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Modeling Risk Contagion in the Italian Zonal Electricity Market

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Abstract

Ensuring the security of stable, efficient, and reliable energy supplies has intensified the interconnections among energy markets. Imbalances between supply and demand due to operational failures, congestions and other sources of risk faced by these connections can lead to a system that is vulnerable to the spread of risk and its spill-over. The main contribution of this paper lies in the adoption of recently proposed network models in an innovative way, which enhances the proper analysis of these market connections. The case of the Italian energy market is studied because it is a clear example of a zonal market where risk can spread across connected zones. We estimate within-day and across-day zonal market interconnections with a multivariate time series of hourly prices, forecast demand and wind generation over the period 2010 – 2016 and evaluate the dynamics and persistence of zonal market connections examining the central market and the spread of risk in the zones of the Italian electricity market. Our findings show that models based purely on prices give a better and more accurate explanation of risk contagion than models with exogenous regressors, revealing that the Central North and Central South zones are the most influential in terms of hub centrality for intraday and inter-day risk transmission, respectively, in the Italian energy market.

Keywords: Bayesian inference, complex networks, energy prices, market efficiency, systemic risk, volatility, zonal power market

JEL: C11; C15; C32; C52; G01; Q41

1. Introduction

For several decades, the hallmark of energy policy and regulation has been the security of energy supply and reliability in many countries. Recently, the focus of the energy sector, has been on improving economic efficiency, increasing productivity and reducing costs, thereby, providing long-term efficiency gains. Specifically, in the electricity sector, many markets have introduced competitive bid-based electricity auctions to set energy prices and capacity, which often accounts for congestion costs (Creti and Fontini, 2019). However, several efficiency mechanisms put in place are facing new and unexpected challenges in terms of transmission and distribution. Since deregulations, there have been upsurges in electricity price volatility,

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with effects on various sectors of the economy. Among the main causes of price volatility are new environmental requirements, which have led to the mass retirement of coal-generation resources, the volatility of fuel prices and the spiky nature of raw materials for energy production. Mitigating the various risk in these markets coupled with the issues of climate change have therefore become topics of major concern.

This paper studies the relationships governing the risk spread over the zones of the Italian electricity market. There are many causes underlying the exposure of the Italian electricity markets to risks of contagion among different zones (see for instance, Creti et al., 2010). The efficiency of zonal pricing is challenged by the fact that it does not take into consideration the behavioral perspective of the public good in network management, because of the indivisibility of network security. In addition, it does not accommodate consumer behaviour in terms of price differentials, which impact on overall social welfare. Despite the different methods adopted in pricing electricity, various network structures inherent in the market need to be explored and provide a first step in understanding the extent of risk exposure in the market. Congestions in transmission lines causes price differences in various zones of the network (Fianu, 2015). In their paper, Bigerna and Bollino (2016) derive optimal zonal prices according to a Ramsey optimal scheme in the Italian spot electricity market estimating a complete system of hourly demands. It is argued that optimal pricing improves welfare in the Italian day-ahead electricity market more than existing methods such as the uniform pricing scheme. Sapio and Spagnolo (2018) examine transmission volatility patterns using the VAR-GARCH estimation approach, before and after the inauguration of a new cable infrastructure, accounting for linkages in electricity market zones rich in intermittent renewable energy sources. Specifically, the SAPEI cable accommodates stronger volatility transmissions towards Sardinia in off-peak periods, while no significant volatility transmissions are observed during peak-load periods. As indicated by Klos et al. (2015), the configuration of the zonal energy market is often a result of political decisions. Among the methods developed to aid zonal delimitation, Klos et al. (2015) present a technique which aims to curb the loop flow effect, an element of unscheduled flows that introduces a loss of market efficiency in addition to a detailed decomposition of power flow in order to carry out zonal partitioning and to identify zones which cause problems in the network.

Our original contributions in this paper are therefore as follows. First, to the best of our knowledge, no paper has considered the application of BG-VAR, specifically, to examine the spread of systemic risk in zonal electricity markets. Our paper is the first to employ this recently proposed methodology in studying energy markets. One of the most important reasons for using this methodology, is the spatial nature of the zonal market, which requires a space-time analysis. Second, the paper introduces two different types of analysis of risk contagion: "intraday" and "inter-day". The intraday mechanism spreading volatility is relevant for very short contagion events, with effects limited to the day of the auction. The inter-day approach also includes contagion transmitted from past auctions. In this way, it is possible to disentangle a pure spatial contagion (intraday) from a mixed spatial and temporal contagion (inter-day). Third, the model enables us to determine the zones that are dominant in the spread of systemic risk. In addition, it detects various hidden network structures and relationships between the various zones. The examination of each zone provides an overview of congestion events pertaining to a zone in relationship to other zones. Finally, all these findings are relevant for policy makers and, if properly taken into account, would ensure good policy design for the proper risk management of energy markets, especially those that are spatial in nature. The application of the procedure provides a platform for making optimal environmental and energy policies, especially when the different congestion events and regimes identified are considered for investment decisions.

The remaining sections of the paper are organized as follows: section 2 reviews the literature about risk propagation, interconnections and linkages in energy markets. Section 3 provides an overview of the structure of the Italian zonal market. It also details the various market operations in the zonal power market. Section 4 presents the underpinning of the graphic methodology used in the paper. The data in the empirical section and results are presented and discussed in section 5. Finally, section 6 presents some concluding remarks and policy recommendations for policymakers, market participants, regulators and governments.

2. Literature review

The theoretical and empirical literature have so far dealt with price differentials from both the supply and the demand side, starting with Bigerna and Bollino (2016). As is well known, in the zonal day-ahead market (MGP: Mercato del Giorno Prima) the so-called "market splitting" occurs in the event of congestion. In this case, prices in contiguous areas are different because, in the area where the supply of electricity is lower than the demand, the prices are higher. Due to market congestion, the Ancillary Services Market (ASM) must be activated in order to find a balance between supply and demand (Cappers et al., 2013). Prices on the ASM may differ greatly from prices on the MGP with a huge risk of price hikes for the end users (Lamadrid and Mount, 2012). Market congestion is a source of concern for market regulators, who must always ensure the right balance between supply and demand in order to avoid power outages.

Another source of risk in electricity markets is price spikes in the form of sudden jumps in power prices. Extreme price changes are common in electricity price time series because electricity cannot be economically stored and must be delivered immediately. It is worth noting that risks from spikes can spread from one zone to others creating a contagion effect. A further source of contagion, which has been observed in recent years, is associate with the massive introduction of renewable sources (RES) such as solar and wind energy (Phan and Roques, 2015). For instance, photovoltaic plants have led to increases in the cost of energy in the evening hours because of the need for operators of conventional power plants to recover investments and idling costs in a shorter time span, when PV generation is unavailable[1]. The share of the production of renewable sources has been increasing over the years due to public policy, which promotes the achievement of the 20/20/20[2] targets under the EU climate and energy package via incentives in the form of a feed–in premium for solar plants and green certificates for all other renewable energy sources[3]. The intermittent nature of RES increases the volatility of prices in zones where solar and particularly wind plants are widespread and this additional volatility can spread to other zones though contagion. Energy market risks affecting market participants, including wholesalers, retailers, and consumers, can be hedged by resorting to futures contracts, but this involves high costs normally reflected in retail prices on deregulated markets.

Consequently, it is essential to study how different types of risk are transmitted from one zone to another. To the best of our knowledge, while many papers have been published

[1] AEEG report to the Senate Industry Commission on 18 April 2012.

[2] 20% reduction in emissions, 20% increase in renewable energies and 20% improvement in energy efficiency by 2020.

