m.), and all calculations are repeated. There are no changes in the basic patterns or in the individual time periods in which the effects take place. Only the magnitudes of the effects of a shock in wind power are slightly different. Furthermore, now the oscillating solar power feed-in during the day and at night is (only) observable for the effects of a solar power shock on the spot price. Figure 5 shows the related SIRF.

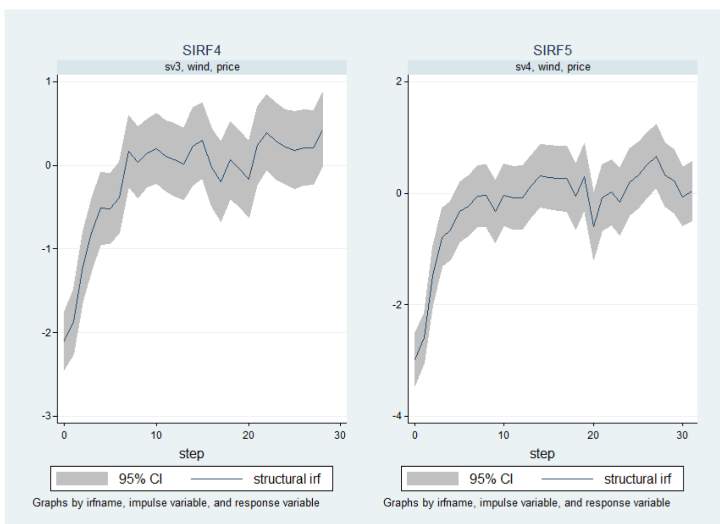
Figure 6 presents the SIRF as a result of a shock in wind power before, and the SIRF after the nuclear moratorium, respectively. This is another important

[10]Consistent SVAR and VAR models for all sensitivity analyses are used with regard to the restrictions given in sections 2.2 and 2.3. Related estimation and test results for all sensitivity analyses are available from the author upon request.



X-axis: Half days, Y-axis: Marginal effects (€/MWh), below title: Name of technical file (irfname). 1956 observations in SVAR.

Figure 5: Effects of solar power shock on spot price



X-axis: Half days, Y-axis: Marginal effects (€/MWh), below titles: Names of technical files (irfname). 755 (left graphic), 1174 (right graphic) observations in SVAR.

Figure 6: Effects of wind power shock on spot price before (left graphic) and after (right graphic) nuclear moratorium

sensitivity analysis because of the possibility of a structural change due to the nuclear moratorium of August 2011. To conduct this analysis, the dataset is divided into the time before (from July 2010 to July 2011) and after (from August 2011 to March 2013) the nuclear moratorium, and all calculations are repeated. Time frequencies are now half days. The basic patterns in the SIRFs as well as the time periods in which the effects take place are very similar to the SIRFs above. Furthermore, in general, there is no difference in the magnitudes of the effects. Again the effects are additionally scaled such that wind power shocks equal 1 GW in order to compare the magnitudes (see section 3). Table 7 shows the effects for both time periods.

Step,half day	impulse: Wind 1st half	impulse: Wind 2nd half
0	-.54567663	-.64794941
1	-.48702345	-.56415683
2	-.31432026	-.32217415
3	-.21074491	-.17182672
4	-.13391032	-.14478755
5	-.13500634	0
Aggregated effect	-1.8266819	-1.8508947
755 observations before and 1174 after nuclear moratorium in SVAR		
SIRFs: Effects of 1 GW wind power shock on spot price (€/MWh)		

Table 7: SIRFs: One-unit shock wind power on spot price before/after nuclear moratorium

The differences are small. Therefore, as stated in Würzburg et al. (2013), shutting down seven nuclear power plants due to the nuclear moratorium does not change the electricity mix to result in different merit order effects. Fossil fuels were likely to replace the eliminated nuclear power instead of renewables such as wind power.
SFEVDs with respect to shocks in wind and solar power on the spot price for all sensitivity analyses present similar results compared to the previously reported SFEVDs. This indicates that there is no change in the importance of a shock in wind or solar power in explaining the fluctuation of the spot price.

