

Spatial Econometrics in Electricity Markets Research

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Abstract

This chapter outlines the theoretical foundations and empirical applications of spatial econometrics in energy markets research. Spatial econometrics deals with spatial autocorrelation and spatial heterogeneity, two key issues in energy finance during the low carbon transition. Indeed, with congested grids and a high penetration of geographically heterogeneous intermittent renewables, the electricity markets can be more accurately modelled and forecasted by taking account of spatial effects. After illustrating the main spatial aspects of electricity pricing, production, and consumption, the chapter summarises the theory of spatial econometrics and highlights its advantages over alternative estimation methods. The existing applications of spatial econometrics to electricity markets are thus reviewed, such as forecasting electricity demand and wholesale electricity prices, as well as assessing the diffusion of photovoltaics. Methodological implications and open issues are discussed in the final section.

Keywords: Spatial econometrics; Electricity prices; Electricity demand; Photovoltaics; Estimation; Forecasting; Spatial weight matrix; Spatial autoregressive model; Spatial error model; Spatial Durbin model.

1. Introduction

The spatial organization of the electricity industry is a key issue in the current energy policy debate in many parts of the world, its relevance being fostered by the policy goals of de-carbonization and of integration among physically separated markets. Balta-Ozkan et al. [2015a] review

the literature on the interdependencies between de-carbonization and local economic development, showing that five trends motivate the study of the electricity industry through the tools of spatial analysis.

First, the potentials for renewable energy generation are spatially uneven, because of geographical differences in average insolation rates, wind speeds, as well as geothermal and hydrological endowments, which reflect local climatic and orographic conditions. Second, and implied by the first trend, the deployment of green energy technologies is spatially concentrated. Spatial patterns of statistical dependence are incorporated in models and forecasts of wind power generation, notably in order to make inference on the distribution of wind speeds in new sites for which time series data are lacking or scarcely available. A third trend is highlighted by the geographical fragmentation in the governance of the liberalized electricity markets. In this new governance setting, relationships between electricity users and producers unfold in space, through both physical and social connections. Prosumers using distributed generation facilities are linked through social ties (which may help spreading information on new technology vintages) and their physical interlinkages are primarily “local”, as they are mediated through the (short-distance, low-voltage) distribution grid instead of the (long-distance, high-voltage) transmission grid. Relatedly, geographical differences in urbanization rates influence the diffusion of distributed generation technologies, marking a fourth trend.

Last, but not least, there are interactions between agglomeration economies and transmission constraints, as a specific instance of the efficiency gains from spatial integration among energy markets. Promoting regional integration, indeed, is based on the presumption that increased cross-border trade fosters productive efficiency by expanding the reach of the most efficient plants, and it improves allocative efficiency by inducing competition among producers that are

geographically separate [Borenstein 2000; Wolak, 2015].¹ The integration of electricity markets across regional areas has played a significant role in the development of electricity markets in the United States, as testified by the PJM Interconnection, and lies at the heart of the European Union energy policy goal of creating an internal market for energy [Glachant 2004, Meeus et al. 2005].² Reconciling the goal of regional integration with de-carbonization targets is however a difficult challenge [Glachant and Ruester, 2014], as demonstrated by recent evidence of market integration being spoiled by the burgeoning growth in renewables, which questions the traditional electricity-fuel nexus (De Menezes et al. 2016, Gianfreda et al. 2016).

As a bottom line, both de-carbonization and market integration policies are significantly conditioned by the spatial organization of the electricity industry. This is true at the policy-making level, as well as in the perspective of private production and investment decisions. However, besides spatial interpolation techniques, such as kriging estimators used to assist wind investment decision-making by Haslett and Raftery [1989], Lenzi et al. [2016] and others, space has been incorporated in forecasting analyses only in time series fashion. For instance, in Gneiting et al. [2006], Hering and Genton [2010] and follow-ups, the mean of the wind speed distribution at one site depends linearly on lagged wind

1

While some simulation analyses corroborate the theoretical expectation of efficiency gains [Wolak 2015, Valeri 2009, Boffa et al. 2010, De Nooij 2011], evidence of collusive behaviours dates back to the California electricity crisis [Cicchetti et al., 2004], down to more recent examples of inefficient arbitrage across interconnectors [Bunn and Zachmann 2010, McInerney and Bunn 2013]. See also Boffa and Sapio [2015].

2

The EU is also part and parcel in large-scale inter-connection projects such as those envisioned in the Mediterranean Solar Plan [Jablonski et al., 2012; Escribano, 2010], within the broader goal of building electricity highways running from the North Sea to Northern Africa [Sanchis et al., 2015; Trieb and Müller-Steinhagen, 2007].

speeds at other locations, resembling a vector autoregressive or a distributed lag model. Similarly, energy econometrics relies primarily upon time series models when it comes to understanding and forecasting electricity prices and consumption, which are extremely relevant both for policy-making and for shaping the expectations of private actors. Spatial econometric methods have not yet gained a comparable status in applied research work, despite the result established by Giacomini and Granger [2004] that in predicting the aggregate of spatially correlated variables, forecasting is inaccurate if spatial effects are overlooked.

Against this background, this chapter outlines the theoretical foundations and the main empirical applications of spatial econometrics in energy markets research. Spatial econometrics is an array of models, estimation methods and tests that can be used when dealing with data samples possibly characterised by spatial dependence [Anselin, 1988]. Spatial dependence arises when the value assumed by a variable in a given location is correlated with the value that the same variable assumes in another place or in a set of other places. More specifically, heterogeneity (heteroscedasticity) and autocorrelation (dependence) are the main issues posed by the treatment of data series related to geographical entities. According to Anselin and Bera [1998], spatial autocorrelation occurs when high or low values for a random variable tend to cluster in space (positive spatial autocorrelation) or locations tend to be surrounded by neighbours with very dissimilar values (negative spatial autocorrelation). The idea that “space matters” was stated by Tobler [1970] with his First Law of Geography: “*Everything is related to everything else, but near things are more related than distant things*”. The problems posed by spatially-organised data characterised by spatial autocorrelation require distinct treatments and prevents the use of approaches based on a one-way direction relationship among different geographical units.

The reviewed evidence sheds light on the value added of spatial econometric models in our understanding of price-setting, demand, and technological diffusion dynamics in the electricity industry, as well as in forecasting electricity prices over time horizons that are relevant for the policy goals of efficiency and reliability of the industry. We thereby expand the reach of recent literature reviews on statistical forecasting of

electricity prices [Weron 2014, Nowotarski and Weron 2017] and demand [Hong 2014; chapter 3 in Weron 2007].