[3] For detailed overview, see Schwartz (2012).

dealing with contagion and systemic risk on financial markets, there are very few empirical studies about contagion on energy markets (Lautier and Raynaud, 2012; Pierret, 2013) and just one concerning contagion on electricity markets (Bollino et al., 2012). This paper, therefore, provides a first-time approach to the use of network analysis in order to examine the direction of contagion in electricity markets. We present a broad overview of the different characterization of networks focusing on the zonal market because it provides a spatial source of information. To this extent, the focus is on systemic risk[4] and how it spreads via the market price. Characterizing the various types of risk in zonal electricity markets is a first step towards providing insight for the proper risk management of energy and commodity markets.

Complex networks are currently gaining ground in various disciplines, for example, in economics, finance, mathematics and many more. The use of complex networks has helped to extract hidden information from various complex systems. In terms of the energy market, it pinpoints the centrality of networks and the volatility that spreads over other networks. They help market participants such as traders, investors and regulators to guard against sudden systemic failures which can negatively impact on many businesses and economies because of the significant socio-economic role played by energy in the global economy. Recent work on systemic risk includes Billio et al. (2012); Diebold and Yilmaz (2014); Ahelegbey and Giudici (2014); Ahelegbey et al. (2016a). Billio et al. (2012) who propose several econometric measures of connectedness based on principal components analysis and Granger-causality networks. According to the authors, systemic risk is inherent in financial systems and groups of interconnected institutions with business relationships so the risk of illiquidity, insolvency and losses can quickly propagate during periods of financial distress[5].

Unlike any other, this paper uses Bayesian graphical vector autoregression (BG-VAR) as recently proposed by Ahelegbey et al. (2016a) by incorporating exogenous and non-exogenous variables to investigate the complex network dynamics of zonal power markets. The Vector AutoRegressive (VAR) model has been widely applied in econometrics to model temporal dependence in multivariate time series. It has recently been used to model interdependence in systemic risk analysis (Billio et al., 2012; Diebold and Yilmaz, 2014; Ahelegbey et al., 2016a). The Bayesian graphical VAR (BG-VAR), proposed by Ahelegbey et al. (2016a), presents a framework to model directional relationships in a multivariate time series that can be operationalized as VAR models. The approach is based on a Bayesian procedure and a graphic representation of VAR models. The methodology involves inferring the underlying dependence structure of the model, which the coefficients of the relevant covariates to be selected and estimated. This setting naturally produces sparse and parsimonious models for effective forecasts and easy interpretation. Knowledge of the underlying dependence structures can help researchers and policymakers to understand directional or causal relationships among market variables. Furthermore, such structures can be visualized to provide insight into the connectivity pattern among variables and to identify communities and channels for risk propagation. For regulators, this captures and helps to identify the central zones that can cause systemic breakdown when severely affected, and to advance policy measures to ensure the stability of the electricity market.

[4]The term systemic risk is uniquely used in this paper to refer to risk propagations and transmissions, which are significant enough to cause the breakdown in energy systems.

[5]See Ahelegbey (2016) for a review of the state of the art for statistical inference and the application of network analysis to financial time series.

3. The Italian zonal power market

This section provides an overview of the Italian zonal power market. The Italian electricity market is known as the Italian power exchange (IPEX). It comprises a spot market, a forward market and an over-the-counter (OTC) session, which provides a platform for the physical delivery of contracts. The spot market comprises three types of markets: the day-ahead (MGP), the intraday (MI: Mercati Infra-giornalieri) with 7 sessions, and the ancillary services markets (MSD: Mercato dei Servizi di Dispacciamento[6]). GME (Gestore dei Mercati Elettrici) manages the IPEX together with the OTC registration platform for forward electricity contracts stipulated on the bidding system. The market embeds 7 foreign virtual zones, 6 physical zones and 5 poles of limited production (national virtual zones)[7]. The geographical zones analyzed in this paper are the North (NORD), Center-North (CNOR), Center-South (CSUD), South (SUD), Sardinia (SARD) and Sicily (SICI) (see Figure 1). A zone can be defined as the representation of a portion of the power grid, where, for system security purposes, there are physical limits to the transfers of electricity to/from other geographical zones. Figure 2 gives further details of the structure of the Italian zonal market in the current regulatory framework. Zonal prices are the market clearing prices, which are characteristic of each geographical and virtual zone in the Day–Ahead Market[8]. The equilibrium price is determined hourly by the intersection supply and demand curves, see Fianu (2015) for further details. Constraints in inter-zonal capacity often lead to congestion in the grid.

Congestion occurs because of different market clearing prices in two zones, creating potential market imperfections. In terms of the operational paradigm, the market is divided into two zones, North and South, with generators located in both. The role of the Market Operator (MO) is to coordinate consumption and generation via the day-ahead market, which is organized on an hourly basis. Therefore, at the beginning of every hour, the MO invites generators to submit a menu of prices at which they are willing to supply with corresponding quantities. The MO, then, forecasts market demands in the various zones. Given the location of each generator and the demand in various zones, the MO solves the optimal dispatch problem subject to an exogenous set of inter–zonal transmission constraints[9]. This determines optimal prices every hour in every zone, along with the amount of transfer between the zones (see Boffa et al., 2010).

In recent years, the Italian energy market has undergone various regulatory transformations, which have helped to ensure fair competition among market participants. In effect, the development of electricity networks and the excess of supply due to the reduction in demand and growth in renewable energy sources have enhanced competition in electricity markets in Italy. Legislative Decree 28/11 came into effect in 2012, transforming incentives for renewable sources. For instance, the green certificate mechanism was replaced by feed-in tariffs, with maximum allowable expenditure in order to provide incentives for capacity with auction procedures reserved for large plants. However, in 2013, a new national energy strategy was approved and confirmed by the Italian government. In the wholesale market, competition is continually improving. For example, the market share of the four largest operators decreased

[6]Abbreviations refer to the Italian market names. See http://www.mercatoelettrico.org/en/\Mercati/MercatoElettrico/MPE.aspx

[7]https://www.terna.it/en-gb/sistemaelettrico/mercatoelettrico.aspx

[8]The Day–Ahead Market hosts most of the electricity transactions.

[9]The aim of optimal dispatch is to minimize the total electricity expenditure of consumers.

by 5% in 2012 compared to 2011 (49%). Specifically, ENEL remains the main market operator with 25% of the market (26% in 2011), followed by ENI (9%), Edison (7.2%) and E.On (4.4%). Furthermore, the collective shares of small operators increased to 30.2%.

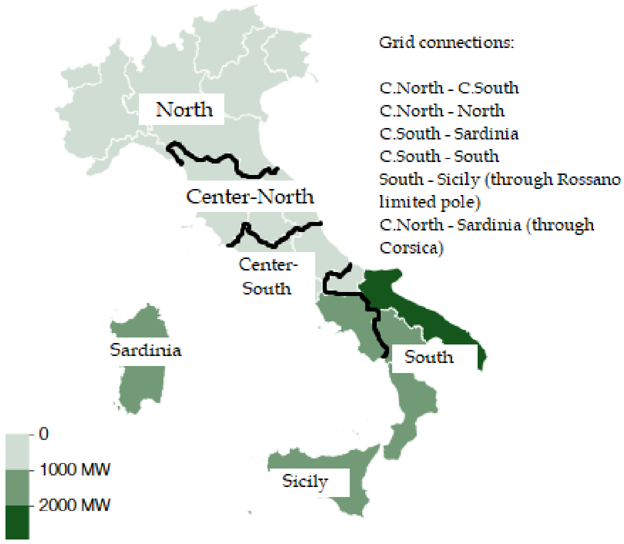

Figure 1: Map of Italy with the regional distribution of installed wind energy capacity (in varying degrees of green) in 2016 and the borders between zones in the transmission grid (thick black lines). The zonal connections, shown in the top right corner, show the basic structure of the market—physical zones. Source: processing by the authors.