5. Concluding remarks

This paper examines the behavior of spot prices over time caused by positive structural shocks in wind or solar power in the German day-ahead electricity spot market using a SVAR and the related SIRFs. The directions of the dynamic negative merit order effects of wind and solar power are not a surprise. More interestingly, wind power shows longer persistence of the effects on spot prices over time. An explanation is that autocorrelation for wind power are significant at larger lags than for solar power. In this sense, the dynamic nature of wind and solar power is transferred to the merit order effect on spot prices. Autocorrelations of wind and solar power are likely to autocorrelated wind speeds and solar irradiances. On average, the total negative effect on spot prices for solar power shocks is larger. The fact that solar coincides with demand peaks and results in a steeper merit order curve might explain the larger magnitudes.

When comparing past empirical results, there are differences in the total average negative merit order effects of wind and solar power. The autocorrelation patterns of wind and solar power could explain the negative effects found on specific days. OLS estimates might be overstated if these dynamics were transferred to merit order effects: The sums of the dynamic SIRF effects – that is, the total average effects – might then have a larger magnitude. Despite the possible explanations given in this paper, the reasons for the dynamic effects on spot prices due to shocks in wind and solar power are open questions and left for further research.

When using subsets of the data on the pre- and post-nuclear moratorium periods as a sensitivity analysis, no different dynamic merit order effects are found, and the basic dynamic patterns remain unchanged. According to Würzburg et al. (2013), fossil fuels are more likely than renewables to have replaced the eliminated nuclear power, leading to no different merit order effects of wind or solar power.

SVAR estimates suggest that private power customers will be able to reduce their costs by purchasing a high amount of power within a time period of two days after a wind increase (and one day after a solar increase) if these users are able to apply smart metering as well as electricity storing techniques in the future. Smart metering may become available sooner than electricity storing techniques. Power end users could then use the time periods in the same way, if smart metering were able to identify the necessary amount of power for all time periods and all household electrical equipment. For example, the electricity needed to operate a washing machine could be purchased within days of a price decrease.

Future research could study the implementation of other possible relevant variables of the German electricity market in the model such as the gas price. However, past research has found no related effects of gas prices on spot prices due to long-term contracts (see Gelabert et al. (2011)).

Acknowledgements

I gratefully acknowledge helpful comments from Carsten Helm, Klaus Eisenack, Erkan Gören, Anna Pechan, and participants in the 2014 Workshop in Applied Economics of the Lower Saxony Institute of Economic Research (NIW), and the participants in the 2014 Young academics Workshop in Environmental and Ressource Economics of the Committee of Environmental and Resource Economics (AURÖ), and researchers of the Ph.D. Program Systemintegration Erneuerbare Energien (SEE).

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Appendix A. Data sources

Total wind power production $wind_t$:
Data sources are Amprion (http://www.amprion.net/windenergieeinspeisung#), TenneT (http://www.tennettso.de/site/Transparenz/veroeffentlichungen/netzkennzahlen/tatsaechliche-und-prognostizierte-windenergieeinspeisung), 50Hertz (http://www.50hertz.com/de/1983.htm), TransnetBW (http://www.transnetbw.de/de/kennzahlen/erneuerbare-energien/windenergie), Transparency-EEX (http://www.transparency.eex.com/de/daten_uebertragungsnetzbetreiber/stromerzeugung/tatsaechliche-produktion-wind).

Total solar power production $solar_t$:
Data sources are Amprion (http://www.amprion.net/photovoltaikeinspeisung#), TenneT (http://www.tennettso.de/site/Transparenz/veroeffentlichungen/netzkennzahlen/tatsaechliche-und-prognostizierte-solarenergieeinspeisung_land?lang=de_DE), 50Hertz (http://www.50hertz.com/de/2792.htm), TransnetBW (http://www.transnetbw.de/de/kennzahlen/erneuerbare-energien/fotovoltaik), Transparency-EEX (http://www.transparency.eex.com/de/daten_uebertragungsnetzbetreiber/stromerzeugung/tatsaechliche-produktion-solar).

Net total load $load_t$:
Data provided by ENTSO-E (total load, https://www.entsoe.eu/db-query/consumption/mhlv-a-specific-country-for-a-specific-month/).

