Locational (In)Efficiency of Renewable Energy Feed-In Into the Electricity Grid: A Spatial Regression Analysis

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ABSTRACT

This paper presents an econometric analysis of curtailment costs of renewable energy sources (RES) in Germany. The study aims at explaining and quantifying the regional variability of RES curtailment, which is a measure to relieve grid overstress by temporarily disconnecting RES from the electricity grid. We apply a Heckit sample selection model, which corrects bias from non-randomly selected samples. The selection equation estimates the probability of occurrence of RES curtailment in a region. The outcome equation corrects for cross-sectional dependence and quantifies the effect of RES on curtailment costs. The results show that wind energy systems connected to the distribution grid increase RES curtailment costs by 0.7% per MW (or 0.2% per GWh) in subregions that have experienced RES curtailment over the period 2015–2017. The implication of this finding is that policymakers should set price signals for renewables that consider the regional grid overstress, in order to mitigate the cost burden on consumers due to excess generation from RES.

Keywords: RES Curtailment, Spatial econometrics, System integration cost, Grid-related cost, Renewable energy sources

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1. INTRODUCTION

In order to mitigate climate change, governments all over the world have been transforming their electricity generation systems from conventional power plants to renewable energy sources (RES). This shift in the electricity generation structure is having severe impacts on the entire electricity system, especially on the grid infrastructure. The challenges arise from central power plants with a steady electricity production being replaced by a multitude of small and dispersed renewables with variable electricity generation.[1] Renewables are primarily connected to the distribution grid, whereas coal-fired or nuclear power plants are connected to the transmission grid.[2] At times of high

1. Between 2010 and 2017, the share of renewables in gross electricity consumption increased from 17% to 36.2% (BMWi, 2018).

2. Based on data from the renewable power plant record issued by the German Federal Network Agency (Bundesnetzagentur, BNetzA) and the German transmission system operators (TSOs), 24.5% of the installed capacity of renewables is con-

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renewable energy output, this can lead to bidirectional power flows and grid overstress. To prevent the failure of electric network components, the responsible system operator (SO) can decrease the electricity output of power plants. If doing so, the SO is obliged to first reduce the output of conventional power plants—the so-called *redispatch*.[3] Only if the conducted redispatch measures are insufficient to relieve the bottleneck in the electricity grid is the SO allowed to curtail the output of renewables—the so-called *RES curtailment*.[4] If the SO does reduce the output of a renewable generator, it has to refund the operator of the generator in question for the restrained electricity. The costs for the curtailment comprise the curtailment compensation for the respective renewable energy technology and the difference between the potential and the realized electricity supply. The SO is authorized to pass on the costs resulting from this RES curtailment to the consumers in the region concerned.

The need for RES curtailment in Germany has increased tremendously over the past years. In 2017, the reduced output of renewables reached 5,518 GWh, whereas it amounted to 555 GWh in 2013 (BNetzA, 2018a). The associated costs for RES curtailment totaled €43.7 million and €610 million in 2013 and 2017, respectively (BNetzA, 2018b). Onshore wind turbines are by far the most frequently and heavily curtailed renewable energy technology in Germany, accounting for 80.8% of the overall quantity of RES curtailment (BNetzA, 2018a). In 2017, 89% of the implemented RES curtailment measures were due to a bottleneck in the transmission grid (BNetzA, 2018a). Furthermore, 89% of all RES curtailment measures were instructed by transmission system operators (TSOs) and conducted by distribution system operators (DSOs) (BNetzA, 2018a). In our analysis, we consider RES curtailment conducted by TSOs and DSOs alike. Most of the implemented RES curtailment measures occurred in northern and eastern Germany, where a high amount of installed renewable energy capacity meets a relatively low electricity load. Figure 1 depicts the amount of RES curtailment compared with the installed capacity of wind energy systems (BNetzA, 2017a, 2018a).

This study aims at identifying the main drivers for RES curtailment measures and at explaining the regional variability of RES curtailment costs. For this purpose, we analyze the RES curtailment costs of four DSOs in Germany.[5] Since the DSOs publish only general information on their curtailment measures—such as the time and duration of a measure and the type of the curtailed renewable energy technology—but not on the curtailment costs, we have calculated the curtailment costs ourselves. To explain the locational differences of the RES curtailment within the DSO regions, we partition the DSO region into smaller subregions based on the high-to-medium voltage substations (Egger, 2017; Hülk et al., 2017). We then allocate all variables to these subregions and apply a two-step Heckit sample selection model (Heckman, 1976). The first part is a probit model that corrects bias from non-randomly selected samples. The second part is a linear model that cap-

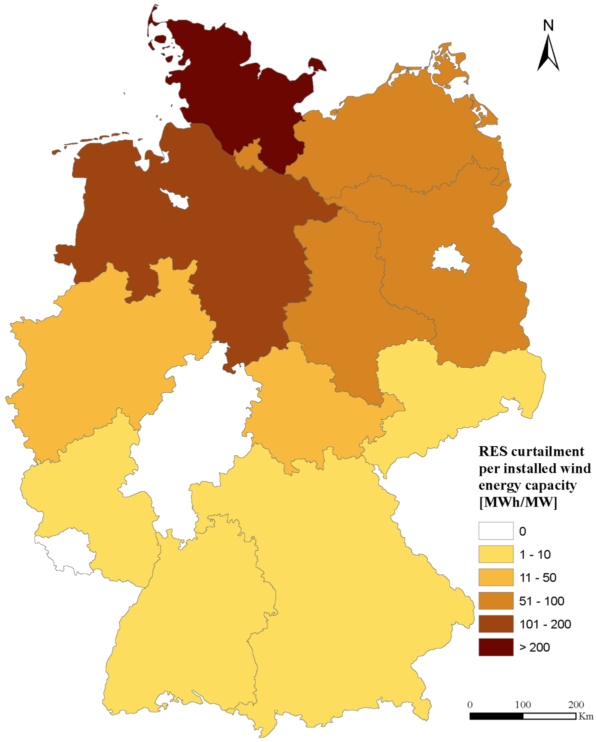
nected to the low voltage grid, 43.4% to the medium voltage grid, 29.7% to the high voltage grid, and 2.4% to the extra-high voltage grid in Germany (BNetzA, 2019).

3. The legal aspects of *redispatch* are covered in Art. 13 EnWG. EnWG stands for the German Energy Industry Act (*Energiewirtschaftsgesetz*).

4. The SO can reduce the output of solar PV systems with a minimum capacity of 30 kW and other renewables with a minimum capacity of 100 kW (EEG 2012, Art. 6 (2)). Thereby, the SO can curtail the renewables to 60%, 30%, and 0% of the generation capacity. The legal aspects of curtailing renewables are covered in Art. 13 EnWG and Art. 14 EEG. EEG stands for the German Act on Granting Priority to Renewable Energy Sources (*Erneuerbare Energien Gesetz*).

5. We incorporate only four out of 890 DSOs into our analysis since these four DSOs account for the majority of RES curtailment measures in Germany (BNetzA, 2017c) and publicly provide well-structured and comprehensive data. The grids of these four DSOs cover an area of approximately 40% of Germany and represent regions with different characteristics—namely wind-dominated, PV-dominated, and low load (Ecofys and Fraunhofer IWES, 2017).

Figure 1: RES curtailment per unit of installed wind energy capacity, by German federal state, 2017



tures cross-sectional dependence via spatial lags of the explanatory variables (SLX) and correlated common effects (CCE). Whereas the first part explains the impact of the explanatory variables on the probability of occurrence of RES curtailment, the second part illustrates the effect of the variables on RES curtailment costs. More specifically, we quantify the increase in RES curtailment costs due to an additional megawatt (MW) of installed renewable energy capacity and an additionally generated gigawatt-hour (GWh) of electricity.

The regional RES curtailment costs are integration costs of renewables in the present, rather inflexible, electricity system. Hirth et al. (2015) classify such integration costs into three categories: grid-related, balancing and profile costs. According to this definition, grid-related costs reflect the marginal value of electricity in different regions and refer to opportunity costs of transporting electricity from the place of generation to the place of consumption. Balancing costs are defined as costs that arise due to forecasting errors of future weather conditions. Profile costs reflect the costs resulting from matching electricity supply and demand and arise due to the variability of the output of renewables. A wide variety of literature exists that investigates the system integration costs of renewables in general and grid-related costs in particular. We refer the interested reader to the publications by Hirth (2015), Hirth et al. (2015), Holttinen et al. (2013), Holttinen et al. (2011), Milligan et al. (2011), and Smith et al. (2007), which also provide reviews of studies on integration costs of renewables.

In contrast to the large number of studies on grid-related integration costs, the number of studies that explicitly incorporate curtailment costs into their analysis is still limited. The following studies, which do incorporate curtailment costs, focus on calculating the costs instead of quantifying and explaining the regional correlation between installed capacity of renewables and RES curtailment costs. Ueckerdt et al. (2013) developed a mathematical definition of integration costs of renewables, comprising profile, balancing, and grid costs. As an example, the authors parametrize these cost components for increasing wind shares in Germany. A simple power system model is used to quantify the profile costs. The balancing and grid costs are parametrized based on a literature review. Grid-related costs incorporate investment costs in the electricity infrastructure as well as congestion management costs. However, the authors do not quantify or explain the reasons for the varying grid costs in different regions in Germany. Strbac et al. (2007) investigated the costs and benefits of wind energy in the United Kingdom using a generic model of the power system. Their simulation model explicitly incorporates the annual curtailed electricity output of wind turbines for different levels of wind capacities. The overall additional costs of integrating wind power consider balancing costs and grid costs, among others. The authors do not distinguish between different wind turbine locations and different grid costs at these locations. Denny and O'Malley (2007) conducted a cost-benefit analysis of wind energy systems, considering different wind turbine capacities, varying power plant mixes, and distinct electricity demand levels for the electricity system in Ireland. The model calculates the net benefits of wind power, including the curtailment and network reinforcement costs. No differentiation between different locations is made. Ecofys and Fraunhofer IWES (2017) qualitatively investigated the reasons for the occurrence of RES curtailment in all of the federal states of Germany. They conclude that the different proportions between installed wind and solar capacity and the load are the decisive factors for the varying amount of curtailed renewable electricity generation. Rural regions with high installed wind or solar capacities and low load experienced the highest amount of RES curtailment. In contrast, suburban and urban areas with little installed wind or solar capacities and a high load exhibit almost no RES curtailment. This aligns with the results of the studies by Agricola et al. (2012) and Büchner et al. (2014). The studies find that wind and solar power are the main drivers for the reinforcement of the distribution grid and that mainly low-load regions are affected by an increased overstress of the grid. The latter three studies find a positive qualitative correlation between the installed capacity of renewables and the overstress of the electricity grid as well as a negative correlation between the load and RES curtailment. However, the studies do not quantify the effect of renewables on curtailment costs. To the best of our knowledge, no comparable published study has so far quantified the impact of different renewable energy technologies on RES curtailment costs.