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In 2016, the Italian government put forward a decree in 2016 to support incentives for other renewable energy sources in addition to photovoltaic systems. The introduction of market coupling with Slovenia, Austria and France provides significant benefits by reducing inefficiencies in the cross-border transmission capacity rights allocation.

The internal grid was modified and upgraded) in 2012 allowing for improved integration between market zones and consequently the improved transmission of electricity throughout CSUD and SUD zones. The main challenge of network regulators in various developed countries is how to synchronize their regulatory frameworks in the context of the penetration of renewable energy sources allowing them to pursue such traditional aims as adequacy, efficiency and security of infrastructure, while serving customers and remaining customer-friendly. The energy market continues to undergo regulatory change.

4. Model formulation

We present the model and estimation procedure adopted in this paper to analyze interdependencies among zones in the Italian electricity market. These interdependencies can be decoupled and broken down into two networks: an intraday (same day) network, in which the dependence occurs on the same day; and an inter-day (day-to-day) network, in which the dependence occurs with a time-lag. We model the intraday and inter-day dependencies from multivariate time series using, respectively, a simultaneous equation and a vector autoregressive model.

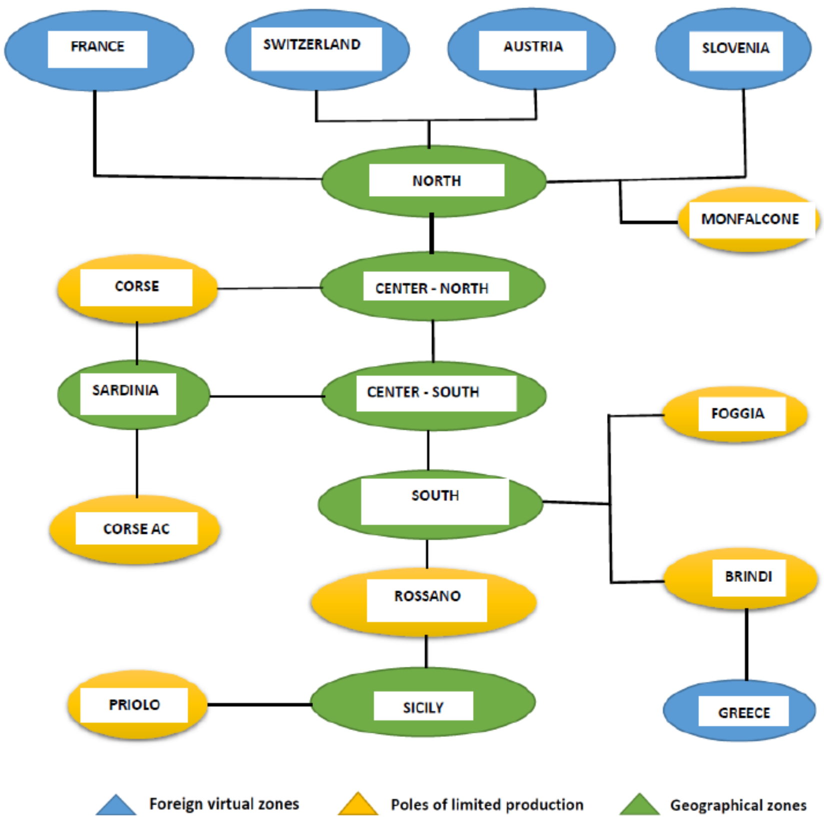

Figure 2: The structure of the Italian zonal market. Source: Processing by the authors based on a map by Terna

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4.1. Modeling Intra-day dependence

Let $Y_t = (Y_{1,t}, \ldots, Y_{n,t})$ be the vector of log price volatilities in n zones at time t, and denote with $Z_t = (Z'_{1,t}, \ldots, Z'_{n,t})$, a vector of exogenous factors. We model the intraday pattern of dependence among zones via a structural equation model with exogenous factors:

$$Y_{i,t} = B_{i,y|y} Y_t + B_{i,y|z} Z_{i,t} + U_{i,t} \tag{1}$$

where $Z_{i,t}$ is a vector of exogenous factors that affects only $Y_{i,t}$. In addition, $B_{i,y|y}$ and $B_{i,y|z}$ are vectors of coefficients, respectively, such that the i-th element of $B_{i,y|y}$ are zeros since $Y_{i,t}$ cannot influence itself. Let $B_{y|y} = (B'_{1,y|y}, \ldots, B'_{n,y|y})'$ and $B_{y|z} = \text{diag}(B_{1,y|z}, \ldots, B_{n,y|z})$ be a stacked representation of $B_{i,y|y}$ and $B_{i,y|z}$. By definition, $B_{y|y}$ is a zero diagonal matrix and $B_{y|z}$ is a zero off-diagonal matrix. Equation (1) can be expressed as

$$Y_t = B_{y|y} Y_t + B_{y|z} Z_t + U_t \tag{2}$$

where $U_t = (U_{1,t}, \ldots, U_{n,t})$ is a vector of structural error terms. Our focus here is to analyze the direction of influence between zones at time t. This is shown in Figure 3.

$$
B_{y|y} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ \beta_{21} & 0 & 0 & 0 & 0 \\ \beta_{31} & 0 & 0 & 0 & 0 \\ 0 & \beta_{42} & 0 & 0 & \beta_{45} \\ \beta_{51} & 0 & \beta_{53} & 0 & 0 \end{pmatrix} \implies
$$

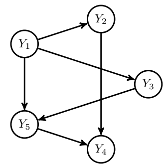

Figure 3: Coefficient matrix and the associated network structure. The non-zero elements in $B_{y|y}$ are real numbers. The column and row labels of $B_{y|y}$ are $(Y_1, Y_2, Y_3, Y_4, Y_5)$ at time t. Links in the network are related to the non-zero elements in $B_{y|y}$ and are directed from column labels to row labels.

4.2. Modeling Inter-day Dependence

We model the inter-day dynamics of Y_t as a p-order VAR with exogenous factors:

$$
Y_t = \sum_{l=1}^{p} A_{l,y|y} Y_{t-i} + A_{y|z} Z_t + V_t \tag{3}
$$

where $t = p+1, \dots, T$; p is the maximum time-lag; $A_{l,y|y}$, $1 \leq l \leq p$, is the matrix of coefficients; $A_{y|z}$ is a zero off-diagonal matrix of coefficients; V_t is a vector of error terms.

Inter-day networks generally comprise autoregressive (own-lagged) and cross-lagged dependencies. In this application, we follow a concept similar to that of Granger causality (Granger, 1969) by focusing on the cross-lagged dependencies. See Figure 4 for an illustration.

$$
A_{1,y|y} = \begin{pmatrix} \alpha_{11} & 0 & 0 & 0 & 0 \\ \alpha_{21} & 0 & \alpha_{23} & 0 & 0 \\ \alpha_{31} & 0 & \alpha_{33} & \alpha_{34} & 0 \\ 0 & 0 & \alpha_{43} & \alpha_{44} & 0 \\ 0 & \alpha_{52} & 0 & 0 & \alpha_{55} \end{pmatrix} \implies
$$

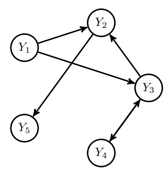

Figure 4: Coefficient matrix of a VAR(1) model and the associated cross-lagged network. The column labels of $A_{y|y}$ are lags of $(Y_1, Y_2, Y_3, Y_4, Y_5)$ and row labels are at time t. Links in the network are results of non-zero elements in $A_{y|y}$ and are directed from column labels to row labels.