Net-exports $net - exports_t$:
Data sources are Amprion (http://www.amprion.net/grenzueberschreitende-lastfluesse#), TenneT (http://www.tennettso.de/site/Transparenz/veroeffentlichungen/netzkennzahlen/grenzueberschreitende-lastfluesse), 50Hertz (http://www.50hertz.com/de/119.htm), TransnetBW (http://www.transnetbw.de/de/kennzahlen/lastdaten/grenzueberschreitende-lastfluesse), Creos S.A. (http://www.creos-net.lu, cross-border load flows between Germany and Luxemburg available upon request).

Conventional power production $conventional_t$:
Data source is Transparency-EEX (http://www.transparency.eex.com/de/daten_uebertragungsnetzbetreiber/stromerzeugung/tatsaechliche-produktion-von-erzeugungseinheiten%20%E2%89%A5%20100%20MW).

EEX day-ahead spot price for power $price_t$:
Data source is EEX (http://www.eex.com/de/). Spot price data available by purchasing the Info-Student package.

Wind and solar capacity:
Data sources are www.ise.fraunhofer.de/de/downloads/pdf-files/aktuelles/stromproduktion-aus-solar-und-windenergie-2012.pdf and http://www.transparency.eex.com/de/daten_uebertragungsnetzbetreiber/stromerzeugung/installierte%20Erzeugungskapazit%C3%A4t%20%3C%20100%20MW.

Network losses:
Data source is http://search.worldbank.org/data?qterm=Network+losses+output&language=EN&format=.

Appendix B. Additional tables

VARIABLES	(1) conventional_d	(2) conventional_d	(3) conventional_d	(4) conventional_d	(5) conventional_d
price	0.0860***	0.0396**	0.0378**	0.0340**	-0.0118
	(0.0176)	(0.0169)	(0.0168)	(0.0165)	(0.0193)
wind		-0.181***	-0.188***	-0.171***	-0.218***
		(0.0321)	(0.0320)	(0.0358)	(0.0332)
solar_d			-0.273**	-0.278**	-0.281***
			(0.108)	(0.108)	(0.104)
load					0.153**
					(0.0617)
net_exports				-0.102	0.0920
				(0.0893)	(0.100)
Constant	5.753***	9.133***	9.281***	9.260***	1.895
	(1.002)	(1.112)	(1.108)	(1.107)	(3.568)
Daily dummies	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes	Yes
Observations	992	992	992	992	992

Newey-West standard errors in parentheses because of autocorrelated and heteroskedastic residuals
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Spot price not significant if load is included

Table B.8: OLS regressions market power

Variables	wind	solar_d	load	net_exports	conventional_d	price
wind	1.000					
solar_d	-0.067	1.000				
load	-0.092	0.003	1.000			
net_exports	0.476	-0.059	-0.587	1.000		
conventional_d	-0.185	-0.031	0.407	-0.228	1.000	
price	-0.432	-0.003	0.733	-0.566	0.315	1.000

Table B.9: Cross-correlations of stationary variables

VARIABLES	(1) price	(2) price	(3) price
wind	-1.018***	-0.964***	-1.027***
	(0.0644)	(0.0764)	(0.0665)
solar_d	-0.349*	-0.484**	-0.361**
	(0.180)	(0.198)	(0.181)
load	1.346***		1.352***
	(0.205)		(0.208)
net_exports	0.864***	-1.376***	0.868***
	(0.221)	(0.337)	(0.222)
conventional_d		0.205**	-0.0437
		(0.0952)	(0.0740)
Constant	-32.18**	52.19***	-32.09**
	(13.14)	(1.793)	(13.09)
Daily dummies	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes
Observations	992	992	992

Newey-West standard errors in parentheses because of autocorrelated and heteroskedastic residuals
*** p<0.01, ** p<0.05, * p<0.1
Conventional power not significant if load is included

Table B.10: Daily OLS regressions: Merit order effect of wind and solar power

VARIABLES	(1) price	(2) price
wind	-1.317***	-0.919***
	(0.0277)	(0.0189)
solar	-0.931***	-0.965***
	(0.0374)	(0.0294)
load		1.164***
		(0.0368)
Constant	46.81***	-21.67***
	(0.577)	(2.027)
Hourly dummies	Yes	Yes
Daily dummies	Yes	Yes
Monthly dummies	Yes	Yes
Yearly dummies	Yes	Yes
Observations	23.817	23.817