After illustrating the main spatial aspects in the functioning of the electricity industry (Section 2), the chapter summarises the modelling, estimation, and testing methodologies in spatial econometrics (Section 3). The existing applications of spatial econometrics to electricity markets are thus reviewed in Section 4, such as modelling and forecasting electricity demand and wholesale electricity prices, as well as assessing the diffusion of photovoltaic panels. The works reviewed here show that explicitly considering spatial correlations improves the forecasting performance and the understanding of electricity market dynamics. Section 5 concludes while offering a discussion of open issues and an outlook for future research on the spatial econometrics of electricity markets.

2. Spatial aspects of electricity markets

As this chapter will show, energy econometrics has only recently recognised the value added of estimating spatial dependance patterns. In fact, it is remarkable how the importance of spatial networks in affecting the decisions of agents producing and consuming electricity has been neglected for long time even in theoretical work. One notable exception was provided by Nijkamp [1983], who explored the nexus between energy policy goals, urban planning, and the spatial distribution of economic activities (as influenced by industrial policy), stressing its strategic relevance for policy makers.

Such a neglect can be traced back to the history of the electricity industry, that has been gravitating between two opposite configurations [Granovetter and McGuire, 1998]. In the early days, in the US, self-producers were prevailing, at a time when long-range interconnections had yet to be sufficiently developed. In the subsequent configuration, that took over approximately from 1920 on, the industry came to be dominated by centralised technical control in the hands of vertically integrated (regulated) monopolists, when electricity was produced by

plants exploiting economies of scale and could be considered, within each country, as a spatially homogeneous, standardised service. Investments in new generation, transmission, and distribution infrastructures were centrally coordinated. Dispatching, planning, and investment decisions were conditioned by the implicit “transport costs” between nodes, but the associated issues were solved within vertically integrated organisations.

Since the late 1970s and the 1980s the growing sensitivity to environmental issues, the progress in information and communication technologies, as well as the fall in the minimum efficient scale following the introduction of combined-cycle gas turbines have been powerful drivers in the transition to a decentralised and deregulated regime, in which facilities along the power supply chain are unbundled [Pollitt 2008]. Drawing on the seminal work of Dosi [1988], Künneke [2008] has interpreted the increasingly distributed technical control in electricity systems as a transition between technological paradigms (from centralized to decentralized). Technological paradigms in the power supply chain differ in terms of the spatial patterns of energy generation, transmission, and distribution, as well as with respect to cost structures and to the degree of involvement and reactivity of energy users, with the emergence of prosumers in the decentralized paradigm (see Schleicher-Tappeser [2012] among others).

In light of the outlined turns in technological paradigms, economic thinking, policy making goals and practices, the time is ripe for the explicit incorporation of spatial correlations in the statistical modelling and forecasting of electricity industry variables. It is worth providing a few more details on the theoretical roots of spatial effects in wholesale electricity prices and in their demand and supply determinants.

In a structural approach to electricity price modelling, the electricity price at a certain time and location is a function of its “fundamentals”, namely electricity demand, fuel prices, transmission constraints, the parameters of strategic reaction functions (associated to dispatchable energy sources), supply components that are non-strategic within the given bidding horizon (i.e. renewable energy sources, derivative contracts), and unobservable determinants, i.e. the error term

in an econometric model (see Carmona and Coulon [2014] for a survey). Such determinants can exercise their effects across time and space, hence they should be included in econometric models with time and spatial lags. In such a structural model, spatial dependence among electricity prices at different locations is due to spatial dependence in electricity price fundamentals and/or in the unobservables. More frequently, though, econometric models of electricity prices are reduced-form models, wherein the time and spatial correlations are modelled directly.

As a matter of fact, one key reason motivating the use of spatial econometrics in modelling electricity prices can be traced back to seminal work by Bohn, Caramanis, and Schweppes [1984] on nodal pricing. Nodal prices are computed as the solution of a system cost minimisation programme, subject to various constraints. Optimal nodal prices were shown to vary stochastically across time and locations, and specifically price differences between two nodes may emerge depending on events throughout the transmission grid. The reason is that whenever an additional power generator injects electricity into the system, the thermal constraints may become binding due to congestion, thereby shifting nodal prices away from marginal costs. Even when transmission lines are congested, price differentials reflect the relative scarcity of electricity at neighbouring locations, so that, following Bushnell and Stoft [1996], the optimal nodal price at one location reflects the average nodal prices at neighbouring locations.

Within such a reduced-form approach to modelling electricity prices, the tests of market integration are well suited to illustrate the potential informative role of spatial econometrics. Indeed, the time series tests performed in the literature offer information on the spatial linkages between electricity prices, but only implicitly. Under perfect market integration, i.e. whenever congestion does not arise, the set of locational (or zonal) prices is typically represented by means of a univariate time series process. When congestion occurs, a multivariate time series model, such as a vector autoregressive (VAR) or a vector error correction (VEC) model is instead assumed. In the former case, prices are equalised across zones, whereas in the latter, correlation among prices is expected to be positive, albeit imperfect, due to common drivers (such as fuel

prices, weather conditions) and because of relative scarcity in neighbouring locations, as mentioned above.

Market integration has been assessed through various approaches, such as testing the time dynamics in correlation between price pairs (Pereira and Soares [2008] on European power exchanges), or testing unit roots in price differentials [Zachmann 2008]. Granger causality has been deployed to identify leader-follower relationships among markets or market zones, as in Dempster et al. [2008] and in Bunn and Gianfreda [2010]. In case unit roots are found in the time series of electricity prices (DeVany and Walls [1999] being among the few) or in fuel prices [Bunn and Gianfreda 2010, Bosco et al. 2010, Gianfreda et al. 2016, De Menezes et al. 2016], the literature has resorted to co-integration tests. Under the null hypothesis of co-integration, the price differential between two locations is mean-stationary with a zero mean, and there is no intercept in the long-term relationship between the prices. In other words, the electricity prices at two locations only differ by a random disturbance (conditional on exogenous covariates, such as fuel prices and deterministic terms).

Thus, in testing market integration, previous works have only implicitly recognised that price information from one location is useful to understand and forecast prices in other locations. The extent of such spatial effects, though, cannot be easily inferred from the existing multivariate time series estimates on electricity prices. One reason is that all locations in a VAR / VEC model are treated equally, regardless of physical or “socio-economic” distance which in spatial econometrics are handled through spatially-weighted matrices, improving efficiency, as we will see in Section 3. Another issue is that time is unidirectional and linear, whereas space has no obvious beginning and direction, and any location can have more than one neighbour in a higher-dimensional network.