4.3. Bayesian Graphical Model Inference

This section discusses the Bayesian graphical framework for multivariate analysis. The models presented in (2) and (3) follow typical multivariate multiple regressions given by:

$$
Y_t = B X_t + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, Q) \tag{4}
$$

where $B = (B_{y|y}, B_{y|z})$ and $X_t = (Y_t', Z_t')'$ in the case of (2); and $B = (A_{1,y|y}, \dots, A_{p,y|y}, A_{y|z})$ and $X_t = (Y_{t-1}', \dots, Y_{t-p}', Z_t')'$ in the case of (3).

Following Ahelegbey et al. (2016a), (4) can be modeled using a graphic framework with the relation $B = (G \circ \Phi)$, where G is a variable selection matrix of binary 0/1 entries, Φ is a matrix of coefficients, and the operator $(\circ)$ is the element-by-element Hadamard's product. The entries of G represent the presence or absence of an edge between pairs of variables. A one-to-one correspondence between B and Φ conditioned on G can be identified based on the above definition. Specifically, $B_{ij} = \Phi_{ij} \neq 0$, if $G_{ij} = 1$; and $B_{ij} = 0$, if $G_{ij} = 0$.

Let $D_t = (Y_t', X_t')'$ and suppose that $D_t \sim \mathcal{N}(\mathbf{0}, \Omega^{-1})$, where Ω is a precision matrix defined as: $\Omega = \Sigma^{-1}$. Let $Y = (Y_1', \dots, Y_T')'$, $X = (X_1', \dots, X_T')'$ and $\mathcal{D} = (D_1, \dots, D_T)$

be a collection of Y_t, X_t and D_t respectively over a fixed window of length T. We denote with Σ_{yy} - the covariances among elements in Y, and Σ_{xy} denotes the covariance between elements in X and Y. The relationship between Ω, B and Σ_ε, such that if $X \sim \mathcal{N}(0, \Sigma_{xx})$ and $Y|X \sim \mathcal{N}(BX, \Sigma_\varepsilon)$, then B and Σ_ε can be obtained from Σ as follows:

$$B = \Sigma_{yx}\Sigma_{xx}^{-1}, \qquad \Sigma_\varepsilon = \Sigma_{yy} - \Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy} \tag{5}$$

Following these relationships, the joint distribution of the variables in D_t can be summarized with a network model and represented by the pair $(G, \Omega) \in (\mathcal{G} \times \Theta)$, where G is a directed acyclic graph (DAG), Ω consists of the model parameters, $\mathcal{G}$ and Θ are the network and parameter space, respectively.

To estimate the topological structure of interactions among the zones, we adopt a Bayesian paradigm where the posterior of the graph (network) combines prior beliefs and marginal likelihood over DAGs, $P(G|\mathcal{D}) \propto P(G)\ P(\mathcal{D}|G)$. The Bayesian method is designed to take into consideration uncertainty in the determination of the presence/absence of a link between zones in the network. Since there are a large number of possible networks that can equally explain the data, the Bayesian approach allowing for model averaging, helps us infer networks in the high-scoring region of the space of network. This enables us to extract and average over models whose edges have a high marginal posterior probability. This method has been shown to perform better than alternative approaches that estimate a single model fitting the data well (Ahelegbey et al., 2016a,b).

In this application, we assume a uniform graph prior by considering each edge in the network as a Bernoulli trial with probability 0.5, i.e., $P(G) \propto 1$. Following Geiger and Heckerman (2002), the marginal likelihood for any DAG model can be expressed as

$$P(\mathcal{D}|G) = \prod_{i=1}^{n} \frac{P(\mathcal{D}_{(i,\pi_i)}|G)}{P(\mathcal{D}_{\pi_i}|G)} = \prod_{i=1}^{n} \frac{P(\mathcal{D}_{f_i}|G)}{P(\mathcal{D}_{\pi_i}|G)} = \prod_{i=1}^{n} P(Y_i|X_{\pi_i}), \tag{6}$$

where $\mathcal{D}_{(a)}$ is a sub-matrix of $\mathcal{D}$ restricted to the indices in set a, π_i is the set of indices of the predictors of the i-th equation, and $f_i = (\pi_i \cup i)$. Following (Ahelegbey et al., 2016b), the probability of Y_i conditional on its direct explanatory variables, X_{π_i}, is given by

$$P(Y_i|X_{\pi_i}) = \frac{\pi^{-\frac{1}{2}T}\ \nu^{\frac{1}{2}\nu}}{(\nu+T)^{\frac{1}{2}(\nu+T)}} \frac{\Gamma\left(\frac{\nu+T-n_f}{2}\right)}{\Gamma\left(\frac{\nu-n_f}{2}\right)} \left(\frac{|\bar{\Sigma}_{(\pi_i)}|}{|\bar{\Sigma}_{(f_i)}|}\right)^{\frac{1}{2}(\nu+T)}, \tag{7}$$

where $n_f = |f_i|$ is the cardinality of f_i and $\bar{\Sigma}_{(a)}$ is the sub-matrix of $\bar{\Sigma}$ restricted to the indices in set a, where $\bar{\Sigma} = \frac{1}{\nu+T}(\nu I + \sum_{t=1}^{T} D_t D_t')$ is the posterior covariance matrix. I is an identity matrix whose dimension is equal to the number of variables in D_t; $\nu > \max(n_f) + 1$ is a degree of freedom parameter and $\Gamma(\cdot)$ is the gamma function.

5. Modeling Risk Contagion in the Italian Energy Market

Network analysis is currently gaining grounds in various disciplines given the fact that almost everything seems to have some kind of interrelationships. Network analysis and its applications, especially in energy markets is no different. With the energy revolution taking place in various countries, the slow but steady transition from non-renewable energy sources is faced by investors and regulators with different forms of uncertainty. This makes the application of network analysis to the study of risk network structures in energy markets relevant and a topic of major concern.

Volatility networks have gained traction in the financial systemic risk literature because of their ability to track the fear of investors (Diebold and Yilmaz, 2014). Employing network techniques in the study of energy and other commodity markets holds promise not only for the present but also for the future. In systemic risk literature, volatility connectedness (referred to as "fear connectedness") has become increasingly important in identifying risk transmission mechanisms in markets. They can be extended to track the spread of risk in energy markets and this could be very useful to investors, policymakers, regulators and government agencies. For instance, they will be a guide to proper risk management and taking investment decisions. The Italian market, with its zonal structure and the close interconnections among zones, provides an ideal framework for original network analysis.

We obtain hourly spot prices (on the day-ahead market) in the 6 physical zones of the Italian electricity market between January 2010 to December 2016 from the Italian Electricity Market website. We also obtain the forecast hourly demand and wind generation of the zonal power markets between March 2014 and December 2016[10]. We analyzed the geographical zones of the North (NORD), Centre North (CNOR), Centre South (CSUD), South (SUD), Sardinia (SARD) and Sicily (SIC). Suppose that $Y_{i,t,j}$ is the observed data for the i-th zone at the j-th hour of day t. Following the literature on volatility estimation from historical data (see Martens and Van Dijk, 2007), we construct daily standard deviations ($\sigma_{i,t}$) as a measure of realized price volatility, defined as follows:

$$\sigma_{i,t}^2 = \frac{1}{N-1}\sum_{j=1}^{N}(Y_{i,t,j} - \bar{Y}_{i,t})^2 \tag{8}$$

where $\bar{Y}_{i,t}$ is the average of Y_i on day t and N is the total number of observations in a day, i.e., $N = 24$. This formula was used to compute standard deviations for prices and exogenous factors - the forecast demand and forecast wind generation.

5.1. Descriptive Statistics

Figure 5 sets out descriptive statistics for price distributions in the Italian zonal power markets in the period 2010-2016. They highlight variations in energy prices in the various zones. A quick glimpse at the prices shows some co-movements in the evolution of energy prices, which initially confirm the existence of some form of structures in the various zones. The distribution of log daily volatilities shows non-negative values almost throughout the sample period. From the various multivariate regression models presented in the previous section, the error terms of the models are assumed to be drawn from a multivariate Gaussian distribution. To satisfy this condition, we standardize the log volatility series to a zero mean and unit variance.