In summary, the main merit of our paper is to quantify and explain the regionally diverging RES curtailment costs by means of an econometric model. The first part of our model elucidates why RES curtailment occurs only in some regions of Germany and not in others. The second part of our model analyzes the correlation of installed capacity and generated output, respectively, of renewables and RES curtailment costs. As part of our analysis, we also calculate the regionally disaggregated amount and costs of RES curtailment in Germany in a higher spatial resolution than available in official publications. These results could, for example, be used to introduce price signals that incentivize a welfare-enhancing deployment of renewables (Haucap and Pagel, 2013). Such price signals would, among other things, incorporate the regionally varying RES curtailment costs. Alternatively, the results of this study could be used to incentivize the reinforcement of the electricity grid or the further implementation of flexibility options in regions with high RES curtailment. Possible flexibility options are energy storage systems, electric vehicles, or power-to-heat and power-to-gas applications.

Although we focus our analysis on four DSOs in Germany, the developed methodology may be applied to other regions and countries worldwide as well. Canada, China, Denmark, Ireland, Italy, Japan, Portugal, Spain, Sweden, and the USA also curtail the output of renewables due to congestions in the electricity grid (Bird et al., 2016).

The remainder of the paper is structured as follows. Section 2 introduces the applied methodology. Section 3 describes the calculation of RES curtailment costs, which is the dependent variable in our regression and gives an overview of the incorporated explanatory variables. Sections 4 and 5 present the study area and the regression results, respectively. Finally, Section 6 summarizes the main insights from our analysis and concludes.

2. METHODOLOGY

We apply a two-step Heckit sample selection model—or Tobit type II model (Heckman, 1976, 1979; Amemiya, 1985)—in order to analyze the effects of different renewable energy technologies on RES curtailment costs. The Heckit model corrects bias from non-randomly selected samples or incidentally truncated dependent variables. The first part of the model is the so-called selection equation and is based on a probit estimator. The resulting estimates are then used to compute the Inverse Mills Ratio (IMR), which is included in the outcome equation to correct for selectivity bias (Heckman, 1979). In our case, the selection equation predicts the likelihood of occurrence of RES curtailment in the considered regions and takes the form (Wooldridge, 2005):

$$y_{1t}^{*} = \alpha_0 + \alpha_1 x_{1t} + \varepsilon_1, \tag{1}$$

$y_{1t} > 0$, $t = 1,...,T$, where y_{1t}^{*} is a latent variable with the following relationship to the observed variable: y_{1t} is one if $y_{1t}^{*} > 0$, and zero if $y_{1t}^{*} \leq 0$. α_0 is the intercept parameter, α_1 depicts the $k \times 1$ vector parameter of coefficients, x_{it} is the $1 \times k$ regressor vector at time $t = 1,...,T$, and ε is the error term. In our case, y is unity if RES curtailment occurred in a region in 2015–2017, and zero otherwise. The model is estimated using the maximum likelihood (ML) estimation method.

The outcome equation is a linear regression model that considers cross-sectional dependencies among the DSO subregions. We introduce these spatial dependencies since the regions are linked via the electricity grid.[6] Neglecting spatial dependence among the dependent variable, the explanatory variables, or the error term might lead to biased and/or inefficient estimates (Anselin, 1988; Anselin et al., 2004; Anselin and Rey, 2010). Two main model types that deal with such cross-sectional dependencies are the common factor models and the spatial econometric models. The former capture the spatial dependence by several observable or latent factors; the latter use spatial weights matrices to incorporate spillovers among regions. Pesaran (2006) developed the correlated common effects (CCE) approach to estimate a model with a multifactor error structure. The basic idea of the CCE estimator is to filter the individual specific regressor by means of cross-section aggregates such that the differential effects of unobserved common factors are eliminated. The idea of spatial models is to incorporate spatial lags of the dependent variable, the explanatory variables, or the error term in order to capture the spatial dependence (Elhorst, 2014; Pace and LeSage, 2010). The Lagrange multiplier test for spatial dependence suggests that spatial dependence in the explanatory variables and in the error term exists. In our setting, the impact of the explanatory variables on RES curtailment costs in neighboring subregions is of special interest, since spillovers to neighboring regions are likely. Hence, we introduce spatial lags of the explanatory variables into the regression. Whether to use CCE or spatial error models (SEMs) to control for the dependence in the error term is related to the concept of weak and strong cross-sectional dependence. Thereby, the SEM (CCE) approach is applied if the spatial dependence is weak (strong) (Pesaran and Tosetti, 2011; Sarafidis and Wansbeek, 2012; Elhorst et al., 2019). However, recent work showed that the CCE approach provides consistent estimates if both forms of cross-section correlation—weak and

6. Furthermore, the Moran I test fails to reject the null hypothesis of zero spatial autocorrelation.

strong—are present (Pesaran and Tosetti, 2011; Bresson G. and Hsiao C., 2008; Ertur and Musolesi, 2017; Chudik et al., 2011). In our case, the CD-test developed in Pesaran (2004, 2015) rejects the null hypothesis of weak cross-section dependence. Hence, we apply the CCE approach in order to capture common unobserved effects.

The outcome equation incorporates spatial lags of the explanatory variables and common correlated effects in order to capture cross-sectional dependence and takes the form (Elhorst, 2014; Pesaran, 2006):

$$\begin{aligned} y^*_{2it} = \quad & \beta_i + \beta x_{2it} + \theta^T \sum_{j=1}^{m} w_{ij} x_{2jt} + e_{it} \\ e_{it} = & \lambda^T_{ij} f_t + \varepsilon_{it}, \end{aligned} \tag{2}$$

$i = 1,...,n, j = 1,...,m,$ where y^*_{2it} is a latent variable that is related to the observed variable by $y_{2it} = y^*_{2it} \times y_1$. β_i is the temporal fixed effects for region $i = 1,...,n$, β and θ represent the estimation parameters of the explanatory variables and their spatial lags, respectively. w_{ij} is an element of the N × N row-stochastic spatial weight matrix W for the $j = 1,...,m$ neighbors of region i. Furthermore, λ_{ij} is the vector of factor loadings, f_t represents the unobserved common effects, and ε_{it} is the unit-specific error term. We construct the spatial weight matrix W based on the row-stochastic first-order queen-contiguity matrix of the form:

$$w_{ij} = \frac{1}{n_1} \tag{3}$$

if i and j ($i \neq j$) share common borders and zero otherwise.[7] In order to control for all spatial-invariant effects that change over time, we use a spatial time-fixed effects model[8] (Arellano, 2003; Baltagi, 2005; Hsiao, 2003).

Note that this model is similar to the sample selection model with spatial dependence of Flores-Lagunes and Schnier (2012). The difference is that we use the CCE instead of the SEM approach to capture spatial dependence in the error term. Furthermore, our outcome equation is related to and based on earlier studies that consider both common factors and spatial effects (Pesaran and Tosetti, 2011; Bai and Li, 2013; Bailey et al., 2016; Yang, 2017).

3. DESCRIPTION OF REGRESSION VARIABLES

For our analysis of RES curtailment costs, we only consider power plants connected to the distribution grid. Furthermore, we restrict our analysis to four DSOs in Germany. In order to conduct this analysis, we need energy sector data of high spatial resolution. However, such data are not publicly available. Hence, we had to derive the necessary data, such as the RES curtailment costs, ourselves.[9] Furthermore, we needed to combine several data sources in order to create the explana-

7. The queen-contiguity matrix guarantees that all regions with a common border are treated as neighbors. Regions without a common border are not treated as neighbors. In contrast the k-nearest neighbor matrix or the fixed or inverse distance matrix might treat regions without a common border as neighbors under certain circumstances. In these forms of the spatial weights matrix, regions that do not share a common border can still be treated as neighbors. In our context, we believe that the queen-contiguity matrix is the most appropriate method. Although the results are relatively insensitive to different weight matrices, the underlying structure of W remains the strongest assumption in spatial models (Anselin, 2002).

8. We do not use a random effects model, since the assumption of zero correlation between the random effects and the explanatory variables is very restrictive (Elhorst, 2014).

9. The data available on RES curtailment measures comprise, among other things, the time and duration of a measure, the ID of the affected renewable energy technology, the reduction stage to which the capacity of the renewable power generator is reduced, the reason for the curtailment, and the responsible SO.

tory variables. The following subsections describe how we compiled the dependent and explanatory variables.

3.1 Dependent Variable

The calculation of RES curtailment costs in the considered DSO subregions comprises three steps: (1) calculating the potential hourly electricity output of renewables during the curtailment measures, (2) computing the reduced power output of renewables stemming from curtailment measures, and (3) determining the RES curtailment costs in the DSO subregions.

The first step (1) is to calculate the potential electricity generation of the affected renewable energy technology during the time of curtailment. The potential electricity output describes the electricity generation of a renewable generator for the case that the SO had not curtailed the respective generator. The output of wind turbines and PV systems depends, amongst other things, on the installed capacity as well as on the prevalent wind speed and global irradiation, respectively. The dataset *MERRA 2* provides spatially disaggregated data of the latter two components in an hourly resolution.[10] A wide range of literature uses *MERRA 2* data to calculate the hourly electricity output of wind turbines (Andresen et al., 2015; Drew et al., 2015; Sharp et al., 2015; Staffell and Green, 2014) and PV systems (Heide et al., 2010; Pfenninger and Staffell, 2016). Knorr (2016) and Killinger (2017) provide even more comprehensive calculations of wind energy and PV electricity output.

The (potential) hourly electricity output of a wind turbine, P_{Wind}, is computed as follows (Gonzalez Aparicio et al., 2016):

$$P_{Wind} = \frac{1}{2} \cdot r^2 \cdot \pi \cdot c_p(\upsilon) \cdot \rho \cdot (\upsilon)^3, \tag{4}$$

where r is the radius of the rotor, c_p is the power coefficient of the wind turbine, which depends on the prevalent wind speed, ρ is the air density at standard atmospheric conditions, and υ is the hourly wind speed at hub height. The wind speed at hub height is computed by vertically interpolating the wind speed from different heights to the hub height of the wind turbine (Engelhorn and Müsgens, 2018; Gonzalez Aparicio et al., 2016; Schallenberg-Rodriguez, 2013; Kubik et al., 2013). See Eqs. (A.1) and (A.2) in the Appendix for details of the interpolation.

The (potential) hourly electricity output of PV systems, P_{PV}, is calculated as follows (Ringler et al., 2016; Huld et al., 2010; Pfenninger and Staffell, 2016):

$$P_{PV} = \eta_{Inverter} \cdot P_{STC} \cdot \frac{G}{G_{STC}} \cdot \eta_{rel}(G', T') \cdot corr \cdot deg, \tag{5}$$

where $\eta_{Inverter}$ is the inverter efficiency, P_{STC} is the power under standard test conditions, G is the in-plane irradiance, and η_{rel} is the instantaneous relative efficiency of the module. $G' = \frac{G}{G_{STC}}$ and $T' = \frac{T}{T_{STC}}$ denote the in-plane irradiance and module temperature, respectively. Both parameters are

10. *MERRA 2* stands for "Modern Era Retrospective-Analysis for Research and Application" and is provided by NASA. The data set comprises hourly and spatially disaggregated data on wind speeds in different heights, diffuse and direct solar irradiance, surface incoming shortwave flux, and surface temperature, amongst others (Rienecker et al., 2011). The spatial resolution is 0.625° longitude and 0.5° latitude.

normalized to standard test conditions. *corr* is a correction parameter to include losses, and *deg* is the degradation of the maximum power output over time.[11] The in-plane irradiance G is comprised of the direct irradiance G_{dir}, the diffuse irradiance G_{diff}, and the reflected irradiance G_{refl}. All of these components depend on the inclination and orientation (azimuth) of the PV system and on the solar altitude angle. We assume that the PV systems have an inclination of 15° and an orientation facing south-west (45°) (Egger, 2017). In contrast to wind turbines and PV systems, where the electricity generation depends on the current weather condition, hydroelectric and biomass power plants generate electricity (more or less) independently of the current weather situation. Hence, we assume that these renewables operate at full nameplate capacity during the curtailment measure.