As previously mentioned, in a structural model perspective, spatial dependence among prices is ultimately due to spatial dependence among price fundamentals. The main electricity price fundamental, electricity demand, in theory is expected to be spatially dependent. Spatial spillovers and spatial clusters can arise when proximate regions

are characterised by socio-economic linkages. Similar life-styles and imitative behaviours made easier by spatial proximity, as well as information conveyed through migration flows can contribute to develop a spatial correlation among regional electricity demand levels. Spatial interdependencies may notably arise whenever the effects of regional energy policies “leak” through regional borders, since e.g. consumers may arbitrage away price differentials induced by location-specific tariffs, or environmental externalities may affect electricity consumption behaviours within the geographical reach of the external effects.

Another key instance of spatial dependence is found in wind power generation and in wind speeds. Wind turbines are usually clustered in wind farms or parks, since the wind resource tends to be spatially concentrated. If two turbines are in a row, given the respective wind direction, the power produced by a turbine that is downwind is reduced by *wake-induced turbulence effects* created by the upwind turbine [Ye et al. 2017]. Wake effects intensify with decreasing distance between turbines, therefore it is essential to account for spatial correlations between wind speeds or wind power generation from different turbines within a wind farm. Because the underlying conditions may differ dramatically from site to site, focusing on only the time dimension would not allow to extrapolate predictions to sites that have not been monitored yet and that are being considered for a new investment. Moreover, failing to consider spatial correlations means that forecasting errors made at a given time in a give site are correlated with forecast errors at neighbouring sites in the following period [Tastu et al. 2011].

It must be noted that spatial correlations matter also when one considers a coarser spatial resolution, as is the case with works taking the aggregate power generated from a wind farm as the unit of analysis. Evidence reported e.g. in literature reviews such as Lei et al. [2009] found that outputs from wind farms spaced less than about 100 kms apart are highly correlated, but such correlation vanishes when the distance is beyond 200 km. On these grounds, one can envisage the geographical distribution of wind farms that minimises the aggregate wind power volatility, the so-called *smoothing effect*. This is a relevant issue in a policy-making perspective, since lower variability in wind outputs

mitigates the volatility of wholesale electricity prices as well as the reliance on ancillary services.

In a longer term perspective, space matters also in influencing decisions to invest in renewable energy generation facilities. Besides geography-dependent insolation rates, the diffusion of photovoltaic panels can be fostered by urbanization, which is expected to facilitate the transmission of information between PV adopters and their peers, as well as offering agglomeration economies in the form of a higher presence of skilled workers in the PV sector, which reduces the cost of maintenance and related services. At the same time, in urbanised areas scarcity of space may deter PV installations.

3. Spatial econometric models

3.1 Introduction to spatial analysis

The last decades have been characterized by a considerable increase of the research incorporating spatial dimensions into applied economic modelling. Spatial analyses were first conducted in the fields of regional economics and economic geography, in line with the idea that “space matters” as stated more precisely by Tobler [1970] with the First Law of Geography: “*Everything is related to everything else, but near things are more related than distant things*”.

Accounting for the presence of spatial linkages is extremely important, in particular when looking at the implications of policies implemented at any place to detect problems of a specific geographical unit. The effects of these policies may spread beyond geographical boundaries and affect also the conditions of neighbouring regions. Spatial econometrics, therefore, represents the set of alternative estimation approaches that can be used when dealing with spatial data samples [Anselin, 1988]. In particular, heterogeneity (heteroscedasticity) and autocorrelation (dependence) are the main issues posed from the treatment of data series related to geographical entities. These problems, common to any econometric application, in the case of spatial data may require distinct treatments. Spatial heterogeneity violates the Gauss-Markov assumption that a single linear relationship exists across the sample data observations. If the relationship varies as we use different spatial units alternative estimation procedures are needed to model this type of variation (random coeffi-

cients, error component models, etc). Similarly, the spatial dependence, arising when the value assumed by a variable in a given location is correlated with the value that the same variable assumes in another place or in a set of other places, prevents to use traditional approaches based on a one-way direction relationship among different geographical units. According to Anselin and Bera [1998], spatial autocorrelation occurs when high or low values for a random variable tend to cluster in space (positive spatial autocorrelation) or locations tend to be surrounded by neighbours with very dissimilar values (negative spatial autocorrelation).

Recently, the spatial analysis has been incorporated also into energy economics modelling since resources, consumption, and production of energy are defined over time and space and therefore have a time as well as a spatial dimension. In this regards, there are lots of applications that should involve the use of spatial models as for example: patterns of energy use across space, spatial externalities of energy production in terms of the environmental affects, spatial clustering in exhaustible natural resources exploration activities, spatial structuring of electricity prices, and so forth.

3.2. Modelling Space

Modelling Spatial dependence requires an appropriate representation of relative spatial positions. When considering a sample of R spatial units, the solution is given by a *spatial neighbors matrix* (\mathbf{W}), that is a square symmetric $R \times R$ matrix with the $(i; j)$ element equal to 1 if spatial units i and j are neighbors of one another (or more generally, are spatially related), and zero otherwise. By convention, the diagonal elements of this “spatial neighbors” matrix are set to zero. In the simplest form, the element w_{ij} represents the spatial proximity based on the concept of binary contiguity. If two spatial units have a common border they will be considered contiguous and will be marked with value 1. Conversely, if they are not contiguous, their coupling will have a value of 0.

However, the simple contiguity measure has some limits: a) it does not account for non-reciprocal interactions because of its symmetrical nature; b) it does not account for other kind of interaction than geographi-

cal proximity; c) it does not distinguish between different types of neighboring regions, with regards to the distance or the morphology of the border area (mountain, hill, plain) or, finally, to the length of the border actually shared. To overcome the latter problem contiguity matrices of higher order than the first can be used ³. Besides, it is possible to associate the contiguity matrix with a matrix of distances or with other matrices that combine distance measurements with border lengths. In this line, one can use the inverse of the distance between the centers (geographical, but also political or administrative) of spatial units and the distance can either be expressed in terms of linear and road distance or in terms of time distance, in relation to travel times. The matrix obtained in this way, assigns to each pair of spatial units a different value that decreases with the distance to account for the stronger influence that closer spatial unit may exert with each other.

The first and second limits are usually overcome by introducing measures of "economic contiguity" between spatial units, like commercial exchanges (which would also distinguish non-reciprocal relationships) or the degree of similarity in productive specialization. Finally, proximity may account also for other types of distances such as cultural, linguistic or administrative.

The best choice regarding spatial neighbors matrix is made taking into account the research goals, that is ensuring that measures of proximity included in the matrix are strongly exogenous respect to the variable object of study.