Table 1 gives the descriptive statistics of the daily log-volatility in individual zones in terms of mean, standard deviation, minimum, maximum, skewness, and excess kurtosis. Sicily and the South recorded the maximum and minimum daily price volatilities, respectively, over the sample period. On average, the price volatility in the North zone was lower than that of South.

[10]Day-ahead prices were downloaded from the website of the Italian Regulator of the electricity market (GME), `www.mercatoelettrico.org`. Forecast wind generation of electricity and forecast electricity demand (one day-ahead horizon) were obtained from the website of the Italian TSO Terna, `www.terna.it`.

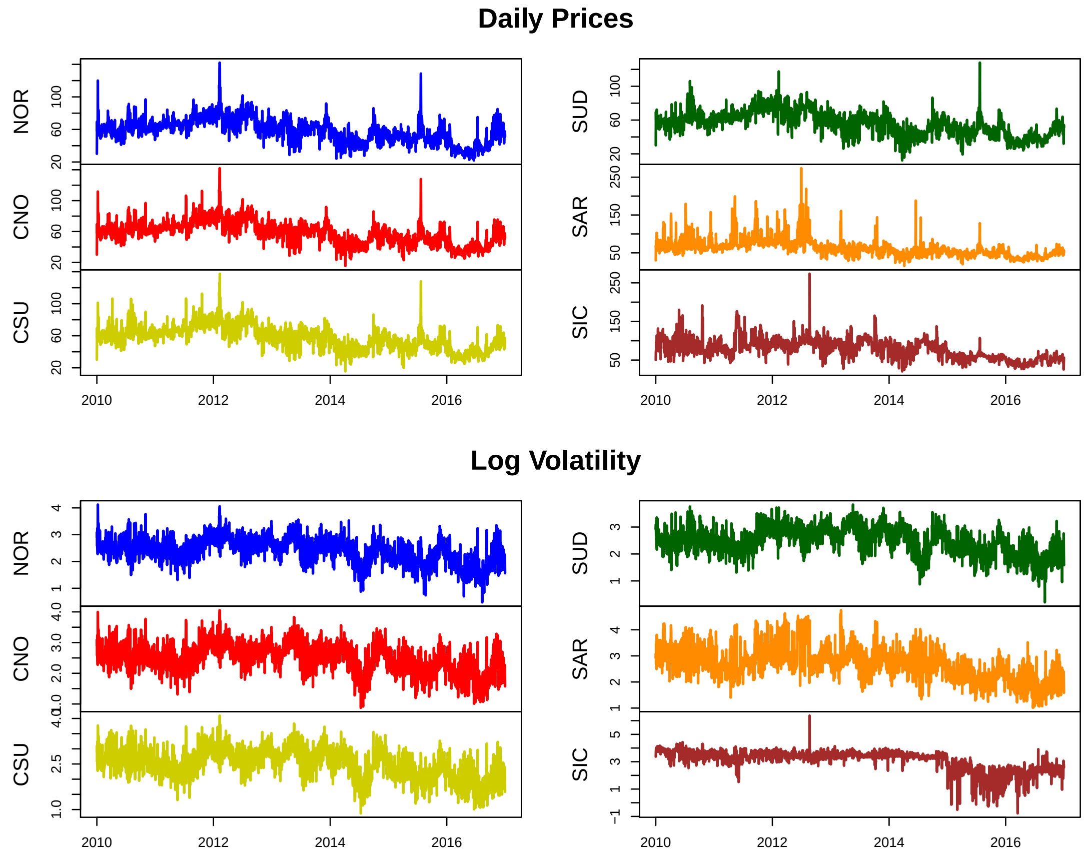

Figure 5: Time series of average daily prices and log volatilities of the Italian zonal electricity market.

	N	Mean	St.Dev	Min	Max	Skew	Ex.Kurt.
NORD	2557	2.4023	0.4872	0.4751	4.1219	-0.3288	0.1207
CNOR	2557	2.4819	0.4908	0.8745	4.0567	-0.2860	0.0164
CSUD	2557	2.5069	0.5084	0.8745	4.0920	-0.2791	-0.1142
SUD	2557	2.4589	0.5101	0.2056	3.8325	-0.2695	-0.0962
SARD	2557	2.6999	0.6465	1.0089	4.7530	0.3106	0.1324
SIC	2557	3.1055	0.7424	-0.7761	6.3674	-1.4152	2.5428

Table 1: Descriptive statistics of the daily log volatility of the individual zones in terms of mean, standard deviation, minimum, maximum, skewness, and excess kurtosis.

With the exception of Sicily, which appeared to be negatively skewed with higher kurtosis, the remaining zones have an approximately normal distribution with skewness ranging from -0.33 to 0.31, and excess-kurtosis ranging between -0.12 and 0.13.

5.2. Zonal Volatility Connectivity

We analyze simultaneous (intraday) and lagged (inter-day) volatility connectivity among the market zones. The estimated network based on network density, in/out-degree, link stability and node centrality (see Appendix A for a brief review of network measures) is discussed by first considering the full-sample period between 2010-2016 and then focusing on yearly sub-periods.

5.2.1. Correlation-Based Analysis

Correlation-based analysis is first conducted to shed some light on the relationship between the price volatilities observed in the various zones. Correlation analysis evaluates the marginal relationship between a pair of continuous variables. Distinctly from common practice in the analysis of relations among different zones of the market (see, for instance, Ignatieva and Trueck, 2016), we compare the correlation matrix with the partial correlations, which evaluate the conditional relationship between couples of variables taking into account the effect and contributions of other variables. This comparison highlights the net linear relationship between couples of zones, excluding the influence of the connection with other zones not involved in the relationship.

Zones	NORD	CNOR	CSUD	SUD	SARD	SIC
	Correlations					
NORD	1	0.8902	0.8436	0.7591	0.6352	0.4443
CNOR	0.8902	1	0.9478	0.8564	0.6832	0.4436
CSUD	0.8436	0.9478	1	0.9041	0.7205	0.4823
SUD	0.7591	0.8564	0.9041	1	0.6515	0.4615
SARD	0.6352	0.6832	0.7205	0.6515	1	0.5279
SIC	0.4443	0.4436	0.4823	0.4615	0.5279	1
	Partial Correlations					
NORD	1	0.5358	-0.0222	-0.0234	0.0515	0.1050
CNOR	0.5358	1	0.6529	0.0121	-0.0138	-0.0991
CSUD	-0.0222	0.6529	1	0.5336	0.2322	0.0669
SUD	-0.0234	0.0121	0.5336	1	-0.0195	0.0729
SARD	0.0515	-0.0138	0.2322	-0.0195	1	0.2906
SIC	0.1050	-0.0991	0.0669	0.0729	0.2906	1

Table 2: Correlation and partial correlation of volatility of the zonal markets in relation to the full sample.

The correlation results in Table 2 suggest a positive degree of association between the zones. A striking feature is that the correlation between Sicily and the other zones appears to be the lowest. This is followed by the correlation between Sardinia and the rest. The strongest correlations occur between North and Central North, Central North and Central South, Central South and Sardinia, and Central South and the South. This is not surprising given the longitudinal nature of Italy, which simply implies that zones that are close to each other will tend to be highly correlated. Hence, the further one zone is from an other, the lower the degree of correlation.