Newey-West standard errors in parentheses because of autocorrelated and heteroskedastic residuals
*** p<0.01, ** p<0.05, * p<0.1
All Variables in levels, stationary

Table B.11: Hourly OLS regressions: Merit order effect of wind and solar power

Variables	lags	RW drift/no drift	RW trend	RW drift
wind	19	6.287e-06	.00004556	8.396e-08
	20	6.338e-06	.00004609	8.476e-08
	21	8.843e-06	.00006399	1.229e-07
	22	.00002728	.00018993	4.294e-07
	23	.00009164	.00055223	1.642e-06
solar	19	.47613992	.72047458	.05348393
	20	.50109013	.7429769	.05894457
	21	.50328511	.75096247	.05946083
	22	.48135155	.74326838	.05447298
	23	.50283747	.7661759	.05935601
load	19	.00412572	.00755218	.00011437
	20	.01123231	.02093833	.00036115
	21	.00239465	.00430228	.00006184
	22	.00264193	.00453999	.00006909
	23	.00300932	.0050952	.00008004
net_exports	19	.00005231	.0000642	8.820e-07
	20	.00024501	.00032803	4.871e-06
	21	.00006897	.00007325	1.198e-06
	22	.00003222	.00002762	5.163e-07
	23	.00005059	.00003813	8.510e-07
conventional	19	.05464416	.16622093	.00240539
	20	.06175021	.18149642	.00280372
	21	.01635505	.05875521	.00056038
	22	.02279832	.07796817	.00083029
	23	.02568132	.08912755	.00095723
price	19	.0006222	.00035351	.0000137
	20	.00197146	.00126446	.00004968
	21	.00012679	.00004994	2.350e-06
	22	.00023023	.00008938	4.549e-06
	23	.00036079	.0001342	7.485e-06
solar_d	19	8.719e-17	8.422e-15	0
	20	1.184e-15	8.101e-14	0
	21	4.499e-14	2.048e-12	0
	22	7.705e-14	3.332e-12	0
	23	3.184e-13	1.180e-11	1.110e-16
conventional_d	19	0	0	0
	20	0	0	0
	21	0	0	0
	22	0	0	0
	23	0	0	0
969-973 observations				

MacKinnon approximate p-values
Null hypothesis: Variable has a unit root
RW: Random walk (with or without drift or including time trend) in test equations
Varying lags chosen due to sword criterion (above/below 21 lags)

Table B.12: Augmented Dickey Fuller test for unit roots

statistic type	statistic	5% critical value	1% critical value
trace	14.95	19.96	24.6
maximum eigenvalue	12.24	15.67	20.2
971 observations			

Number of cointegration relationships: zero (rank 0)
Null hypothesis: No cointegration
21 lags chosen due to sword criterion
Non-zero constant trend included in test equations

Table B.13: Johansen tests for cointegration

Lag	FPE	AIC	HQIC	SBIC
0	1002415.3	30.845185	30.856649	30.875305
1	6311.2921	25.777357	25.8576	25.988193
2	5581.8169	25.654522	25.803545	26.046076
3	4921.8136	25.528665	25.746467	26.100935
4	4586.7413	25.458119	25.744701	26.211106
5	3337.3668	25.14007	25.495431	26.073774
6	2322.3531	24.777378	25.201519	25.891799
7	1757.0065	24.498282	24.991203	25.79342
8	1632.0829	24.424362	24.986062	25.900216
9	1672.9806	24.448898	25.079378	26.10547
10	1687.774	24.457437	25.156697	26.294725
11	1724.2958	24.478523	25.246562	26.496528
12	1750.94	24.49347	25.330289	26.692192
13	1726.8874	24.479182	25.384781	26.858621
14	1697.8994	24.461722	25.4361	27.021878
15	1732.5252	24.481298	25.524456	27.222171
16	1812.5531	24.525755	25.637692	27.447344
17	1851.8592	24.546416	25.727133	27.648722
18	1933.6679	24.588753	25.838249	27.871776
19	1997.6927	24.62033	25.938606	28.08407
20	2015.4829	24.628087	26.015143	28.272545
972 observations				