The spatial neighbors matrices are usually transformed into "spatial weight" matrices following the most common approach of the "row-standardization", consisting in dividing each row element by the sum of all the elements in the row.

3

For example, a second order matrix identifies those areas that are contiguous to regions showing the value one in the first order matrix.

Row-standardized spatial weights matrix is particularly attractive because its elements can be interpreted as the fraction of total spatial influence on unit i attributable to unit j and, when weights are based on the inverse distances, they decrease with increasing distances. In spite of its popularity, row-normalized weighting has its drawbacks. In particular, row normalization alters the internal weighting structure of the matrix so that comparisons between rows become somewhat problematic. In view of this limitation, an alternative transformation is represented by the simple *scalar normalization* consisting in multiplying each element of the neighbors matrix by a single number ($\alpha \cdot W$). This procedure removes any measure-unit effects but preserves relations between all rows of W .

3.3 The Exploratory Spatial Data Analysis to test spatial dependence

It is important to test for spatial autocorrelation when using data at the region level because in presence of spatial dependence, regression analysis of spatially distributed variables can lead to incorrect statistical inference when proper corrections for spatial effects are not incorporated in the model specification [Voss et al., 2006].

Following Anselin [2005], exploratory spatial data analysis (ESDA) represents a useful set of instruments to test for the presence of spatial dependence. ESDA is a collection of techniques aimed to describe and visualize spatial distributions; identify atypical locations or spatial outliers; discover patterns of spatial association, clusters or hot-spots; and suggest spatial regimes or other forms of spatial heterogeneity. Central to this conceptualization is the notion of spatial autocorrelation or spatial association, i.e., the phenomenon where locational similarity (observations in spatial proximity) is matched by value similarity (attribute correlation). If either high or low values are found in a spatial unit and its adjacent, it would be an instance of positive spatial autocorrelation. Spatial clustering is said to occur with positive spatial autocorrelation [Anselin et al., 2000]. By contrast, negative spatial autocorrelation would occur if units with low levels for the variable of interest surround a spatial unit with a high value. For those spatial units where no correlation exists between variable's values and their locations, the spatial pattern is considered to exhibit zero spatial autocorrelation [Holt, 2007].

There are several tests in the literature to verify the presence of spatial autocorrelation.

The most common test for the existence of global spatial autocorrelation is due to Patrick Moran and is usually referred to as Moran's-I statistic [1948]:

where x_i represents the variable describing the phenomenon under study in region i , μ is the sample mean and w_{ij} is the weight of a row-standardized spatial matrix. The expected value of the Moran index ($E(I)$) is equal to $-1/(R-1)$. With R large enough the standardized I is normal distributed therefore the rejection of the null hypothesis of no spatial autocorrelation implies the presence of spatial dependence. Values of I greater than the expected value indicate positive spatial autocorrelation, which means that regions with high (low) values tend to be located close to other regions with high (low) levels. Values of I less than the expected value indicate a negative association, and hence a tendency for dissimilar values in nearby regions.

Local indicators of spatial clustering analysis consider the relationship between each region and its neighbors, identifying hot spots (high-value clusters) and cold spots (low-value cluster). Among these tests there are the Getis-Ord statistic [Getis and Ord, 1992; Getis and Ord, 1995; Sokal et al., 1998], the Moran scatterplot [Anselin, 1996] and the Local Indicator of Spatial Association LISA, [Anselin, 1995].

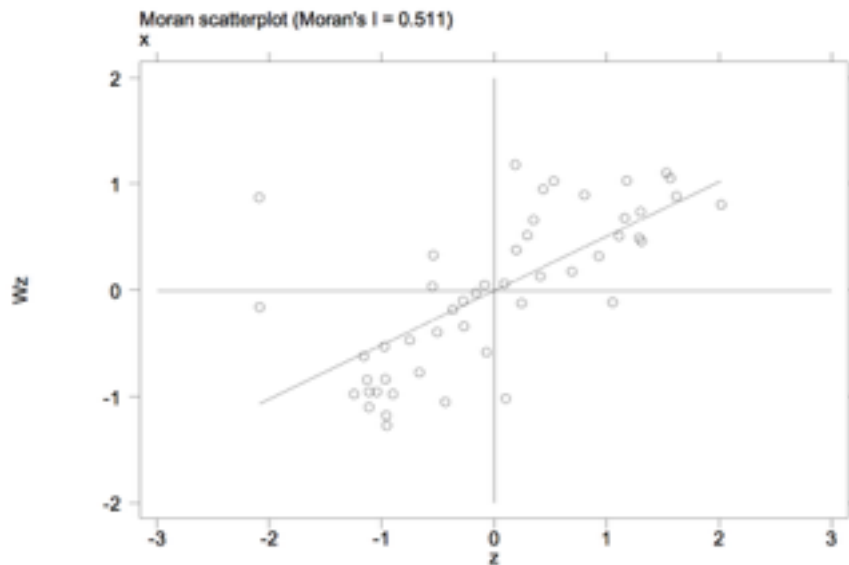
The Getis-Ord test refers to the concentration of values of the variable of interest in the neighborhood of region i . The original statistic is as follows:

$$\text{with } j \neq i$$

where w_{ij} is the corresponding element of a non-standardized symmetric binary weights matrix which attributes 1 to neighboring regions and 0 to the others and to the pivot region. Once standardized, positive values of G_i indicate spatial clustering of highly values around region i , while negative values indicate a cluster of regions showing low values.

The Moran scatterplot is given by a graph centered on the mean value of the variable of interest x for a number of spatial units. The horizontal

axis returns the standardized values of the variable (Z) while the vertical one returns the spatially lagged value of the standardized variable (WZ) [Anselin, 2005; Anselin et al., 2000]. The slope of the linear regression line that runs through the scatter plot is the Moran's-I coefficient [Anselin et al., 2000]. If the points are equally dispersed between the four quadrants this will indicate no correlation (the slope is zero). If, however, there is a clear relationship, the Moran Scatterplot can be used to distinguish different types of spatial autocorrelation depending on the quadrant. High-high (upper right) and low-low (lower left) represent positive spatial autocorrelation (spatial clusters) and low-high and high-low are negative spatial autocorrelation (spatial outliers) [Anselin, 2005; Anselin et al., 2000].



Since Moran scatterplots do not assess the statistical significance of spatial associations it is useful to associate this global indicator, and its graphical representation, with a local autocorrelation indicator that is able to measure interdependence for each of the regions concerned. The Local Indicator of Spatial Association (LISA) effectively enables for each spatial unit to associate a measure of the spatial association level

with its surroundings and to assess its statistical significance. The indicator commonly used as LISA is the local version of Moran's I statistic for each spatial unit i :

A positive value for I_i indicates spatial clustering of similar values (high or low) whereas a negative value indicates spatial clustering of dissimilar values between region i and its neighbours.