Note that the applied procedure overestimates the electricity output of both wind turbines and PV systems. This is in line with the existing literature (Yi et al., 2011; Egger, 2017; Engelhorn and Müsgens, 2018; Pfenninger and Staffell, 2016). In order to adjust the calculated generation to the actual generation, we apply correction factors,[12] and verify the calculated yearly electricity generation of wind energy and PV systems by comparing these with the published figures of ENTSO-E.[13] Figures A.1 and A.2 in the Appendix show the comparison between the calculated and the published electricity output of wind turbines and PV systems in Germany for the years 2015-2017.

The second step (2) is to calculate the reduced power output of renewables due to curtailment measures. The reduced output of a curtailment measure is the difference between potential (step 1) and realized electricity generation. The realized hourly output of a renewable energy generator is the reduction stage—60%, 30%, or 0% of the nameplate capacity—multiplied by the capacity of the power plant. In principle, renewable energy operators can choose between two possibilities to calculate the lost power output due to curtailment measures: the so-called *flat-rate* procedure and the *peak-billing* procedure (BNetzA, 2014). The former assumes that the affected renewable energy technology could have generated the same amount of electricity during the curtailment as in the last complete measured quarter-hour before the curtailment. In the latter, the actual possible electricity output of the renewable power generator during the curtailment is computed as shown in eqs. (4) and (5). We have adopted the peak-billing procedure to calculate the reduced power output of renewables.

The third step (3) encompasses the calculation of RES curtailment costs per generator and the allocation of these costs to the considered DSO regions. The costs associated with RES curtailment measures are obtained by multiplying the reduced power output by the fixed remuneration tariff of the affected renewable energy technology.[14] Subsequently, we aggregate the RES curtailment costs per generator per year and allocate the aggregated RES curtailment costs to the DSO subregions. Figure 2 shows the cumulative RES curtailment costs in the DSO subregions between 2015 and 2017. Table A.2 in the Appendix shows the calculated RES curtailment costs for the four DSOs

11. We do not include the degradation of the maximum power output over time in our analysis.

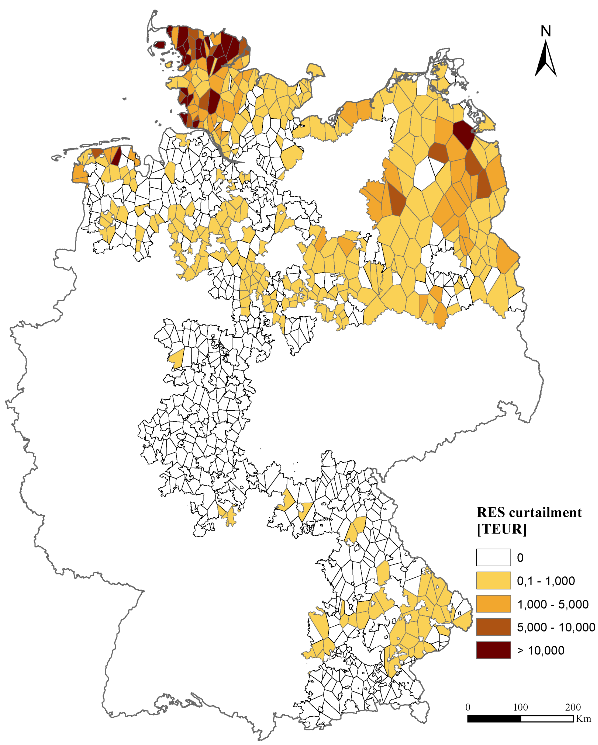
12. For PV systems, we correct the energy yields directly by comparing the calculated with the actual yearly electricity generation, as suggested by Pfenninger and Staffell (2016). In the case of wind turbines, we correct wind speeds instead of adjusting energy yields, as proposed by Staffell and Pfenninger (2016). To calculate these wind speed correction factors, we follow the suggestions of Engelhorn and Müsgens (2018) and raise the ratio of empirical to calculated electricity generation to the power of one-third.

13. ENTSO-E stands for European Network of Transmission System Operators for Electricity. The data can be downloaded at the transparency platform of ENTSO-E: https://transparency.entsoe.eu/

14. The remuneration of renewables is type-specific and differs depending on the commissioning date and installed capacity. Of this remuneration tariff, the power plant operator receives 100% if the respective renewable energy generator was installed before 2012 or if the compensation payment exceeds 1% of the annual revenues of the generator (BNetzA, 2014). In this analysis, we assume that the power plant operator receives 100% of the lost remuneration.

and compares these with the published RES curtailment costs of the German federal states in which the DSOs operate. As can be seen, we underestimate these curtailment costs in the federal states. This has several reasons. First, in most cases, one DSO does not cover the total area of the relevant federal state. Hence, other DSOs might be responsible for some curtailment measures conducted in the respective federal state. Second, we only include curtailment measures of renewables that are within the DSO regions. This entails that curtailments of offshore wind turbines are not included. Third, using the peak-billing procedure to calculate the lost electricity output generally underestimates the curtailment costs, while the flat-rate procedure overestimates them (Ostermann et al., 2017). Thus, the calculated RES curtailment costs can be regarded as the minimum costs arising due to reducing the output of renewables.

Figure 2: Cumulative RES curtailment costs in the German DSO subregions considered, 2015–2017



3.2 Explanatory Variables

The primary drivers for an overstress of the electricity grid and, therefore, the main reasons for the increasing RES curtailment costs, are the expansion of wind turbines and solar PV systems (Agricola et al., 2012). Secondary drivers are the development of bioenergy, hydroelectric, geothermal, and conventional power plants, as well as the deployment of storage systems, and the amount of load in a region (Agricola et al., 2012). Since we base our analysis on DSO regions and the RES curtailment costs conducted on the DSO level, we only include power plants connected to the distribution grid. According to the low installed capacities of conventional base-load power plants, geothermal power plants and storage systems in the distribution grid of the regions considered, we do not include these in our analysis.

In contrast to the above-explained variables, which contribute to rising grid overstress and RES curtailment costs, the regional electricity demand decreases the probability of grid overstress (Agricola et al., 2012; Büchner et al., 2014; Ecofys and Fraunhofer IWES, 2017). A reason for this is that the capacity of the distribution grid is higher in urban and suburban regions (Agricola et al., 2012; Büchner et al., 2014; Ecofys and Fraunhofer IWES, 2017). Since no data on regionally disaggregated electricity demand with such a high spatial resolution are publicly available, we calculate the electricity demand in the subregion based on the recommendations of Robinius (2016) and Hülk et al. (2017). Based on their suggestions, we distribute the overall electricity demand in Germany to the DSO subregions based on the population and the gross value added (GVA) of the subregions.

Table 1 shows the descriptive statistics for the dependent and explanatory variables. Table A.1 in the Appendix depicts the data sources used. Furthermore, Figures A.3, A.4, and A.5 in the Appendix show the installed capacity of different types of power plants as well as the electricity demand, and the average wind speed per DSO subregion.

Table 1: Descriptive statistics for the dependent variable and the explanatory variables

Variable	Unit	Year	Mean	Std. dev.	Min	Max	Total
RES curtailment	[€]	2015–2017	286,737	1,385,723	0	23,722,656	763,868,462
Wind energy	[MW]	2017	31.4	53.0	0	625	27,887
PV systems	[MW]	2017	17.0	20.4	0	216	15,105
Bio energy	[MW]	2017	3.5	6.4	0	140	3,118
Hydro energy	[MW]	2017	0.4	1.4	0	16	389
Conv. peak-load	[MW]	2017	17.0	99.5	0	1,770	15,101
Load	[GWh]	2017	146.9	327.3	5.8	7,441	130,480
Wind speed	[W/m^2]	2015–2017	7.7	0.9	3.4	9.6	
Wind energy	[GWh]	2017	67.2	159.8	0	1,619	59,715
PV systems	[GWh]	2017	14.0	17.0	0	191	12,379
Bio energy	[GWh]	2017	18.6	34.8	0	758	16,747
Hydro energy	[GWh]	2017	1.6	5.1	0	57	1,419
Conv. peak-load	[GWh]	2017	32.7	195.9	0	3,670	29,067

4. STUDY AREA

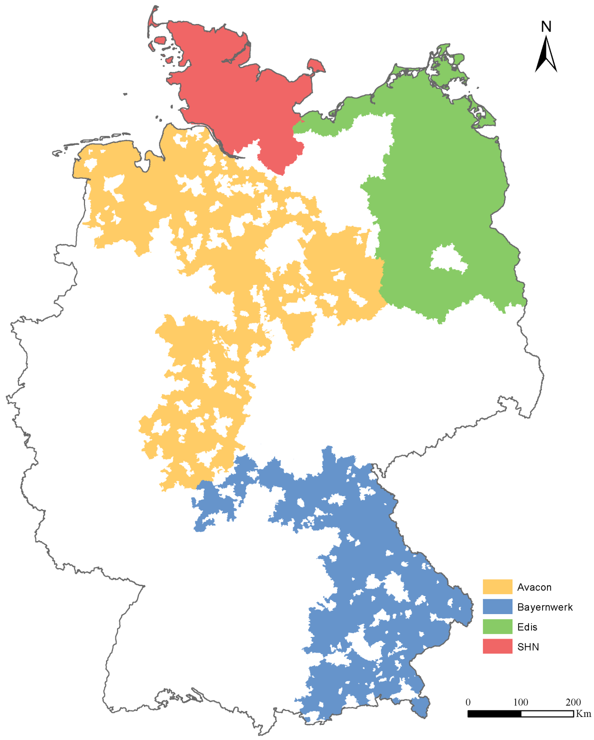
As a case study for our analysis, we select the four German DSOs Schleswig-Holstein Netz AG (*SHN*), Avacon Netz AG (*Avacon*), E.DIS Netz AG (*Edis*), and Bayernwerk Netz GmbH (*BW*). Ecofys and Fraunhofer IWES (2017) defined four different classes of DSOs. In three of these classes, RES curtailment measures occurred in the past. The DSOs considered in our study cover these three classes. Figure 3 shows the location of the DSOs in Germany. Table A.3 in the Appendix provides additional information about the DSO regions.

The first DSO class represents wind-dominated regions in northern Germany, such as the federal state of Schleswig-Holstein. The characteristic of this class is a high amount of installed wind energy capacity, a low amount of PV systems, and low electricity demand. The occurrence of RES curtailment is already very high and will likely rise in the future. The DSO *SHN* represents this first class in our analysis.

The second DSO class comprises low-load regions that are mainly located in eastern Germany, such as the federal state of Brandenburg. In these regions, the installed capacity of wind turbines and PV systems is very high. The electricity demand is in the medium range of all German federal states. Compared to the first class, the amount of curtailed output of renewables is lower but still relatively high. In our study, the DSOs *Avacon* and *Edis* are representatives of this DSO class.