The results of the partial correlations in Table 3 show the degree of association between pairs of zones conditional on physically connected zones. The table shows that the degree of association does not change significantly on the basis of the penetration of renewable energy sources such as forecast wind generation alone $(Y|W)$ and forecast demand $(Y|W, D)$. The highest degree of partial correlations among the zones occurs between North and Central North, Central North and Central South, Central South and South. The price volatility in the two Islands (Sardinia and Sicily) seems not to be correlated with other zones, including zones connected through cables, i.e. Sicily with the South and Sardinia with the Central North zone. Both correlation and partial correlation only show the association between zones, but

Zones	NORD	CNOR	CSUD	SUD	SARD	SIC
			Partial Correlations (Y)			
NORD	1	0.45	-0.06	-0.08	-0.01	0.01
CNOR	0.45	1	0.74	0.03	-0.07	-0.04
CSUD	-0.06	0.74	1	0.51	0.26	-0.08
SUD	-0.08	0.03	0.51	1	0.05	0.17
SARD	-0.01	-0.07	0.26	0.05	1	0.31
SIC	0.01	-0.04	-0.08	0.17	0.31	1
			Partial Correlations (Y|W)			
NORD	1	0.44	-0.06	-0.08	-0.01	0.01
CNOR	0.44	1	0.74	0.03	-0.07	-0.04
CSUD	-0.06	0.74	1	0.51	0.26	-0.08
SUD	-0.08	0.03	0.51	1	0.05	0.17
SARD	-0.01	-0.07	0.26	0.05	1	0.32
SIC	0.01	-0.04	-0.08	0.17	0.32	1
			Partial Correlations (Y|W, D)			
NORD	1	0.42	-0.05	-0.06	0	0.03
CNOR	0.42	1	0.74	0.03	-0.07	-0.05
CSUD	-0.05	0.74	1	0.50	0.26	-0.07
SUD	-0.06	0.03	0.50	1	0.05	0.15
SARD	0	-0.07	0.26	0.05	1	0.31
SIC	0.03	-0.05	-0.07	0.15	0.31	1

Table 3: Partial correlations of daily log volatility in the Italian zonal power market, 2014-2016.

do not provide any information about dependencies or the direction of influence between the zones. That information is provided by network analysis.

5.3. Intraday Volatility Networks

This subsection presents the results of the intraday networks among the zones in the period 2010-2016. First, we analyze the evolution of the yearly network topology for the log price volatilities denoted by SEM(Y). Figure 6 presents the dynamics of yearly intraday volatility in the above period. For most of the years, CNOR $\rightarrow$ NORD, CSUD $\rightarrow$ SARD, CSUD $\rightarrow$ SUD and CSUD $\rightarrow$ CNOR, the arrows depict the direction of linkage between the zones. Figure 7 shows network density for each sub-year. The most dense networks are recorded in 2011, 2013 and 2015, and the least dense in 2010.

The ranking of the zones based on in/out-degree measures is presented in Table 4. Highly (scarcely) connected zones in terms of in/out degree are ranked first (last). The Central South zone is ranked first in terms of out-degree every year, whilst Sicily was ranked last. In terms of in-degree, the North ranked first and Sicily last for most of the years considered.

Comparing intraday Network Models

The analysis of rolling-window intraday volatility connectedness over the sample period was carried out by comparing networks estimated via SEM(Y) with models that include exogenous variables, i.e., SEM(Y|W) and SEM(Y|W,D). We estimate SEM(Y|W) and SEM(Y|W,D) conditional on forecast wind generation and forecast demand. For the purpose of comparison, we estimate all three models for the sub-period between March 2014 and December 2016. This allows us us to investigate the impact of the penetration of renewable

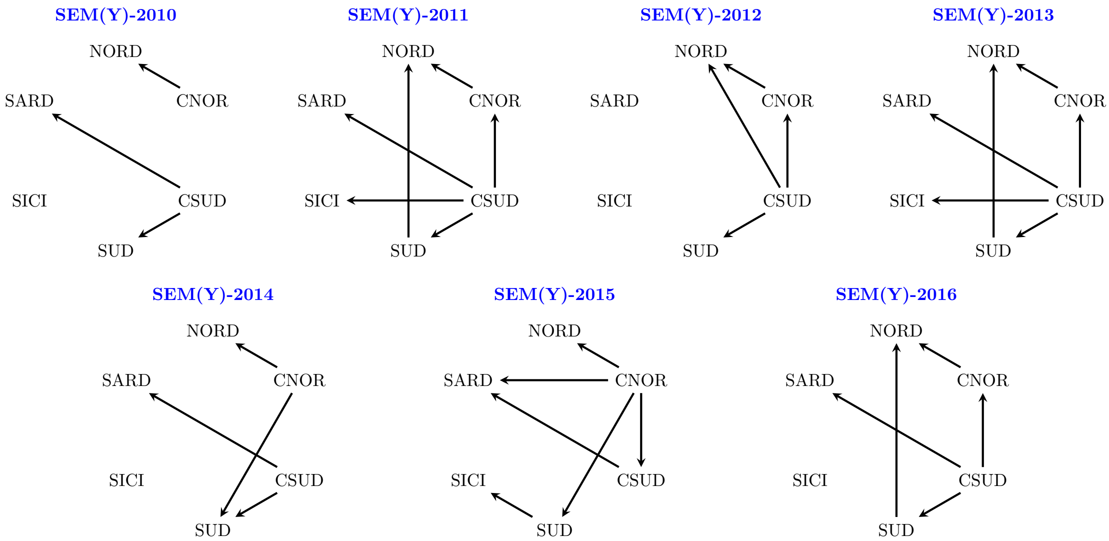

Figure 6: Intraday networks among zones in the Italian electricity market between 2010–2016.

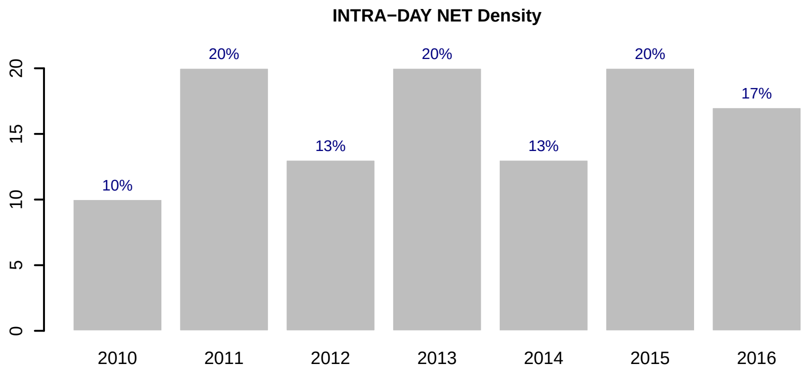

Figure 7: Intraday network densities for zones in the Italian electricity market between 2010–2016.

energy sources (in our case wind) on volatility connectivity among the market zones in the last three years (2014-2016) of the sample. We analyze the dynamics in zonal volatility connectedness by considering a yearly (365 days) rolling window estimation. The first rolling window estimation is from March 1, 2014 to February 28, 2015 and the last is from January 2, 2016 to December 31, 2016 leading to 673 rolling windows altogether.

Table 5 shows the average network matrix for the three different models over the rolling windows. The top panel represents the average matrix for SEM(Y), the middle is SEM(Y|W) and the bottom is SEM(Y|W,D). For a clear understanding of the table, the column labels are represented as explanatory variables and the row labels indicate the dependent variables. The variables FWG (forecast wind generation) and FD (forecast demand) are zone-specific attributes.