3.4 Spatial econometrics models: a taxonomy

The spatial econometrics literature distinguishes different ways of modeling spatial interaction [Anselin, 1988]. Depending on the type of interaction between observations of neighboring units, the estimation may follow different approaches. In what follows we present some of the model specification for a cross-section data context⁴.

- Spatial Autoregressive Models (SAR), when levels of the dependent variable y depend on the levels of y in the neighboring regions (spatial lag dependence). In this case, the formal model is:

where λ is the spatial autoregression parameter, which typically has to be estimated from the data, W is a predefined R by R spatial weighting matrix, X is a vector of explanatory variables and ε is an independently and identically distributed error term for region i with zero mean and variance σ^2 . Wy represents the spatially lagged values of the dependent variable accounting for the idea of spatial spillover within nearby regions. The significance of λ indicates the presence of spatial autocorrelation. For an individual observation, the basic spatial lagged autoregression equation is simply:

4

For panel dataset specifications, please refer to Elhorst (2010a, 2011).

- Spatial Error Models (SEM), when error terms are correlated across space (spatial error dependence). This situation may occur when some determinants of the dependent variable omitted from the model are spatially autocorrelated or when unobserved shocks follow a spatial pattern. The resulting model is written as follows:

with \mathbf{v} assumed to be normal with zero mean and variance $\sigma^2 \mathbf{I}$.

- Spatial Durbin Models (SDM) containing a spatially lagged dependent variable and spatially lagged independent variables.

In order to verify whether a spatial model is more appropriate to describe the data than a model without spatial interdependences, the suggestion is to run the Lagrange Multiplier test for a spatially lagged dependent variable (LMlag) and for the spatial error autocorrelation (LMerr) using a baseline non-spatial model [Anselin et al., 2006; LeSage and Pace, 2009, 2010]. The null hypothesis for these tests is the absence of spatial dependence. The alternative hypotheses are, respectively, the presence of spatial lag and spatial error dependence. Robust Lagrange-Multiplier tests can also be performed to test for the existence of one type of spatial dependence conditional on the other. Finally, the likelihood ratio (LR) and the Wald tests can be performed to verify whether the SDM can be simplified to the spatial lag model or to the spatial error model [Elhorst 2010a, 2010b, 2011].

Regarding the estimation procedures, it is important to remember that the spatially lagged dependent variable (Wy) is correlated with the errors, even when these are identical and independently distributed. In other words, the spatial lag of the dependent variable should always be considered as endogenous. This means that the OLS estimation approach be-

comes inadequate because producing biased and inconsistent estimators (typically those deriving from simultaneity problems). Among the alternative methodologies, chosen to overcome these drawbacks, the most widely used is the Maximum Likelihood (ML) estimation technique. Indeed, under specific conditions⁵, all the classic properties of its estimator (non-distortion, efficiency, and asymptotic normality) remain valid when including spatially lagged dependent variables.

4. Reviewing the spatial econometric literature on electricity markets

Statistical modelling and forecasting in the restructured and liberalised electricity industries concerns various variables, depending on the goals of the interested parties. Wholesale market-clearing prices, fuel prices, wholesale demand, wholesale generation from intermittent, non dispatchable renewables (such as wind and photovoltaic), and the diffusion trajectories of renewable energy sources have all been attracted scholarly, business, and policy interests. Recently, literature reviews on forecasting electricity prices through statistical methods have been provided by Weron [2014] and Nowotarski and Weron [2017], whereas statistical forecasting of electricity demand is the topic of the survey in Hong [2014] and of chapter 3 in Weron [2007].

This section reviews the main existing applications of spatial econometrics with a focus on electricity prices, electricity demand, and residential PV uptake. Fuel prices and wind power forecasting are not included in our picture. While fuel prices are determined in international markets, and thus induce common dynamics among zonal markets in the same country, the literature on forecasting wind speeds and power has ignored spatial econometric models, although it has long made use of spatial information, as mentioned in the Introduction. In the kriging estimators used by Haslett and Raftery [1989], Lenzi et al. [2016] and

5

The conditions regard the differentiability of the function, the existence of partial derivatives, and the existence of a positive and non-singular covariance matrix.

others, the non-diagonal entries of the covariance matrix of the error term decline exponentially with the distances between wind turbine sites. In Gneiting et al. [2006] and in Hering and Genton [2010], the location and scale of the predictive distribution of wind speed at one site is assumed to depend also on wind speeds at other sites.

Statistical modelling and forecasting the variables under focus involve methodological dilemmas which we will briefly illustrate in each subsection before providing details on the existing applications and results. Issues to be solved in the econometric design include measurement, spatial granularity, and the choice of the spatially-weighted matrix.

As a general note, electricity market forecasting is performed over various time horizons, from real-time to day-ahead, to longer forward contracts, as well as monthly or annual averages when it comes to demand and supply variables. In this context, short-term usually refers to a range between few minutes and few days ahead, while medium-term extends to a weekly horizon and long-term stretches from monthly, to quarterly and annual. Short-term forecasting is specifically useful to transmission system operators to ensure reliability, while being essential also for power generating companies to shape their bidding strategies in the shorter-term wholesale market segments. Long-term forecasting helps making investment and planning decisions as well as allocating resources to long-term contracts on both the supply or demand side. While short- and medium-term forecasting relies on econometric models, long-term forecasting is based on a detailed modelling of the system at hand, whether economic (oligopoly or auction models in the case of prices) or physical / meteorological (in the case of wind and solar power), and is exposed to modelling risk, related to the tall challenge of predicting regulatory and technological change.

Demand forecasting is a relatively mature paradigm; instead, accurate short-term predictions of electricity prices are still rather challenging to achieve, in spite of the striking progress documented in comprehensive methodological surveys, such as the one by Weron [2014]. Wholesale electricity prices display seasonalities (annual, weekly, and within day), volatility clustering, skewness, jumps, spikes,

and excess kurtosis. The uncertainty in forecasting wind power, solar power, and electricity demand only add to the difficulties in predicting wholesale electricity prices.

4.1 Electricity demand

4.1.1 Roots and issues

The electric power consumption in terms of kWh per capita is strictly linked to countries development level. World Development Indicators [World Bank, 2017] highlight a considerable difference in terms of per capita electricity consumption between upper middle and lower middle income countries that in 1971 were, respectively, 305.33 and 89.95 kWh and in 2014 rise to 3533.37 and 769.5 kWh. In the same period, higher income countries raised their consumption by an average annual rate of 2.6% while less developed countries showed an increase of 17.16%.