PV systems dominate the third DSO class. In contrast, relatively few wind turbines and a very high electricity demand are present in this DSO class. RES curtailment occurs rarely and only

Figure 3: Map of Germany and DSO regions considered



in a low, but rising amount. The federal state of Bavaria is an example of this DSO class. In our analysis, this federal state is represented by the DSO *BW*.

The last DSO class represents urban and suburban regions with high electricity demand and low renewable energy capacities. No RES curtailment occurs in such regions. Hence, we do not consider DSOs of this class in our analysis.

To analyze the regional differences within the DSO regions, we perform a spatial division of the DSO regions into smaller subregions. We perform this spatial partition by means of the so-called Voronoi tessellation[15] (Egerer et al., 2014; Hülk et al., 2017). The seeds of the Voronoi cells are the DSO's substation at the high-to-medium voltage level. The resulting Voronoi cells are the DSO subregions. The Voronoi tessellation constructs the subregions by allocating all points (e.g. renewables, conventional power plants, or municipalities) to the subregion with the closest substation. This procedure considers that the power plants are connected to the closest substation (Egerer et al., 2014).We use the resulting DSO subregions as the regional units of our regression models and allocate all regression variables to these DSO subregions.

5. RESULTS

The results presented apply for the four German DSOs considered and for the period of 2015–2017. Furthermore, only RES curtailment measures of power plants connected to the distribution grid are considered.

15. A Voronoi tesselation is a particular kind of partition of a plane into several regions based on so-called seeds. The regions consist of all points closer to that seed than to any other.

Of the 1,111 considered DSO subregions, 223 regions experienced RES curtailment in three consecutive years (2015–2017). None of these subregions is located in the south-western part of Germany, where Bayernwerk Netz GmbH operates. Table 2 provides the estimation results for the two-step Heckit sample selection model separately for the installed capacity (models 1 and 2) and the generated electricity (models 3 and 4) of different power plants present in the subregions. Thereby, models 1 and 3 are the selection equations and models 2 and 4 are the outcome equations.

As expected, the results of the probit models indicate that the installed capacity (model 1) and the yearly generated electricity (model 3) of all types of renewables—except hydroelectric power plants—increased the probability of occurrence of RES curtailment in a DSO subregion. In contrast, conventional peak-load power plants did not have any effect on RES curtailment. The prevalent load reduced the probability that RES curtailment measures occurred. An increase in the installed capacity of wind energy raised the probability of occurrence of RES curtailment in the respective DSO subregion by 0.3% per MW.[16] Correspondingly, increasing the generated electricity of wind energy systems by one GWh raised the likelihood of RES curtailment in a DSO subregion by 0.07%. PV systems increased the probability of having to conduct RES curtailment by 0.3% per MW and 0.5% per GWh. Similarly, biomass systems raised the need for RES curtailment in a DSO subregion by 0.3% per MW and 0.07% per GWh. In contrast, an additional GWh of load in a DSO subregion decreased the necessity of RES curtailment by 0.04%.[17] These quantitative results align with the qualitative findings of Agricola et al. (2012), Büchner et al. (2014), and Ecofys and Fraunhofer IWES (2017).

The results of the outcome equations (models 2 and 4) illustrate the marginal RES curtailment cost increase in those DSO subregions that experienced RES curtailment in all years between 2015 and 2017. Both models capture cross-sectional dependencies between the subregions by introducing spatial lags of the explanatory variables and common correlated effects. Furthermore, the two-step Heckit sample selection method accounts for bias from non-randomly selected samples. The corresponding results of models (2) and (4) show that only wind turbines have a significant effect on RES curtailment costs (at the 1% significance level). Moreover, the results of the models depict that wind energy systems affect only those DSO subregions in which they are located and not on neighboring DSO subregions. An additional MW capacity of wind energy increases the yearly RES curtailment costs by 0.7% in the respective DSO subregion. Increasing the generated electricity by one GWh raises the RES curtailment costs by 0.2% in the DSO subregion. In the least affected subregions—i.e. the lowest quartile of all subregions that experience RES curtailment between 2015 and 2017—this is associated with costs of 18 €/MW per year. The cost per generated unit of electricity in the least affected subregions amounts to 0.005 €/MWh in the respective subregion. Whereas these costs are almost negligible, the costs in the most affected subregions (i.e. the highest quartile) rise to 28,277 €/MW per year. In other words, in the examined period between 2015 and 2017, the yearly RES curtailment costs in the affected subregion induced by an additional MW of capacity of wind energy amount to approximately 1.8% of the average overall costs of wind energy systems in Germany.[18] Furthermore, the RES curtailment costs increase by 8.10 €/MWh in the most affected subregions. The average remuneration for onshore wind turbines in Germany between 2015 and

16. The probability of occurrence refers to the DSO subregions. The average capacity of wind energy in the subregions is 31.4 MW.

17. The average load in a DSO subregion is 146.9 GWh.

18. The most frequently installed wind turbine in Germany has a capacity of 3–4 MW and a hub height of 120–140 m (Deutsche WindGuard, 2015). The associated overall costs—including investment, planning, development, grid connection, and foundation costs—of these wind turbines amount to 1,567,000 /MW (Deutsche WindGuard, 2015).

Table 2: Regression results

	Installed capacity [MW]		Generated electricity [GWh]	
	Selection eq.[a] (1)	Output eq. (2)	Selection eq.[a] (3)	Output eq. (4)
Wind energy	0.003***	0.007***	0.0007***	0.002***
	(0.004)	(0.002)	(0.0002)	(0.001)
PV systems	0.003***	0.004	0.005***	0.002
	(0.002)	(0.005)	(0.002)	(0.007)
Bio energy	0.003**	–0.003	0.0007***	–0.001
	(0.005)	(0.009)	(0.0008)	(0.002)
Hydro energy	0.004	–0.035	0.002	–0.229
	(0.032)	(1.340)	(0.008)	(0.367)
Conv. peak-load	0.0001	–0.001	0.000	–0.001
	(0.0003)	(0.001)	(0.0002)	(0.001)
Spatial Lag Wind energy		–0.0002		0.001
		(0.002)		(0.001)
Spatial Lag PV systems		0.003		0.010
		(0.008)		(0.010)
Spatial Lag Bio energy		0.007		0.002
		(0.009)		(0.002)
Spatial Lag Hydro energy		–1.351		–0.386
		(2.007)		(0.551)
Spatial Lag Conv. peak-load		–0.001		–0.001
		(0.002)		(0.001)
Load[b]	–0.0004***		–0.0004***	
	(0.0003)		(0.0003)	
Wind speed[c]	0.085***	0.609*	0.063***	–0.797*
	(0.087)	(0.344)	(0.069)	(0.410)
BW dummy	–0.044		–0.130***	
	(0.114)		(0.112)	
Edis dummy	0.249***	0.350	0.270***	–0.020
	(0.079)	(0.460)	(0.081)	(0.525)
SHN dummy	0.269***	1.351***	0.263***	1.333***
	(0.102)	(0.391)	(0.085)	(0.427)
dummy	0.024		0.032	
	(0.087)		(0.079)	
dummy	0.043**		0.054***	
	(0.078)		(0.073)	
IMR		–2.843***		–3.272***
		(0.547)		(0.638)
Constant	–3.754***		–2.822***	
	(0.656)		(0.567)	
Observations	2,664	642	2,664	642
(Pseudo-)R^2	0.309	0.482	0.273	0.489
Adjusted R^2		0.469		0.476
Log Likelihood	–1,181.963		–1,243.583	
Akaike Inf. Crit.	2,389.876		2,513.166	
F Statistic		41.580***		47.741***
		(df=14;625)		(df=14;625)
Sensitivity	0.897		0.877	
Specificity	0.605		0.596	

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
[a] Marginal effects are provided for all variables; for the constant, the coefficient is given. [b] In GWh. [c] In m/s.

2017 amounts to 84–91 €/MWh[19] (BDEW, 2017). Hence, the direct RES curtailment costs equal approximately 9.2% of the remuneration tariff. Table 3 depicts the cost increase of an additional

19. The remuneration tariff for onshore wind turbines in 2015, 2016, and 2017 amounts to 90 €/MWh, 91 €/MWh, and 84 €/MWh, respectively (BDEW, 2017).

MW of installed capacity and an additional GWh of generated electricity in the DSO subregions for the four quartiles.

Table 3: Marginal costs of renewables per quartile

Variables	Unit	1st Q.	2nd Q.	3rd Q.	4th Q.
Wind energy	[€/MW]	18	302	2,939	28,277
Wind energy	[€/MWh]	0.005	0.10	0.80	8.10

The costs only apply for regions that experienced RES curtailment in the three consecutive years from 2015–2017.

6. CONCLUSIONS

In this paper, we analyze the negative effects of introducing renewables into an inflexible electricity system. More specifically, we investigate the grid-related costs of temporarily reducing the output of renewables in order to prevent the overstress of the electricity infrastructure—the so-called RES curtailment costs. The paper aims to quantify the regionally varying impact of different renewable energy technologies on RES curtailment costs in Germany. To this end, we partition the regions of four German DSOs into smaller subregions based on the transformer stations on the high-to-medium voltage level. Subsequently, we allocate all power plants and the electricity demand to these DSO subregions.

In order to derive the regionally varying impacts of renewables on RES curtailment, we apply a spatial econometric model. More specifically, we use a two-step Heckit sample selection model that corrects bias from non-randomly selected samples. The first part of the model is the selection equation and is based on a probit estimator. The corresponding binary dependent variable is zero if no RES curtailment occurred in the respective DSO subregion in 2015–2017 and unity otherwise. The second part is the outcome equation. This part captures cross-sectional dependencies by introducing spatial lags of the explanatory variables and correlated common effects (CCE). The dependent variable is the yearly RES curtailment cost in the considered DSO subregion. Whereas the first part considers all DSO subregions, the second part only considers those subregions that experienced RES curtailment between 2015 and 2017. We apply the two-step Heckit sample selection model once for the installed capacity of the power plants (in MW) and once for the generated electricity (in GWh).

The results of the probit model show that all renewable energy technologies, except hydroelectric power plants, have a significant impact on the occurrence of RES curtailment in a DSO region. By contrast, additional load in the DSO subregions decreases the need for RES curtailment measures. Both outcome equations show that only wind energy systems significantly increase RES curtailment costs in the respective DSO subregion. An additional MW of capacity of wind energy raises the yearly RES curtailment costs by 0.7%. This amounts to costs in the most affected subregions (i.e. the highest quartile) of up to approximately 28,250 €/MW. An additional GWh of generated electricity by wind turbines increases RES curtailment costs by 0.2% in the respective DSO subregion. This accounts for 8.10 €/MWh. The quantitative results of our analysis are perfectly in line with the qualitative findings of Agricola et al. (2012), Büchner et al. (2014), and Ecofys and Fraunhofer IWES (2017), and with the report of BNetzA (2017c). An important extension of our study, compared to the above-mentioned studies, is that we can actually quantify the effect of renewables on regional RES curtailment costs.