Lag selection criteria

Table B.14: Lag selection criteria

Lags for residuals	statistic	p-value
1	43.249144	.18934092
2	29.594732	.76579042
3	30.024853	.74780492
4	35.42833	.49559511
5	35.647536	.48521901
6	40.257247	.28735366
7	54.843861	.02294731
8	52.745227	.03541439
9	41.784478	.23393501
10	41.188197	.25396012
11	46.622222	.11061656
12	50.860656	.05134567
13	44.032276	.16815907
14	50.553657	.0544561
15	41.975176	.22775867
16	33.124707	.60608152
17	31.206481	.69587384
18	18.59199	.99272753
19	42.190577	.22091563
20	38.092457	.3743801
975 observations in VAR		

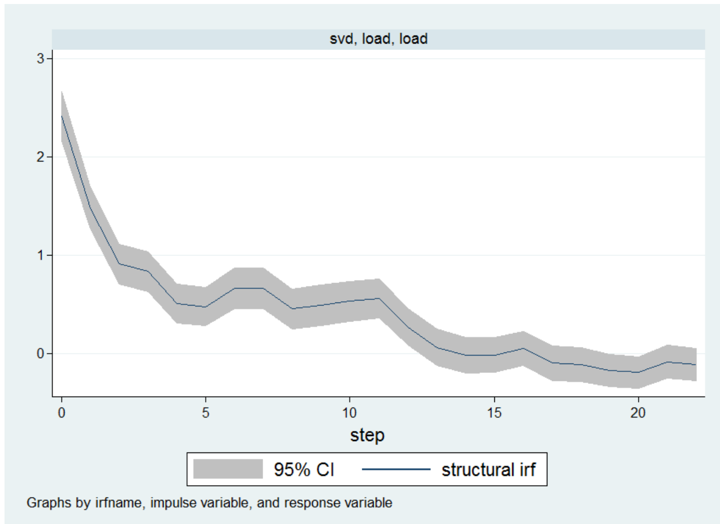
Null hypothesis: No mutually autocorrelated residuals at specific lag
17 lags chosen due to underlying VAR
Test statistic has chi-squared distribution