Since the seminal work of Houthakker [1951], that analyzed the electricity consumption in Great Britain, several empirical studies have been conducted with the purpose to find the main determinants of electricity demand. Income level and electricity price, demography, climate, industrialization, price, and availability of alternative energy resources, together with standard of living have been indicated as the main factors driving electricity demand in developed countries [Fisher and Kaysen, 1962; Silk and Joutz, 1997; Alberini and Filippini, 2011; Filippini and Pachauri, 2004; Flaig, 1990; Houthakker, 1980]. For developing countries, instead, the degree of urbanization is an additional covariate to capture further economic development characteristics affecting residential electricity consumption [Holtedahl and Joutz, 2004].

The factors determining electricity demand can exercise short and long term effects. The elasticities, usually calculated by means of dynamic models, show that electricity may be in general treated as a normal good with long-term price-elasticity values larger than short-term ones [Atalla et al. 2017]. Some exceptions are found in the case of cross-prices for substitute goods, such as natural gas [Fullerton et al., 2015], because of difficulties in switching from one power source to another for many types of appliances.

At first, econometric analyses on electricity demand were mostly performed at country level. However, from the 1960s several governments started promoting regional development, in order to reduce the existing disparities within countries, and great efforts were made to support the local energy provision. This change in energy policies implied a larger concern about analyses focused on a regional level aimed to evaluate the effectiveness of regional measures and to identify the main channels influencing local functions of consumption and provision of electricity.

The early studies on regional demand for electricity followed two contrasting hypotheses. On the one hand, regions characterized by different socio-economic and climatic conditions were supposed to have different needs in terms of electrical energy, both in the private (households and firms) as well in the public sectors [Bernstein and Griffin, 2006; Contreras et al., 2009]. The idea was that model specification and estimation results could strongly differ among regions within the same country. Hence, very often the studies on the electricity demand were referred to individual regions. In this vein, Fullerton et al. [2012, 2015] give some evidences for specific states of the US. On the other hand, some studies, conducted on aggregate regional panel data sets, found that price and income elasticities of electricity demand do not vary across regions [Alberini and Filippini, 2011; Houthakker, 1980; Hsing, 1994; Maddala et al., 1997 and Paul et al., 2009].

The presence of a spatial correlation between the consumption of electric energy in different geographical locations has been long neglected. However, recently, as mentioned in the introduction of this chapter, empirical studies on energy economics recognized the importance of including the spatial dimension into analyses dealing with resources, consumption, and production of energy. Extending these analyses to the spatial component finds a motivation in spatial spillovers and spatial clusters in electricity consumption that may arise when proximate regions are characterized by socio-economic linkages. In fact, common life-styles, imitative behaviors or the presence of migration flows may induce spatial autocorrelation between regional electricity demands. Finally, spatial interdependences may be driven also by regional energy policies affecting nearby regions. In all these cases, ignoring the presence of spatial interdependence would lead to biased

and inefficient estimates [Anselin, 2010; Anselin et al., 2008; LeSage and Pace, 2010] of the determinants of the local demand for electricity.

The presence of a spatial interaction among nearby regions and the need to account for these influences require the use of spatial econometric procedures that, differently from the standard OLS or fixed effects approaches, enable to separate direct effect of an independent variable on the regional demand of electricity from those due to spatial spillovers. Spatial interactions either may refer to the spatially lagged dependent variable (i.e. the value of a dependent variable in a neighboring region), the spatially lagged omitted variables (affecting the error term) or the spatially lagged independent variables (see Section 3).

4.1.2 Literature review

A few empirical studies of electricity demand at regional level have recognized the role of spatial interactions. Among them, Yaylaci et al. [2011] use tools of ESDA in order to verify the presence of spatial autocorrelation of electricity consumption among Turkish provinces in 2006. Results of their analysis, that considers adjacent provinces as neighbors, reveal the presence of a positive spatial autocorrelation using both global and local spatial local indicators (Moran's-I and $G_i^*(d)$ statistics). Provinces belonging to hot spots are characterized by a high degree of industrial activity and high population densities.

An attempt to test the presence of a spatial autocorrelation following a spatial econometric approach, without considering any other factors determining electricity demand, was done by Ohtsuka et al. [2010] and Ohtsuka and Kakamu [2011] who observed the regional electricity consumption for Japanese regions in the time interval 1992-2003. The authors used a spatial autoregressive ARMA model (SAR-ARMA) in order to improve the forecasting of electricity demand in Japan. Yet again, the spatial proximity considered in these studies is based on the concept of a binary contiguity between regions and spatial weight elements are obtained by a row-standardization procedure.

Among the studies that test the presence of spatial effects of the residential electricity demand using a more complex model, i.e. including the main determinants suggested by the energy economics

literature, Yu et al. [2012] find that the SAR model specification overperforms the SEM one. The authors control for gross regional domestic production, population and energy prices and find a statistically significant spatial correlation in energy consumption among Chinese provinces over the period 2007-2009. In particular, they implement the Gibbs sampling method based on Markov Chain Monte Carlo (MCMC) and construct a Bayesian spatial econometric model to solve the potential problem of heteroscedasticity driven by differences in terms of geography, economy, society, science, technology, population, and culture characterizing Chinese provinces.

Blazquez Gomez et al. [2013], by employing a spatial autoregressive model with spatial autoregressive errors (SARAR), estimate income and price elasticities of electricity demand testing also for the presence of spatial effects. They control for socio-economic factors, such as income, population and number of households, electricity own price and substitute power sources price (i.e. natural gas) as well as for climatic conditions. The analysis was referred to 46 Spanish provinces observed over the period 2001-2010. Lagrange multiplier tests suggested that the SARAR model was an appropriate specification as both spatial effects, spatial lag and spatial error, are confirmed to exist. In addition, the authors analyzed also the impact of the 2009 crisis on electricity demand by testing the effects of substantial changes in disposable income. Results evidence the crucial role that spatial effects had in determining differences in provincial responses to the economic crisis, which give some insights to address regional energy policies and to electricity companies planning their investments on an intense activity of forecasting.

The last, in order of time, is a recent study by Akarsu [2017] that used a dynamic spatial lag panel model to test for the presence of spatial effects in the local electricity demand in Turkey. The author has based its analysis on various datasets that differ for the length and the geographical disaggregation level (provinces and regions) and controls for gross domestic product, real electricity price, urbanization ratio, heating and cooling degree-days and province/region fixed effects. Results highlight the presence of spatial spillovers and, similarly to other studies (Diabi [1998] for Saudi Arabia and Erdogdu [2007] for Turkey), he finds both price and income short- and long-term inelasticity.