The political implication of our study is that the German legislation should incentivize a welfare-enhancing deployment of renewables. A welfare-enhancing deployment implies that all costs associated with the electricity generation and transmission are internalized. Regionally differing price signals might be such a policy regime contributing to achieving a welfare-enhancing deployment of renewables. Such locational price signals would target grid-related costs caused by congestions in the transmission and distribution grid. Possible political instruments related to our findings are grid connection charges and grid usage charges (Eicke et al., 2019). The former comprise single payments to the SO for connecting the power plant. These payments are levied per unit of installed capacity. The latter are fees for using the transmission and distribution grid. Such fees are charged per unit of generated electricity. Different mechanisms, which are not applied in Germany but in other countries, are locational marginal pricing and market splitting (Eicke et al., 2019). Both instruments consider the available transmission capacity between the different zones or nodes, respectively. Alternatively, legislation could allow SOs to restrict the installation of wind turbines in certain regions. This would improve the market power of SOs and enable bargaining between SOs and wind turbine operators. A further possibility would be to incentivize the installation of flexibility options, such as, for example, energy storage systems, electric vehicles, or power-to-heat and power-to-gas applications in regions with a high amount of RES curtailment.

In the past, the German legislator has introduced several mechanisms to incentivize a further regional distribution of renewables (BMWi, 2017; BNetzA, 2017b; BMWi, 2019). The first mechanism, which was introduced in 2000, addresses the siting of wind turbines (EEG 2000, Art. 7). This mechanism penalizes locations with high wind speed and gives extra support to locations with low wind speed—the so-called *Reference Yield Model*. However, this mechanism does not explicitly consider grid constraints and has not prevented the accumulation of wind turbines in northern and eastern Germany so far. The second mechanism, which was introduced in 2018, penalizes renewables that are connected to the distribution grid and are located in regions where renewable energy infeed exceeds demand—the so-called *Distribution System Component* (GemAV 2018, Art. 10). However, the considered regions refer to administrative instead of grid-related regions. This might lead to penalizing regions without grid overstress. Finally, the German legislator defined a so-called *Network Development Area*. This mechanism is a quantity cap for wind energy systems for the most grid-constrained regions in Germany (EEG 2017, Art. 36c). The *Network Development Area* covers the complete northern part of Germany. Thus, it does not distinguish between regions with and without RES curtailment. So far, these mechanisms have not significantly reduced the need for RES curtailment. A regionally varying price signal for renewables that incorporates grid overstress and that defines the regions based on grid-related characteristics might mitigate the need for RES curtailment measures.

Future studies would benefit from more detailed and publicly available data on RES curtailment costs, the grid infrastructure, and on characteristics of renewables, such as e.g. the rotor diameter and hub height of wind turbines. Furthermore, having information on the capacity, location, and age of the substations and cables would enhance the model results. Further developments in open and free-of-charge data platforms might mitigate this problem in the future.

Future research could apply similar econometric methodologies to analyze grid-related integration costs in different countries worldwide. This would enable a comparison of different policy regimes and their ability to reduce grid-related integration costs. Furthermore, an investigation of RES curtailment costs in Germany for the following years would reveal the effect of the recently introduced measures.

REFERENCES

Agricola, A., B. Höflich, P. Richard, J. Völker, C. Rehtanz, M. Greve, B. Gwisdorf, J. Kays, T. Noll, J. Schwippe, A. Seack, J. Teuwsen, G. Brunekreeft, R. Meyer, and V. Liebert (2012). *dena Verteilnetzstudie—Ausbau- und Innovationsbedarf der Stromverteilnetze in Deutschland bis 2030* German Energy Agency (Deutsche Energie-Agentur GmbH, dena) Berlin, Germany.

Amemiya, T. (1985). *Advanced Econometrics.* Harvard Univ. Press, Cambridge, Mass., USA. ISBN 978-0674005600.

Andresen, G.B., A.A. Søndergaard, and M. Greiner (2015). "Validation of Danish Wind Time Series from a New Global Renewable Energy Atlas for Energy System Analysis." *Energy* 93: 1074–1088. ISSN 03605442. https://doi.org/10.1016/j.energy.2015. 09.071.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models.* Volume 4. Springer, Dordrecht, the Netherlands. ISBN 978-90-481-8311-1. https://doi.org/10.1007/978-94-015-7799-1.

Anselin, L. (2002). "Under the Hood Issues in the Specification and Interpretation of Spatial Regression Models." *Agricultural Economics* 27(3): 247–267. ISSN 01695150. https://doi.org/10.1016/S0169-5150(02)00077-4.

Anselin, L., R.J.G.M. Florax, and S. J. Rey (2004). *Advances in Spatial Econometrics.* Springer, Berlin, Heidelberg, Germany. ISBN 978-3-642-07838-5. https://doi.org/10.1007/978-3-662-05617-2.

Anselin, L. and S.J. Rey (2010). *Perspectives on Spatial Data Analysis.* Springer, Berlin, Heidelberg, Germany. ISBN 978-3-642-01975-3. https://doi.org/10.1007/978-3-642-01976-0.

Arellano, M. (2003). *Panel Data Econometrics.* Advanced texts in econometrics. Oxford Univ. Press, Oxford, UK. 1st edition. ISBN 0-19-924528-2.

Bai, J. and K. Li (2013). "Spatial Panel Data Models with Common Shocks." *SSRN Electronic Journal* 2013(MPRA Paper No. 52786): 1–65. ISSN 1556-5068. https://doi.org/10.2139/ssrn.2373628.

Bailey, N., G. Kapetanios, and M.H. Pesaran (2016). "Exponent of Cross-Sectional Dependence: Estimation and Inference." *Journal of Applied Econometrics* 31(6): 929–960. ISSN 08837252. https://doi.org/10.1002/jae.2476.

Baltagi, B.H. (2005). *Econometric Analysis of Panel Data.* Wiley, Chichester, UK. 3rd edition. ISBN 9780470014561.

BDEW (2017). *Erneuerbare Energien und das EEG: Zahlen, Fakten, Grafiken 2017.* Federal Association of Energy and Water Industry (Bundesverband der Energie- und Wasserwirtschaft e.V., bdew) Berlin, Germany.

Bird, L., D. Lew, M. Milligan, E.M. Carlini, A. Estanqueiro, D. Flynn, E. Gomez-Lazaro, H. Holttinen, N. Menemenlis, A. Orths, P.B. Eriksen, J.C. Smith, L. Soder, P. Sorensen, A. Altiparmakis, Y. Yasuda, and J. Miller (2016). "Wind and Solar Energy Curtailment: A Review of International Experience." *Renewable and Sustainable Energy Reviews* 65: 577–586. ISSN 13640321. https://doi.org/10.1016/j.rser.2016.06.082.

BMWi (2017). *Verordnung zu den gemeinsamen Ausschreibungen für Windenergieanlagen an Land und Solaranlagen: GemAV.* Federal Ministry for Economic Affairs and Energy (Bundesministerium für Wirtschaft und Energie, BMWi) Berlin, Germany.

BMWi (2018). *Energiedaten: Gesamtausgabe: Stand: August 2018.* Federal Ministry for Economic Affairs and Energy (Bundesministerium für Wirtschaft und Energie, BMWi) Berlin, Germany.

BMWi (2019). *Gesetz für den Ausbau erneuerbarer Energien (Erneuerbare-Energien-Gesetz—EEG 2017).* Federal Ministry for Economic Affairs and Energy (Bundesministerium für Wirtschaft und Energie, BMWi) Berlin, Germany. Date of issue July 21, 2014 and last amended November 20, 2019.

BNetzA (2014). *Leitfaden zum EEG-Einspeisemanagement—Abschaltrangfolge, Berechnung von Entschädigungszahlungen und Auswirkungen auf die Netzentgelte.* Federal Network Agency (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, BNetzA) Bonn, Germany.

BNetzA (2017a). *EEG in Zahlen 2017.* Federal Network Agency (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, BNetzA) Bonn, Germany.

BNetzA (2017b). *Gemeinsame Ausschreibungen von Windenergieanlagen an Land und Solaranlagen.* Federal Network Agency (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, BNetzA) Bonn, Germany.

BNetzA (2017c). *Monitoringbericht 2017.* Federal Network Agency (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, BNetzA) Bonn, Germany.

BNetzA (2017d). *Quartalsbericht zu Netz- und Systemsicherheitsmaßnahmen: Viertes Quartal und Gesamtjahr 2016.* Federal Network Agency (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, BNetzA) Bonn, Germany.

BNetzA (2018a). *Monitoringbericht 2018.* Federal Network Agency (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, BNetzA) Bonn, Germany.

BNetzA (2018b). *Quartalsbericht zu Netz- und Systemsicherheitsmaßnahmen: Viertes Quartal und Gesamtjahr 2017.* Federal Network Agency (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, BNetzA) Bonn, Germany.

BNetzA (2019). *EEG-Anlagenstammdaten.* Federal Network Agency (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, BNetzA) Bonn, Germany.

Bresson G. and Hsiao C. (2008). *A Functional Connectivity Approach for Modeling Cross-Sectional Dependence with an Application to the Estimation of Hedonic Housing Prices in Paris: Working Papers ERMES.* ERMES, University Paris 2.

Büchner, J., J. Katzfey, O. Flörcken, A. Moser, H. Schuster, S. Dierkes, T. van Leeuwen, L. Verheggen, M. Uslar, and M. van Amelsvoort (2014). *Moderne Verteilernetze für Deutschland (Verteilernetzstudie).* Federal Ministry for Economic Affairs and Energy (Bundesministerium für Wirtschaft und Energie, BMWi) Berlin, Germany.

Chudik, A., M.H. Pesaran, and E. Tosetti (2011). "Weak and Strong Cross–Section Dependence and Estimation of Large Panels." *The Econometrics Journal* 14(1): C45–C90. ISSN 13684221. https://doi.org/10.1111/j.1368-423X.2010.00330.x.

Denny, E. and M. O'Malley (2007). "Quantifying the Total Net Benefits of Grid Integrated Wind." *IEEE Transactions on Power Systems* 22(2): 605–615. ISSN 0885-8950. https://doi.org/10.1109/TPWRS.2007.894864.

Deutsche WindGuard (2015). *Kostensituation der Windenergie an Land in Deutschland—Update.* Federal Association of Wind Energy (Bundesverband WindEnergie e.V.) Varel, Germany.

Drew, D., D. Cannon, D. Brayshaw, J. Barlow, and P. Coker (2015). "The Impact of Future Offshore Wind Farms on Wind Power Generation in Great Britain." *Resources* 4(1): 155–171. ISSN 2079-9276. https://doi.org/10.3390/resources4010155.

Ecofys and Fraunhofer IWES (2017). *Smart-Market-Design in deutschen Verteilnetzen: Entwicklung und Bewertung von Smart Markets und Ableitung einer Regulatory Roadmap.* Agora Energiewende Berlin, Germany.

Egerer, J., C. Gerbaulet, R. Ihlenburg, F. Kunz, B. Reinhard, C. von Hirschhausen, A. Weber, and J. Weibezahn (2014). *Electricity Sector Data for Policy-Relevant Modeling: Data Documentation and Applications to the German and European Electricity Markets: No. 72. Data Documentation.* German Institute for Economic Research (Deutsches Institut für Wirtschaftsforschung, DIW) Berlin, Germany.

Egger, K. (2017). *The Simulation of Potential Photovoltaic Production with MERRA Data in Germany.* Master's thesis University of Natural Resources and Life Sciences Vienna, Austria.