Table B.15: Johansen test for mutually autocorrelated VAR residuals

Eigenvalue number	real	complex	modulus
1	.61237295	.77914575	.99099381
2	.61237295	-.77914575	.99099381
3	-.22097255	.96017321	.98527227
4	-.22097255	-.96017321	.98527227
5	-.8776507	.41865053	.9723883
6	-.8776507	-.41865053	.9723883
7	.9650264	0	.9650264
8	.9488727	0	.9488727
9	.58605988	.73596715	.94080488
10	.58605988	-.73596715	.94080488
11	.55817119	.72573167	.91555531
12	.55817119	-.72573167	.91555531
13	.852849	.31800191	.91020692
14	.852849	-.31800191	.91020692
15	.90900433	.02655304	.90939207
16	.90900433	-.02655304	.90939207
17	.67636754	.60380998	.906675
18	.67636754	-.60380998	.906675
19	-.22522557	.87345907	.90202955
20	-.22522557	-.87345907	.90202955
21	.31281689	.84197199	.89820445
22	.31281689	-.84197199	.89820445
23	.85545685	.22673485	.88499441
24	.85545685	-.22673485	.88499441
25	-.27868423	.8382489	.88336069
26	-.27868423	-.8382489	.88336069
27	.39411478	.7875752	.88068221
28	.39411478	-.7875752	.88068221
29	.23243107	.84919583	.88043044
30	.23243107	-.84919583	.88043044
31	-.8780167	0	.8780167
32	.85964893	.16004133	.87441953
33	.85964893	-.16004133	.87441953
34	.01795846	.87422705	.87441148
35	.01795846	-.87422705	.87441148
36	.77341534	.40662921	.87379552
37	.77341534	-.40662921	.87379552
38	.74132927	.44977405	.86710194
39	.74132927	-.44977405	.86710194
40	-.48819066	.71628573	.86683064
41	-.48819066	-.71628573	.86683064
42	.3559355	.78773055	.86441281
43	.3559355	-.78773055	.86441281
44	-.10695798	.85412954	.86080037
45	-.10695798	-.85412954	.86080037
46	-.73200168	.45021666	.85937274
47	-.73200168	-.45021666	.85937274
48	-.8534778	.08321838	.85752531
49	-.8534778	-.08321838	.85752531
50	-.39469875	.76128471	.85752056
51	-.39469875	-.76128471	.85752056
52	-.58948251	.62051235	.85587686
53	-.58948251	-.62051235	.85587686
54	-.80730999	.28299819	.85547496
55	-.80730999	-.28299819	.85547496
56	.57526653	.63161972	.85432725
57	.57526653	-.63161972	.85432725
58	-.6563199	.54374575	.85229998
59	-.6563199	-.54374575	.85229998
60	-.80729711	.26378257	.84929963
61	-.80729711	-.26378257	.84929963
62	-.83033328	.17497547	.84856924
63	-.83033328	-.17497547	.84856924
64	.7428605	.3866239	.83744836
65	.7428605	-.3866239	.83744836
66	.20652267	.80502779	.83109648
67	.20652267	-.80502779	.83109648
68	-.69903254	.44762544	.83006929
69	-.69903254	-.44762544	.83006929
70	.011978	.82947049	.82955697
71	.011978	-.82947049	.82955697
72	-.54188385	.62627923	.82816893
73	-.54188385	-.62627923	.82816893
74	-.49784486	.65553381	.82314888
75	-.49784486	-.65553381	.82314888
76	-.27351253	.77416163	.82105745
77	-.27351253	-.77416163	.82105745
78	.56538298	.58121878	.8108472
79	.56538298	-.58121878	.8108472
80	.15843332	.79194883	.80764105
81	.15843332	-.79194883	.80764105
82	.650172	.46881976	.8015707
83	.650172	-.46881976	.8015707
84	-.3781314	.70528385	.80025537
85	-.3781314	-.70528385	.80025537
86	-.11750823	.77390945	.78277967
87	-.11750823	-.77390945	.78277967
88	-.77256826	0	.77256826
89	-.62169283	.44690144	.76565193
90	-.62169283	-.44690144	.76565193
91	-.70496249	.29449137	.76400084
92	-.70496249	-.29449137	.76400084
93	.75871017	0	.75871017
94	.06376385	.70740112	.71026908
95	.06376385	-.70740112	.71026908
96	-.63738399	0	.63738399
97	.57229632	.22045923	.6132906
98	.57229632	-.22045923	.6132906
99	.59233623	0	.59233623
100	.0781323	.36437829	.37266096
101	.0781323	-.36437829	.37266096
102	-.33367055	0	.33367055
975 observations in VAR			

Eigenvalues of companion matrix of VAR
17 lags chosen due to VAR
VAR stationary if modulus of each eigenvalue less than one

Table B.16: Test for stationarity of VAR



X-axis: Days, Y-axis: Marginal effects (GW), below title: Name of technical file (irfname). 971 observations in SVAR. Time dummies included in SVAR.

Figure B.7: Effects of load shock on load

Dependent variable in VAR	statistic	p-value
wind	163.98967	2.455e-36
solar_d	44.325559	2.370e-10
load	979.70972	1.81e-213
net_exports	3.5850257	.16654115
conventional_d	41.585326	9.330e-10
price	90920.578	0
ALL	92153.774	0
975 observations in VAR		

Null hypothesis: Normal distribution
17 lags chosen due to underlying VAR
Test statistic has chi-squared distribution

Table B.17: Lütkepohl test for normally distributed VAR residuals

Test	Wooldridge score	Regression based F
Statistic	6.61207	6.58089
p-value	0.0101	0.0105
979 observations in 2SLS regression		

Wooldridge score and regression based F tests for exogeneity
Null hypothesis: Load is exogenous
Tests robust to autocorrelated and heteroscedastic residuals
Tests conducted after running 2SLS instrumental variable regression
Endogenous load depends on its own 14 lags (days)
Price dependent variable, regressors: Wind, solar_d, conventional_d, net_exports, load (endogenous), time dummies
Test results basically unchanged if lagged values of load or regressors in price regression are varied

Table B.18: Tests for exogeneity of load

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