The table shows a strong and persistent intraday link between some zones among the various competing models. For example, Central North has a strong impact on the North in the SEM(Y) and SEM(Y|W) models, but this falls significantly when account is taken of forecast demand for the North. On the other hand, only forecast demand seems to have a

Rank	2010	2011	2012	2013	2014	2015	2016
				Out-Degree			
1	CSUD	CSUD	CSUD	CSUD	CNOR	CNOR	CSUD
2	CNOR	CNOR	CNOR	CNOR	CSUD	CSUD	CNOR
3	NORD	SUD	NORD	SUD	NORD	SUD	SUD
4	SUD	NORD	SUD	NORD	SUD	NORD	NORD
5	SARD	SARD	SARD	SARD	SARD	SARD	SARD
6	SIC	SIC	SIC	SIC	SIC	SIC	SIC
				In-Degree			
1	NORD	NORD	NORD	NORD	SUD	SARD	NORD
2	SUD	CNOR	CNOR	CNOR	NORD	NORD	CNOR
3	SARD	SUD	SUD	SUD	SARD	CSUD	SUD
4	CNOR	SARD	CSUD	SARD	CNOR	SUD	SARD
5	CSUD	SIC	SARD	SIC	CSUD	SIC	CSUD
6	SIC	CSUD	SIC	CSUD	SIC	CNOR	SIC

Table 4: Ranking of zones based on out/in-degree of intraday volatility connections.

Zones	NORD	CNOR	CSUD	SUD	SARD	SIC	FWG	FD
				SEM(Y)				
NORD	0	**1**	0	0.24	0.02	0.03		
CNOR	0	0	0.21	0.09	0	0		
CSUD	0	**0.56**	0	0.23	0	0		
SUD	0	**0.55**	**0.66**	0	0	0		
SARD	0	**0.60**	**0.84**	0.16	0	0		
SIC	0.09	0	0	0.23	0.24	0		
				SEM(Y|W)				
NORD	0	**0.99**	0.04	0.08	0.10	0.17	0.12	
CNOR	0	0	0.35	0.19	0.07	0	0.19	
CSUD	0	**0.52**	0	0.25	0.16	0	0.01	
SUD	0	**0.61**	**0.61**	0	0.27	0	0.10	
SARD	0	**0.62**	0.47	0.18	0	0	0.20	
SIC	0	0	0.02	0.36	0.28	0	**0.64**	
				SEM(Y|W, D)				
NORD	0	0.44	0.15	0	0.02	0.25	0.21	**1**
CNOR	0.49	0	0.24	0.06	0	0	0.22	0.45
CSUD	0.06	**0.65**	0	0.25	0.13	0	0	0.04
SUD	0.05	**0.79**	**0.52**	0	0.14	0.08	0.07	0.39
SARD	0	**0.75**	**0.55**	0.48	0	0.18	0.20	0
SIC	0.05	0	0.04	0.36	0.07	0	**0.65**	0.40

Table 5: Intraday average network matrix. Links are directed from column labels to row labels. FWG stands for Forecast Wind Generation, which is specific for each zone; and FD denotes the Forecast Demand for each zone. Boldface values indicate averages above 0.5.

persistent effect on the North. Central South has a strong impact on Sardinia conditional or not on forecast wind and demand jointly. This effect, however, diminished slightly when conditional on forecast wind generation alone. Finally, there is no evidence of a simultaneous effect of any zone on Sicily. However, the only factor that seems to drive volatility in Sicily

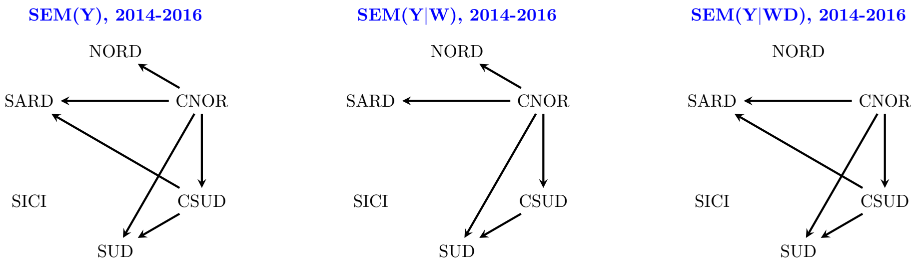

Figure 8: Intraday average threshold network.

is forecast wind generation. Figure 8 shows the resulting network structure of the competing models when the average network matrix is threshold at 0.5. The common links among the three models are CNOR $\rightarrow$ CSUD, CNOR $\rightarrow$ SARD, CNOR $\rightarrow$ SUD, and CSUD $\rightarrow$ SUD.

Rank	SEM(Y)		SEM(Y|W)		SEM(Y|W,D)	
	Hub Centrality					
1	CNOR	**(1)**	CNOR	**(1)**	CNOR	**(1)**
2	CSUD	(0.62)	CSUD	(0.30)	CSUD	(0.78)
3	NORD	(0)	NORD	(0)	NORD	(0)
4	SUD	(0)	SUD	(0)	SUD	(0)
5	SARD	(0)	SARD	(0)	SARD	(0)
6	SIC	(0)	SIC	(0)	SIC	(0)
	Authority Centrality					
1	SARD	**(1)**	SUD	**(1)**	SARD	**(1)**
2	SUD	**(1)**	NORD	(0.77)	SUD	**(1)**
3	NORD	(0.62)	CSUD	(0.77)	CSUD	(0.56)
4	CSUD	(0.62)	SARD	(0.77)	NORD	(0)
5	CNOR	(0)	CNOR	(0)	CNOR	(0)
6	SIC	(0)	SIC	(0)	SIC	(0)

Table 6: Ranking of Hub and Authority centrality of the intraday zonal power market network. Boldface indicates the most central zone for each metric.

To gain insight into the importance of the zonal structure in the intraday transmission of risk in the Italian electricity market, we analyze the centrality of the average threshold network of the three models. The ranking of the zones based on hub and authority centrality is shown in Table 6. The results reveal that Central North ranks highest in terms of hub centrality, i.e., it plays an influential role as a source of risk transmission. It is closely followed by Central South. Sardinia and South are equal in rank in terms of authority centrality according to the SEM(Y) and SEM(Y|W,D) models, while SEM(Y|W) ranks South highest. It is, therefore, safe to conclude that South is the highest ranked authority central zone and consequently is highly vulnerable to the transmission of risk from other zone.

5.4. Inter-day Volatility Connections

The inter-day volatility network among the zones of the market is analyzed first by estimating the time-lag parameter following the lag selection of the VAR model. The modified BIC approach is used for graphical VAR models as in Ahelegbey et al. (2016b). Table 7 summarizes the statistics for the time-lag parameter for $p \in \{1, 2, \dots, 7\}$ over the 673 rolling windows. The modified BIC favors lag $p = 1$, since it recorded the minimum average and median BIC. Thus, the optimal time-lag of dependence among the zones is at most 1 day.

Lag	Min	Max	Median	Mean	SDev
p=1	2059.18	4800.84	3226.41	**3298.67**	558.81
p=2	2097.43	4852.13	3291.42	3361.67	543.26
p=3	2126.35	4897.97	3382.17	3435.00	541.85
p=4	2148.49	4940.40	3448.04	3484.96	538.30
p=5	2249.80	5015.45	3545.37	3559.14	527.68
p=6	2236.92	5054.32	3482.44	3546.51	580.38
p=7	2300.54	5082.37	3540.47	3592.62	538.04

Table 7: Distribution of the time-lag parameter of dependence among zones in the period 2010-2016.

Using the estimated time-lag parameter, we analyze the inter-day network by investigating the years between 2010-2016. VAR(Y) represents the lagged multivariate model for log price volatilities. Figure 9 shows the yearly inter-day volatility network among the zones in 2010-2016.