Eicke, A., T. Khanna, and L. Hirth (2019). *Locational Investment Signals in Electricity Markets—How to Steer the Siting of New Generation Capacity?* German National Library of Economics (Leibniz Information Centre for Economics, ZBW) Kiel, Hamburg, Germany.

Elhorst, J.P. (2014). *Spatial Econometrics.* Springer, Berlin/Heidelberg, Germany. ISBN 978-3-642-40339-2. https://doi.org/10.1007/ 978-3-642-40340-8.

Elhorst, J.P., M. Gross, and E. Tereanu (2019). "Spillovers in Space and Time: Where Spatial Econometrics and Global VAR Models Meet." *European Central Bank Working Paper Series* 2019(2134).

Engelhorn, T. and F. Müsgens (2018). "How to Estimate Wind-Turbine Infeed with Incomplete Stock Data: A General Framework with an Application to Turbine-Specific Market Values in Germany." *Energy Economics* 72: 542–557. ISSN 01409883. https://doi.org/10.1016/j.eneco.2018.04.022.

Ertur, C. and A. Musolesi (2017). "Weak and Strong Cross-Sectional Dependence: A Panel Data Analysis of International Technology Diffusion." *Journal of Applied Econometrics* 32(3): 477–503. ISSN 08837252. https://doi.org/10.1002/jae.2538.

Flores-Lagunes, A. and K.E. Schnier (2012). "Estimation of Sample Selection Models with Spatial Dependence." *Journal of Applied Econometrics* 27(2): 173–204. ISSN 08837252. https://doi.org/10.1002/jae.1189.

Gonzalez Aparicio, I., A. Zucker, F. Careri, F. Monforti, T. Huld, and J. Badger (2016). *EMHIRES Dataset.* Volume 28171 of *EUR* Publications Office of the European Union (OP), Luxembourg. ISBN 9279631934.

Haucap, J. and B. Pagel (2013). "Ausbau der Stromnetze im Rahmen der Energiewende: Effizienter Netzausbau und Struktur der Netznutzungsentgelte." *List Forum für Wirtschafts- und Finanzpolitik* 39(3): 235–253. ISSN 0937-0862. https://doi.org/10.1007/BF03373052.

Heckman, J.J. (1976). "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for such Models." In *Annals of Economic and Social Measurement*." Volume 5, Number 4," NBER Chapters National Bureau of Economic Research 475–492.

Heckman, J.J. (1979). "Sample Selection Bias as a Specification Error." *Econometrica* 47(1): 153. ISSN 00129682. https://doi.org/ 10.2307/1912352.

Heide, D., L. von Bremen, M. Greiner, C. Hoffmann, M. Speckmann, and S. Bofinger (2010). "Seasonal Optimal Mix of Wind and Solar Power in a Future, Highly Renewable Europe." *Renewable Energy* 35(11): 2483–2489. ISSN 09601481. https://doi.org/10.1016/j.renene.2010.03.012.

Hirth, L. (2015). “Market Value of Solar Power: Is Photovoltaics Cost-Competitive?” *IET Renewable Power Generation* 9(1): 37–45. ISSN 1752-1416. https://doi.org/10.1049/iet-rpg.2014.0101.

Hirth, L., F. Ueckerdt, and O. Edenhofer (2015). “Integration Costs Revisited—An Economic Framework for Wind and Solar Variability.” *Renewable Energy* 74: 925–939. ISSN 09601481. https://doi.org/10.1016/j.renene.2014.08.065.

Holttinen, H., P. Meibom, A. Orths, B. Lange, M. O’Malley, J. O. Tande, A. Estanqueiro, E. Gomez, L. Söder, G. Strbac, J.C. Smith, and F. van Hulle (2011). “Impacts of Large Amounts of Wind Power on Design and Operation of Power Systems, Results of IEA Collaboration.” *Wind Energy* 14(2): 179–192. ISSN 10954244. https://doi.org/10.1002/we.410.

Holttinen, H., M. O’Malley, J. Dillon, D. Flynn, A. Keane, H. Abildgaard, and L. Soder (2013). “Steps for a Complete Wind Integration Study.” In R. H. Sprague (editor), *46th Hawaii International Conference on System Sciences (HICSS 2013)*, IEEE, Piscataway, NJ. ISBN 978-1-4673-5933-7 2261–2270. https://doi.org/10.1109/HICSS.2013.497.

Hsiao, C. (2003). *Analysis of Panel Data* Volume 34 of *Econometric Society Monographs.* Cambridge University Press, Cambridge, UK. 2nd edition. ISBN 9780521522717.

Huld, T., R. Gottschalg, H.G. Beyer, and M. Topič (2010). “Mapping the Performance of PV Modules, Effects of Module Type and Data Averaging.” *Solar Energy* 84(2): 324–338. https://doi.org/10.1016/j.solener.2009.12.002.

Hülk, L., L. Wienholt, I. Cußmann, U.P. Müller, C. Matke, and E. Kötter (2017). “Allocation of Annual Electricity Consumption and Power Generation Capacities Across Multiple Voltage Levels in a High Spatial Resolution.” *International Journal of Sustainable Energy Planning and Management* 2017(13): 79–92.

Killinger, S. (2017). *Anlagenscharfe Simulation der PV-Leistung basierend auf Referenzmessungen und Geodaten.* Fraunhofer Institute for Solar Energy Systems (Fraunhofer-Institut für Solare Energiesysteme, ISE), Karlsruhe Institute of Technology (Karlsruher Institut für Technologie, KIT) Karlsruhe, Germany.

Knorr, K. (2016). *Modellierung von raum-zeitlichen Eigenschaften der Windenergieeinspeisung für wetterdatenbasierte Windleistungssimulationen.* Fraunhofer Institute for Wind Energy Systems (Fraunhofer Institut für Windenergie und Energiesystemtechnik, IWES), University of Kassel (Universität Kassel) Kassel, Germany.

Kubik, M.L., P.J. Coker, J.F. Barlow, and C. Hunt (2013). “A Study into the Accuracy of Using Meteorological Wind Data to Estimate Turbine Generation Output.” *Renewable Energy* 51: 153–158. ISSN 09601481. https://doi.org/10.1016/j.renene.2012.08.084.

Milligan, M., E. Ela, B.-M. Hodge, B. Kirby, D. Lew, C. Clark, J. DeCesaro, and K. Lynn (2011). “Integration of Variable Generation, Cost-Causation, and Integration Costs.” *The Electricity Journal* 24(9): 51–63. ISSN 10406190. https://doi.org/10.1016/j.tej.2011.10.011.

Ostermann, A., S. Köppl, and T. Estermann (2017). *Analysen zum Einspeisemanagement: Regionalisierter Flexibilitätsbedarf und Auswirkung auf den Strommarkt.* Forschungsstelle für Energiewirtschaft e.V. (FfE) Munich, Germany.

Pace, R.K. and J.P. LeSage (2010). “Omitted Variable Biases of OLS and Spatial Lag Models.” in A. Páez, J. Gallo, R.N. Buliung, and S. Dall’erba (editors), *Progress in Spatial Analysis. Advances in Spatial Science, The Regional Science Series.* Springer-Verlag, Berlin, Heidelberg. ISBN 978-3-642-03324-7 17–28. https://doi.org/10.1007/978-3-642-03326-1-2.

Pesaran, M.H. (2004). *General Diagnostic Tests for Cross Section Dependence in Panels: Cambridge Working Papers in Economics.* Faculty of Economics, University of Cambridge.

Pesaran, M.H. (2006). “Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure.” *Econometrica* 74(4): 967–1012. ISSN 00129682.

Pesaran, M. H. (2015). “Testing Weak Cross-Sectional Dependence in Large Panels” *Econometric Reviews* 34(6-10): 1089–1117. https://doi.org/10.1080/07474938.2014.956623.

Pesaran, M.H. and E. Tosetti (2011). “Large Panels with Common Factors and Spatial Correlation.” *Journal of Econometrics* 161(2): 182–202. ISSN 03044076. https://doi.org/10.1016/j.jeconom.2010.12.003.

Pfenninger, S. and I. Staffell (2016). “Long-Term Patterns of European PV Output Using 30 Years of Validated Hourly Reanalysis and Satellite Data.” *Energy* 114: 1251–1265. ISSN 03605442. https://doi.org/10.1016/j.energy.2016.08.060.

Rienecker, M.M., M.J. Suarez, R. Gelaro, R. Todling, J. Bacmeister, E. Liu, M.G. Bosilovich, S.D. Schubert, L. Takacs, G.-K. Kim, S. Bloom, J. Chen, D. Collins, A. Conaty, A. da Silva, W. Gu, J. Joiner, R. D. Koster, R. Lucchesi, A. Molod, T. Owens, S. Pawson, P. Pegion, C.R. Redder, R. Reichle, F.R. Robertson, A.G. Ruddick, M. Sienkiewicz, and J. Woollen (2011). “MERRA: NASA’s Modern-Era Retrospective Analysis for Research and Applications.” *Journal of Climate* 24(14): 3624–3648. ISSN 0894-8755. https://doi.org/10.1175/JCLI-D-11-00015.1.

Ringler, P., H. Schermeyer, M. Ruppert, M. Hayn, V. Bertsch, D. Keles, and W. Fichtner (2016). *Decentralized Energy Systems, Market Integration, Optimization.* Volume Band 12 of *Produktion und Energie* KIT Scientific Publishing, Karlsruhe, Germany. ISBN 978-3-7315-0505-1.

Robinius, M. (2016). *Strom- und Gasmarktdesign zur Versorgung des deutschen Straßenverkehrs mit Wasserstoff.* Volume 300 of *Schriften des Forschungszentrums Jülich Reihe Energie & Umwelt / Energy & Environment.* Forschungszentrum Jülich, Jülich, Germany. ISBN 978-3-95806-110-1.

Sarafidis, V. and T. Wansbeek (2012). "Cross-Sectional Dependence in Panel Data Analysis." *Econometric Reviews* 31(5): 483–531.

Schallenberg-Rodriguez, J. (2013). "A Methodological Review to Estimate Techno-Economical Wind Energy Production." *Renewable and Sustainable Energy Reviews* 21: 272–287. ISSN 13640321. https://doi.org/10.1016/j.rser.2012.12.032.

Sharp, E., P. Dodds, M. Barrett, and C. Spataru (2015). "Evaluating the Accuracy of CFSR Reanalysis Hourly Wind Speed Forecasts for the UK, Using in Situ Measurements and Geographical Information." *Renewable Energy* 77: 527–538. ISSN 09601481. https://doi.org/10.1016/j.renene.2014.12.025.

Smith, J. C., M.R. Milligan, E.A. DeMeo, and B. Parsons (2007). "Utility Wind Integration and Operating Impact State of the Art." *IEEE Transactions on Power Systems* 22(3): 900–908. ISSN 0885-8950. https://doi.org/10.1109/TPWRS.2007.901598.

Staffell, I. and R. Green (2014). "How Does Wind Farm Performance Decline with Age?" *Renewable Energy* 66: 775–786. ISSN 09601481. https://doi.org/10.1016/j.renene.2013.10.041.

Staffell, I. and S. Pfenninger (2016). "Using Bias-Corrected Reanalysis to Simulate Current and Future Wind Power Output." *Energy* 114: 1224–1239. ISSN 03605442. https://doi.org/10.1016/j.energy.2016.08.068.