4.3 Uptake of residential photovoltaic systems

4.3.1 Geographical clustering in residential photovoltaic panels diffusion

The recent decades have been characterized by a worldwide deployment of the renewable energy mainly driven by higher concerns for security of energy supply, implications of climate change and the uncertainty given by the variability of price in the liberalized energy market. Achieving these goals requires both a deep reform of global and national energy policies and an intense teamwork involving institutions, producers as well as consumers of energy. To this end, the role played by householders may be crucial. These, with an adequate legislative and financial support, may change their habits undertaking more efficient actions in terms of energy consumption. They may even contribute to promote technological innovation by becoming self-producers of the energy they need while mitigating the environmental impact of their consumption activities.

In this line, the European Union by means of different Directives (Electricity Production from Renewable Energy Sources 2001/77/EC and Renewable Energy Directive 2009/28/EC) promoted a strong reduction of carbon dioxide emissions, to reach by the middle of the current century, establishing that 20% of the energy consumed by all member states should come from renewable resources. In order to achieve this result, several governments introduced market-pull policies favoring the decarbonization by boosting renewable energies. Among the available typologies, photovoltaic (PV) panels represent a valid system capable to be installed by householders for domestic needs.

The empirical literature dealing with the uptake of PV panels highlights the importance of market-pull policies and feed-in-tariff schemes promoted by national and/or local governments. These resulted

to be fundamental for the initial trigger of the PS system characterized by high installation costs, above all for domestic applications.

Several studies have examined the channels and the factors favoring the PV deployment in the domestic segment, i.e. families' decision to install cells on their roofs, while less has been done for the other two segments of this market, namely the non-domestic rooftops and the ground-mounted. The latter usually feeds the higher voltage distribution network while both the domestic- and non-domestic-rooftops are mainly connected to consumers' premises providing them directly the required amount of electricity.

The empirical evidence on small-scale PV systems, namely the residential uptake, in addition to market-pull policies [Cherrington et al., 2013], focuses also on socio-economic, technical and geographical factors suggested by energy economics [Westacott and Candelize, 2016; Schaffer and Brun, 2015; Gooding et al., 2013; Richter, 2013; Kwan, 2012]. Among the economic factors, energy costs saving, influenced by feed-in tariffs, self-consumption and lower installation costs, make it particularly profitable to uptake PV panels. Moreover, household disposable income, level of education and environmental concerns seem to influence positively the turnaround to PV. There is evidence that PV diffusion depends also on the degree of urbanization, with higher density urban areas, facilitating information transmission between PV adopters and their peers [Lutzenhiser, 1993; Wallace and Wang, 2006; Rode and Weber, 2016; Bollinger and Gillingham, 2012], or ensuring a greater presence of skilled workers employed in the PV system itself [Schaffer and Brun, 2015]. On the contrary, some studies [Müller and Rode, 2013; Snape and Rynikiewicz, 2012; Snape, 2016] find that the likelihood of installing PV is greater in less densely populated area, away from large conurbations. Eshchanov et al. [2013] show that residents of urban area have low opportunities of installing PV panels because of the unavailability of sufficient space both on their rooftops and in the neighborhoods. This uneven distribution of installations would not have been the expected result if households' choices were mainly the result of market-pull policies (feed-in-tariff) and return on investment.

This evidence suggests the importance of geographical factors. In particular, geography plays a key role for the solar exposition and the

following average annual solar radiation detected by a region, both affecting the efficiency and the profitability of PV installations [Schaffer and Brun, 2015].

4.3.2 Literature review

Most of the empirical analyses, conducted at a regional or more disaggregated levels (provinces or counties), shed light on the presence of a spatial clustering in the residential PV system deployment, confirming the importance of geographical proximity. Above all, this is true for socio-technical factors, like peer effects and clusters of skills together to the solar radiation exposition. Peer effects, in particular, can be either active, when individuals persuade somebody else to turn to the same energy power system, or passive when the decision is taken after simply observing what neighbors do. While these effects are highly localized, they tend to spread across adjacent regions arising spatial spillovers. Consequently, ignoring the presence of a spatial dependence in the residential decision to install PV panels may lead to inconsistent results. In this line, a large part of the recent studies on the PV deployment at local level are based on spatial analysis methodologies.

Dharshing [2017] finds strong peer effects and neighboring spillovers investigating households' solar panel installation as an example of the dynamics of technology adoption in the domestic segment of the market. The author considers a panel dataset including almost one million of PV systems in 402 German counties over the period 2000-2013. County-level spatial proximity is taken into account by using a row standardized rook binary contiguity matrix. The presence of a spatial dependence among neighboring counties is confirmed by the results of the Moran's-I global indicator. The econometric analysis is then performed through a spatial autoregressive and a spatial error model showing the presence of a strong spatial dependence that goes beyond pure socio-economic and demographic factors and settlement structures. Similar results for Germany were also found by Schaffer and Brun [2015] who, by means of a SAR panel model, found that PV diffusion varies among counties due to different solar radiation expositions and neighborhood effects because of an uneven diffusion of specified craft skills and/or intermediary agents.

The UK context has been widely analyzed, too. Richter [2013], investigating for the social learning determinants of PV installations, found that passive peers, i.e. the observation of local installations, strongly influenced the dynamics of further installations at a post-code areas level of geographical disaggregation. The author underlined also the necessity to account for the presence of spatial spillovers between adjacent areas. In this view, Snape [2016] checked for the presence of spatial effects by means of a descriptive analysis, using a mixed strategy based on quantitative data on PV adoptions and qualitative information on energy policies over the period 2010-2015. The use of a global spatial indicator (Moran's-I index) proves the presence of a positive spatial autocorrelation at post-code district level. The local indicators (LISAs), instead, describing the geographical position and the strength of the clusters, site the clusters of high intensity capacity in the southwest of England and highlight the emergence of a positive spatial autocorrelation also in the east of England. The analysis confirms the presence of low-low clusters around large cities like London, Birmingham, Manchester and Liverpool.