Strbac, G., A. Shakoor, M. Black, D. Pudjianto, and T. Bopp (2007). "Impact of Wind Generation on the Operation and Development of the UK Electricity Systems." *Electric Power Systems Research* 77(9): 1214–1227. ISSN 03787796. https://doi.org/10.1016/j.epsr.2006.08.014.

Ueckerdt, F., L. Hirth, G. Luderer, and O. Edenhofer (2013). "System LCOE: What Are the Costs of Variable Renewables?" *Energy* 63: 61–75. ISSN 03605442. https://doi.org/10.1016/j.energy.2013.10.072.

Wooldridge, J.M. (2005). *Introductory Econometrics: A Modern Approach.* Thomson South-Western, Mason, Ohio, USA. 2nd edition. ISBN 9780324113648.

Yang, C.F. (2017). *Common Factors and Spatial Dependence: An Application to US House Prices: MPRA Paper.* No. 89032. University Library of Munich, Germany.

Yi, Y., J.S. Kimball, L.A. Jones, R.H. Reichle, and K.C. McDonald (2011). "Evaluation of MERRA Land Surface Estimates in Preparation for the Soil Moisture Active Passive Mission." *Journal of Climate* 24(15): 3797–3816. ISSN 0894-8755. https://doi.org/10.1175/2011JCLI4034.1.

APPENDIX

Interpolation of wind speeds between different hub heights

$$V_{hub} = V_{10} \left(\frac{z}{10}\right)^{S} \tag{A.1}$$

$$S = \frac{ln(V_{50}) - ln(V_{10})}{ln(50) - ln(10)} \tag{A.2}$$

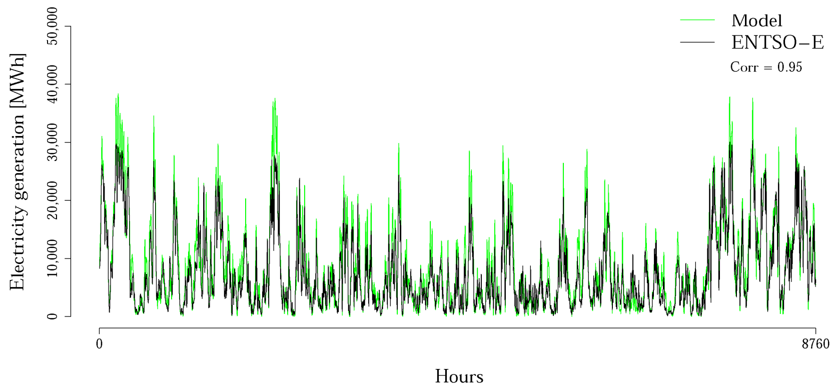
where V_{hub} is the wind speed at hub height, V_{10} and V_{50} are the wind speeds at 10 m and 50 m, respectively, z is the wind turbine hub height, and S is the shear coefficient, which measures the vertical change in wind speeds.

Table A.1: Data sources and content

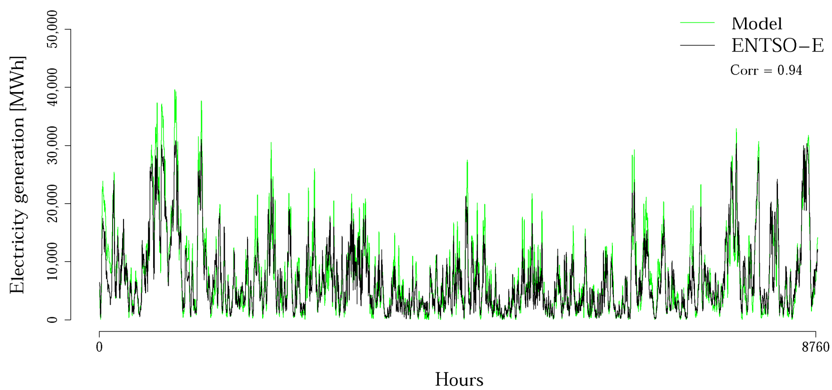
Source	Content	Download
Renewable power plant record[a]	Installed capacity, voltage level, type, and postcode of the renewable generator	www.netztransparenz.de
Open Power System Data	Location of the renewable generator	www.open-power-system-data.org
Engelhorn and Müsgens (2018)	Hub height, rotor diameter, turbine model, and power curves of wind turbines	
MERRA 2[b]	Hourly wind speed at 10 m and 50 m. Diffuse and direct irradiance, and surface incoming shortwave flux	https://gmao.gsfc.nasa.gov
List of remuneration tariffs	Remuneration for different renewable energy technologies based on commissioning year and capacities	www.netztransparenz.de
Power plant record[c]	Installed capacity, voltage level, type, and postcode of power plant	www.bundesnetzagentur.de
Open Street Map	Boundary map of German municipalities	https://wambachers-osm.website
destatis[d]	Population on LAU level (municipality level) in Germany	www.regionalstatistik.de
Statistics Authorities[e]	Gross value added on NUTS 3 level (administrative district level) in Germany	www.statistik-bw.de/VGRdL/

[a] Published by the German Transmission System Operators (TSOs) and the German Federal Network Agency.
[b] Modern-Era Retrospective-Analysis for Research and Applications provided by NASA. Spatial resolution of 0.625° longitude and 0.5° latitude.
[c] Published by the German Federal Network Agency.
[d] Municipality Directory of the German Federal Office of Statistics (destatis).
[e] Statistics Authorities of the German federal states. Dataset "National Accounts of the Federal States, 2016".

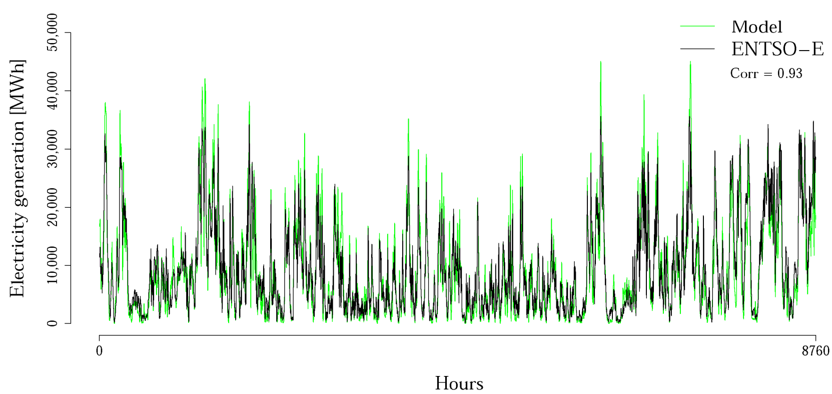
Figure A.1: Hourly wind electricity generation in Germany provided by ENTSO-E vs. model outcome, 2015–2017



(a) 2015

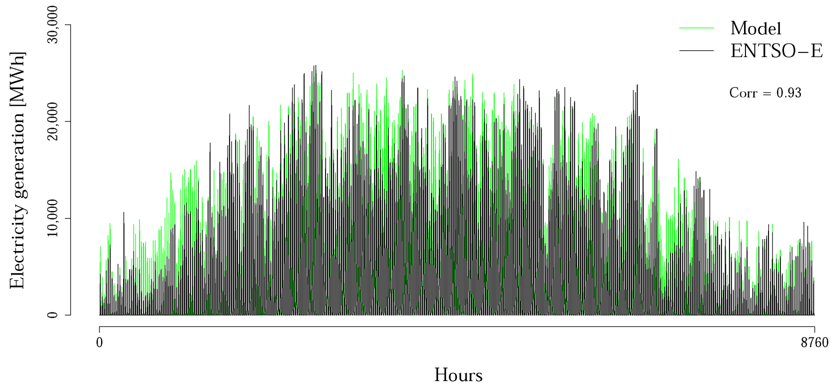


(b) 2016

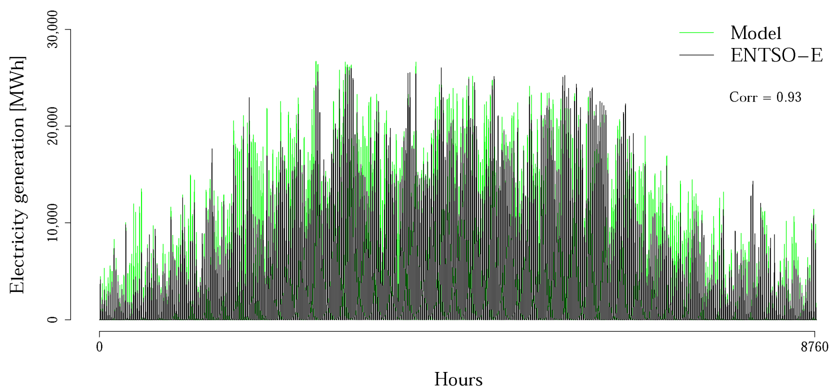


(c) 2017

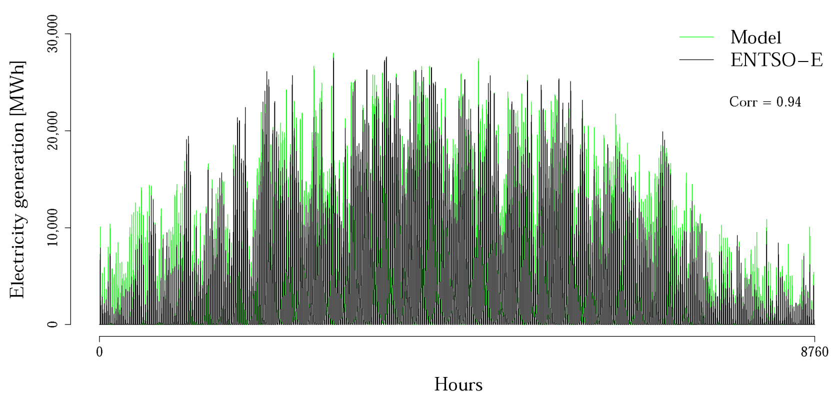
Figure A.2: Hourly PV electricity generation in Germany provided by ENTSO-E vs. model outcome, 2015–2017



(a) 2015

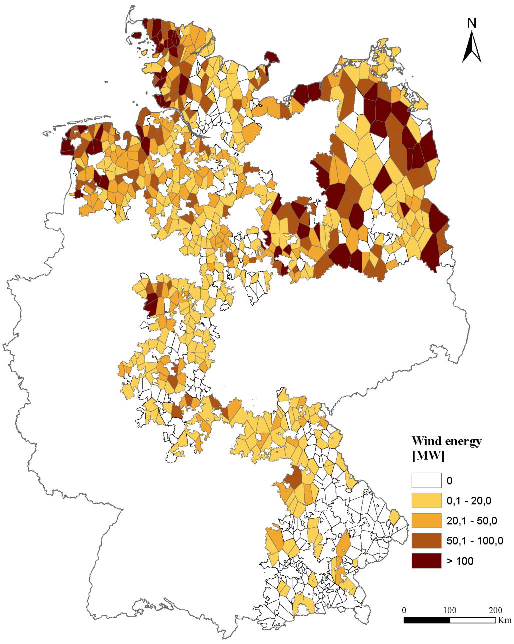


(b) 2016

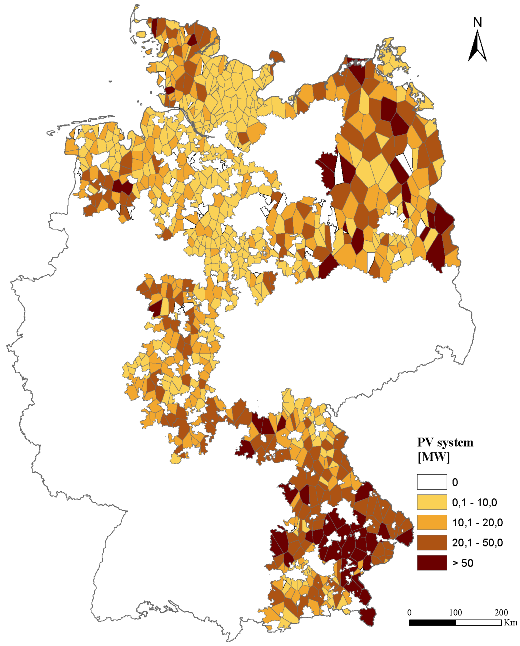


(c) 2017

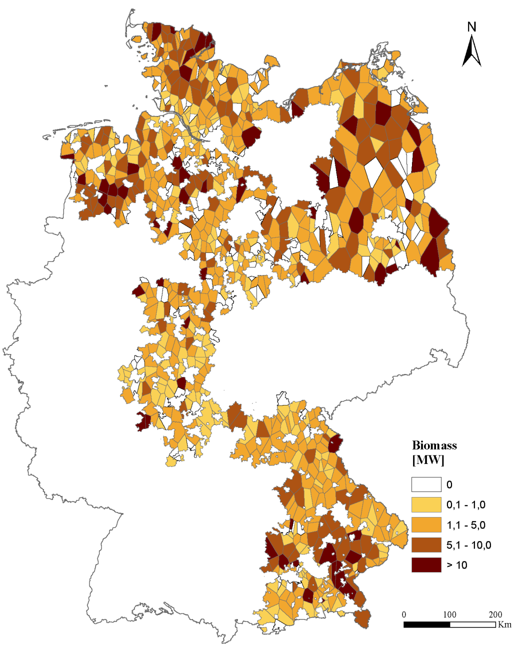
Figure A.3: Average installed capacity of different power plants in the DSO subregions, 2015–2017



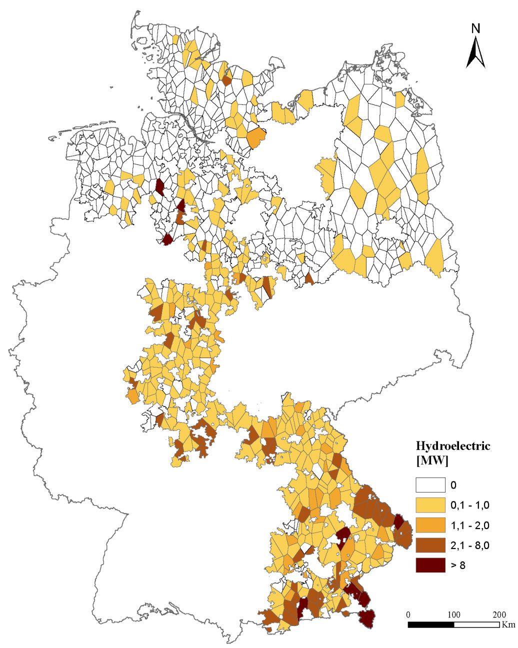
(a) Wind power



(b) Solar power



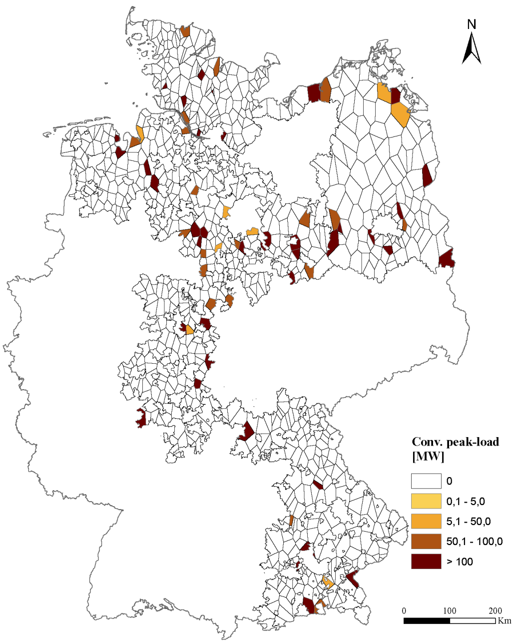
(c) Biomass power plants



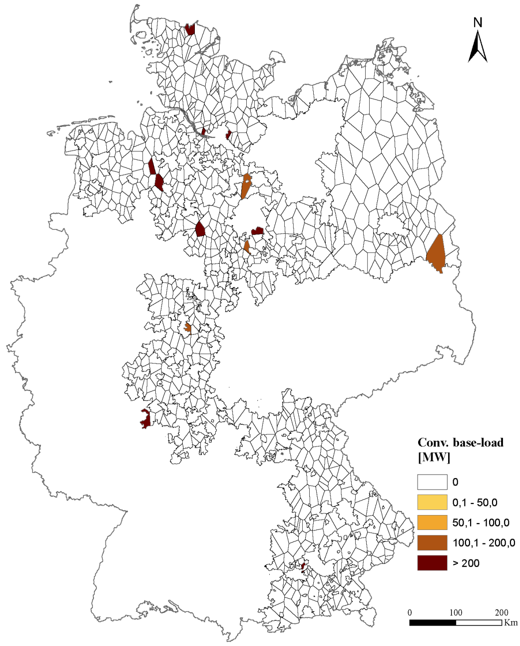
(d) Hydroelectric power plants

(continued)

Figure A.3: Average installed capacity of different power plants in the DSO subregions, 2015–2017 *(continued)*



(e) Conventional peak-load power plants



(f) Conventional base-load power plants

Figure A.4: Average electricity demand in the DSO subregions, 2015–2017

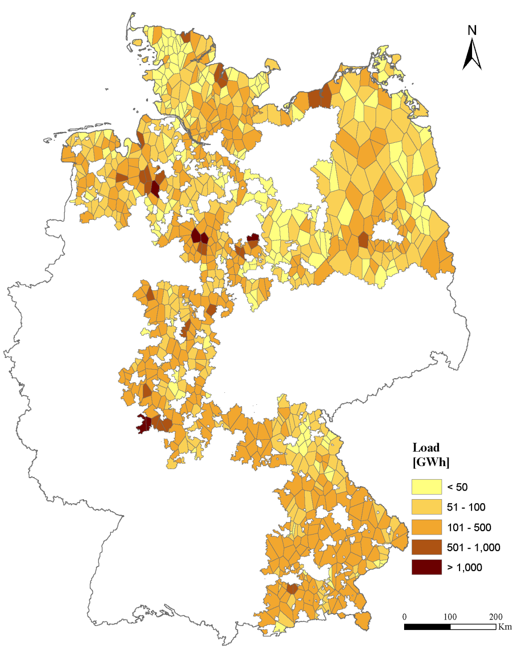


Figure A.5: Average wind speed in the DSO subregions, 2015–2017

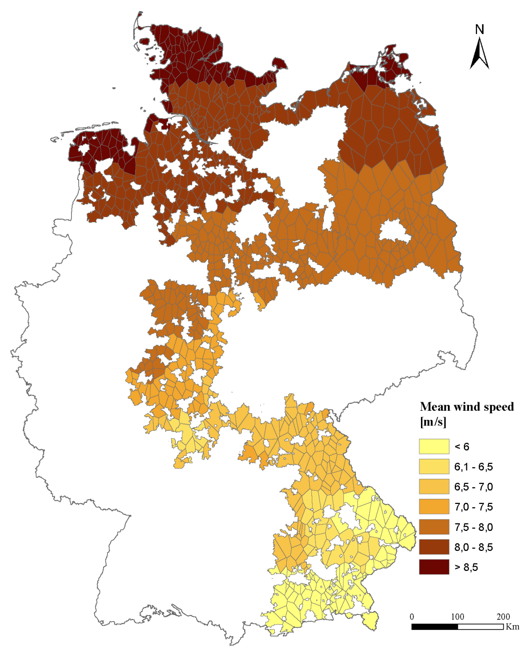


Table A.2: Comparison of calculated and published RES curtailment costs

DSO[a]	Federal States (FS)[b]	Area covered [%][c]	Year	DSO costs [€][d]	FS costs [€][e]	Share [%][f]
Avacon	LS, SA, Hesse	59.7	2015	6,541,760	57,908,856	11.3
			2016	5,718,869	31,223,962	18.3
			2017	37,465,927	180,712,239	20.7
BW	Bavaria	57.8	2015	41,105	333,345	12.3
			2016	58,891	292,782	20.1
			2017	232,192	585,290	39.7
Edis	Brandenburg, MW	71.7	2015	45,574,389	96,229,679	47.4
			2016	26,910,325	63,901,645	42.1
			2017	26,910,325	62,274,651	43.2
SHN	SH	99.4	2015	265,360,723	312,942,279	84.8
			2016	126,665,577	273,012,271	46.4
			2017	200,474,705	351,246,341	57.1
Overall			2015	317,517,978	467,414,159	68.0
			2016	181,267,336	368,430,660	43.3
			2017	265,083,149	594,818,522	44.6

[a] *Avacon* = Avacon Netz AG, *BW* = Bayernwerk Netz GmbH, *Edis* = E.DIS Netz AG, *SHN* = Schleswig-Holstein Netz AG.
[b] Federal states in which the respective DSO operates. Note: LS = Lower Saxony, SA = Saxony-Anhalt, MWP = Mecklenburg-Western Pomerania, and SH = Schleswig-Holstein
[c] Share of federal state area covered by respective DSO.
[d] RES curtailment costs in the respective DSO region as calculated in this study.
[e] RES curtailment costs in the respective German federal states as published by the German Federal Network Agency (BNetzA, 2017d, 2018b).
[f] Share of calculated to published RES curtailment costs.

Table A.3: Characteristics of the considered DSO subregions

Parameter	Unit	Avacon[a]	BW[a]	Edis[a]	SHN[a]
Population	[-]	1,947,418	4,706,253	2,047,377	1,341,030
Area of DSO region	[km^2]	57,511.4	40,812	35,519	13,457
Length of electric cables, LV	[km]	34,696.3	99,079	46,957	31,167
Length of electric cables, MV	[km]	17,508.5	46,196	26,613	17,425
Length of electric cables, HV	[km]	12,327,6	9,046	5,515	2,948
Installed capacity (transformer level), MV/LV	[MVA]	11,076.8	12,707	6,560,580	3,727
Installed capacity (transformer level), HV/MV	[MVA]	5,063.7	21,338	9,071,900	10,218

Note: LV, MV and HV stand for low-voltage, medium-voltage, and high-voltage level, respectively.
[a] *Avacon* = Avacon Netz AG, *BW* = Bayernwerk Netz GmbH, *Edis* = E.DIS Netz AG, *SHN* = Schleswig-Holstein Netz AG.

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Both publications have earned SCIMago Journal Ratings in the top quartile for Economics and Econometrics publications.

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