Finally, the spatial autocorrelation of PV installations appears to increase over time after the introduction of feed-in-tariffs. Balta-Ozkan et al. [2015b] employ a spatial econometric model to perform a comprehensive analysis of the determinants of domestic PV deployment in British regions. Their analysis includes a large number of explanatory variables accounting for financial constraints (per capita income), density (population and house density), environmental conditions (share of domestic and industrial emissions in total emissions) electricity demand and solar irradiation. The presence of a positive spatial dependence between neighbors is confirmed by the outcome of the Moran's-I test. The authors use an inverse distance weight matrix assuming that the spatial dependence is inversely related with the distance between regions. According to the result of the spatial autocorrelation test, they follow a general-to-specific approach [Elhorst, 2010a, 2010b] in order to identify the most appropriate spatial model specification. The Lagrange Multiplier test indicates that the Spatial Durbin model (SDM) may be properly used to describe the PV deployment in British regions and significant spatial spillover go through both the dependent variable (PV uptake) and the explanatory variables. In order to account for potential

endogeneity bias, a generalized spatial two-stage least squares procedures (GS-2SLS) is estimated using as instruments the spatially lagged explanatory variables. Results show that SDM and GS-2SLS are similar suggesting the presence of spillovers between neighboring regions. This result is obtained by running spatial correlation tests based on Lagrange Multiplier statistics as suggested by Anselin [1988] and LeSage and Pace [2009].

5. Conclusion and open issues

In spite of the inherently spatial nature of most activities in the electricity industry, which stimulate the interest of policy-makers and private decision-makers alike, the econometric literature has so far relied almost exclusively on a time series approach to estimation and forecasting. This chapter restores the role that spatial dependence deserves as a fruitful interpretive concept in the field of electricity market studies. As shown by the reviewed evidence, spatial econometric models can ameliorate the economic understanding of price-setting, demand, and technological diffusion dynamics in the electricity industry, while improving the forecasting performance of pricing models over time horizons that are relevant for ensuring reliability in electricity transmission and efficiency in bidding strategies. The chapter has also explored some practical issues that applied researchers can face in their econometric design, such as measurement issues, the spatial granularity of the data, the criteria for choosing the spatially-weighted matrix, and the setup and interpretation of the statistical tests that are essential to evaluate the presence of spatial dependence in the data under analysis and discriminate among different spatial model specifications.

Just like any field in its growth stage, spatial energy econometrics still needs to tackle some open methodological issues. A theme so far underplayed in the empirical literature on wholesale electricity prices is the simultaneous inclusion of serial and spatial correlation terms in the same model. Douglas and Popova [2011] implicitly did so by using the day-ahead price as a proxy for the information available before the spot price quotation, while the approach taken by Maciejowska and Weron [2015] is more effective, since their

estimated factors capture the common drivers between observation units in both the space and the time dimensions. Yet, some more articulate pattern of serial correlation may have to be allowed as in Burnett and Zhao [2017].

Notably, specifying a serial correlation structure alongside the spatial correlation terms could allow to inspect the issue of leader-follower relationships between power generating companies or locations. Leader-follower dynamics are epitomised by the role that the German electricity market may be playing in mittel-Europa, as well as by companies that possess informational advantages on import/export balance by running assets on both sides of a transmission link (e.g. Electricité de France in the plant-level VAR analysis performed by Bunn et al. [2015]). Identifying leading companies or locations at a fine spatial resolution would be very useful, as it would provide information on which nodes in the network are more critical for the competitive functioning of the electricity market.

Leader-follower relationships are typically explored through the aid of VAR models. As it is well known, recovering the structural VAR coefficients from the reduced form VAR estimates requires some restrictions on the causal chain among the variables. Unlike in macroeconomics, theoretical models of nodal electricity pricing under perfect competition are unable to suggest an expected causal chain, as a consequence of Kirchhoff's law. In the same vein, the well-known theoretical result by Bushnell and Stoft [1996] that optimal nodal prices reflect the average nodal prices at neighbouring locations is yet another instance of the reflection problem highlighted by Manski [1993]. Theoretical models explicitly assuming a leader-follower dynamics, such as the Stackelberg model, while seldom used [Chen et al. 2006, Lee 2014], have not been specified at the nodal scale as they are essentially framed for a longer-term assessment of electricity planning and competition policies (see Neuhoff et al. [2005] and the review in Ventosa et al. [2005]). Identification of the likely leader is then left to the inspection of business and regulatory documents, in a qualitative fashion that needs to be reinforced by sound quantitative testing. In this respect, graph-based causality identification methods recently introduced could be helpful. In Moneta et al. [2013], the higher-order moments of the non-

Gaussian VAR residuals are exploited to obtain the restrictions needed to compute structural VAR coefficients from the reduced-VAR ones, with no need for a priori theoretical restrictions. Extensions of this methodology to allow for spatial autocorrelations would be extremely valuable in this respect.

Another critical point is the endogeneity due to simultaneity, omitted variables or measurement errors, considered among the main sources of inconsistency in the econometric estimations. The progress of spatial econometrics offers different strategies to overcome these problems. To obtain consistent results from spatial lag models with additional endogenous variables it has been proved that is possible to run a two-stage least squares, including the lower orders of the spatial lags of the exogenous variables [Anselin and Lozano-Gracia 2008; Dall’Erba and Le Gallo 2008]. Kelejian and Prucha [2007] consider a general spatial regression model that allows for endogenous regressors, their spatial lags and other exogenous regressors. Their model represents one of the equations of a simultaneous system but they show that it is applicable also to tackle the general problem of endogeneity. Fingleton and Le Gallo [2010] suggest the use of an augmented spatial Durbin model to be estimated using a 2-stage least square (2SLS) and SHAC procedure in order to account for endogeneity due to omitted variables in a model that presents also spatial dependence in the error terms.

Finally, it is worth suggesting that spatial econometrics could find valuable applications in further areas of interest for energy economics and policy. Novel estimates of spatial econometric models have been recently published by Sunak and Madlener [2015, 2016] on the impact of wind farm positioning and visibility on housing prices in Germany; by Lv et al. [2017] on energy efficiency in a sample of Chinese regions, with the goal of assessing spatial spillovers; by Liu et al. [2017] on neighbor effects in the adoption of hybrid-electric vehicles in the USA; and by Bowen and Lacombe [2017], who take spatial autocorrelation into account in assessing the impact of renewable portfolio standards on renewable generation at the state level in the USA. In a yet unpublished paper, Orea et al. [2016] study the cost functions of Norwegian electricity distribution companies, illustrating one more field of application. In the latter, in particular, spatial correlation allows to

solve an omitted variables problem caused by the lack of data on weather conditions that are influential on the operation of the distribution grid and, in turn, on the costs of providing the service. One remarkable gap in the spatial econometric literature is represented by wind and solar power modeling and prediction. Existing studies reviewed by Kusiak et al. [2009] face the limitations of time series econometrics in dealing with space, namely, they impose a directionality (past/future) in a VAR logic that space does not have, whereas forecasting in Ye et al. [2017] relies on a physical model. To our knowledge, the only application of spatial econometrics to wind power has been published by Croonenbroeck and Ambach [2015].