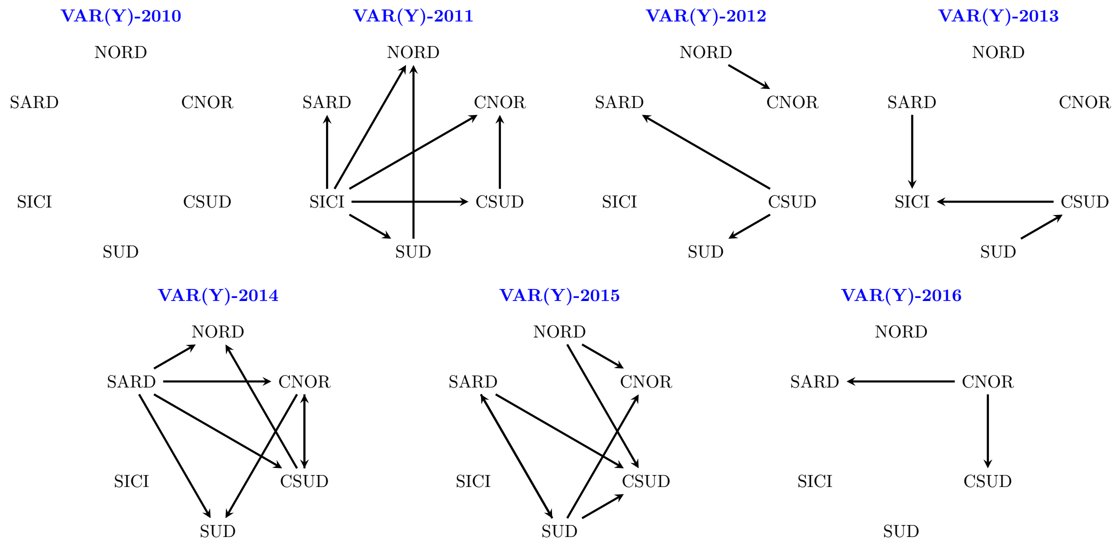

Figure 9: Inter-day networks among Italian zonal energy markets for sub-years from 2010 to 2016.

The 2011 and 2014 networks in the figure show Sicily and Sardinia as highly connected with outgoing links, whilst the 2015 network shows Central South as highly connected with incoming links. Figure 10 shows a plot of the network density for each year. The densest networks were in 2014, followed by 2011 and 2015.

Table 8 shows the ranking of the zones in the inter-day networks based on in/out-degree measures. For out-degree, there are different top ranked zones for each of the years between 2010-2016 with Central South dominating in 2012 and 2013. For in-degree, the North dominates in three years (2010, 2011, 2014) whilst Central South is highly ranked in 2015 and 2016. In both the in- and out-degree ranking, Sicily is lowest and Sardinia second lowest.

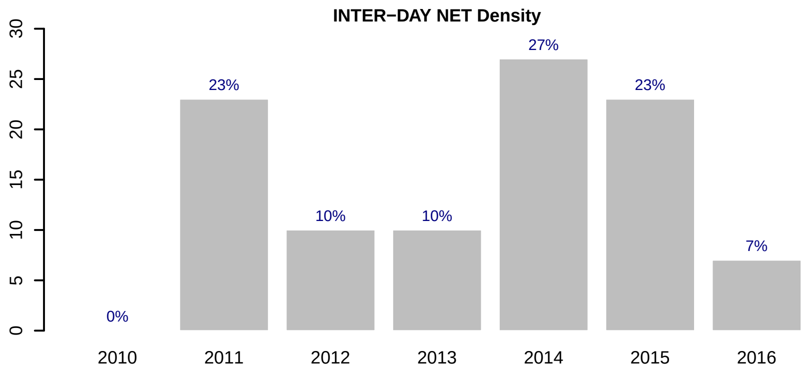

Figure 10: inter-day networks among Italian zonal energy markets for sub-years from 2010 to 2016.

Rank	2010	2011	2012	2013	2014	2015	2016
				Out-Degree			
1	NORD	SIC	CSUD	CSUD	SARD	SUD	CNOR
2	CNOR	CSUD	NORD	SUD	CNOR	NORD	NORD
3	CSUD	SUD	CNOR	SARD	CSUD	SARD	CSUD
4	SUD	NORD	SUD	NORD	NORD	CNOR	SUD
5	SARD	CNOR	SARD	CNOR	SUD	CSUD	SARD
6	SIC	SARD	SIC	SIC	SIC	SIC	SIC
				In-Degree			
1	NORD	NORD	CNOR	SIC	NORD	CSUD	CSUD
2	CNOR	CNOR	SUD	CSUD	CNOR	CNOR	SARD
3	CSUD	CSUD	SARD	NORD	CSUD	SUD	NORD
4	SUD	SUD	NORD	CNOR	SUD	SARD	CNOR
5	SARD	SARD	CSUD	SUD	SARD	NORD	SUD
6	SIC	SIC	SIC	SARD	SIC	SIC	SIC

Table 8: Ranking of zones based on out/in-degree in inter-day volatility connections.

Comparing inter-day Network Models

Comparing inter-day network models, we analyze the rolling-window inter-day volatility connectedness over the sample period by comparing networks estimated from VAR(Y) with models that include exogenous variables, i.e., VAR(Y|W) and VAR(Y|W,D). VAR(Y|W) and VAR(Y|W,D) are estimated by incorporating covariates like forecast wind generation and forecast demand. In this paradigm, we estimate the rolling-window network for all three models between March 2014 and December 2016, which enables us to investigate the impact of the penetration of renewable energy sources (in our case wind) on inter-day volatility connectivity between the zones of the market in the last three years (2014-2016) of the sample. As for the intraday models, we analyze the dynamics in inter-day zonal volatility connectedness by considering a yearly (365 days) rolling window. One rolling window estimation goes from March 1, 2014 - February 28, 2015 and the other from January 2, 2016 - to December 31, 2016. Table 9 shows the averaged inter-day network matrix for competing models over all the rolling windows. The top panel represents the average matrix for VAR(Y), the middle panel is VAR(Y|W) and the bottom panel is VAR(Y|W,D). Again, the column labels represent the explanatory variables and the row labels the dependent variables. Columns FWG and FD are forecast wind generation and forecast demand for each specific zone.

Zones	NORD	CNOR	CSUD	SUD	SARD	SIC	FWG	FD
	VAR(Y)							
NORD	**1**	0	0.12	0.22	0.18	0.22		
CNOR	**0.55**	**0.51**	0.24	**0.54**	0.33	0.21		
CSUD	0.43	0.47	0.36	**0.55**	0.48	0.23		
SUD	0.03	0.36	0.09	**0.78**	0.41	0.32		
SARD	0.19	0.21	0.13	**0.53**	**0.59**	0.43		
SIC	0.07	0	0	0.14	0.21	**1**		
	VAR(Y|W)							
NORD	**1**	0.03	0.15	0.34	0.18	0.25	0.05	
CNOR	**0.60**	**0.52**	0.29	**0.56**	0.40	0.22	0.11	
CSUD	**0.54**	**0.51**	0.47	**0.60**	**0.51**	0.26	0.09	
SUD	0.07	0.38	0.13	**0.82**	0.48	0.38	0	
SARD	0.36	0.24	0.23	**0.60**	**0.64**	0.44	0	
SIC	0.08	0	0	0.14	0.23	**1**	**0.55**	
	VAR(Y|W, D)							
NORD	**1**	0.05	0.17	**0.51**	0.18	0.30	0.06	**0.78**
CNOR	**0.61**	**0.53**	0.39	**0.58**	0.45	0.23	0.13	0.33
CSUD	**0.54**	**0.51**	**0.66**	**0.61**	**0.54**	0.27	0.11	0.17
SUD	0.11	0.39	0.15	**0.84**	**0.50**	0.36	0.01	0.11
SARD	0.41	0.27	0.39	**0.60**	**0.65**	0.46	0	0
SIC	0.10	0	0	0.15	0.22	**1**	**0.56**	0.15

Table 9: Inter-day average network matrix. The arrows are directed from column labels to row labels. FWG: Forecast Wind Generation specific for each zone; FD: Forecast Demand specific for each zone. Boldface indicates the most central zone for each metric.

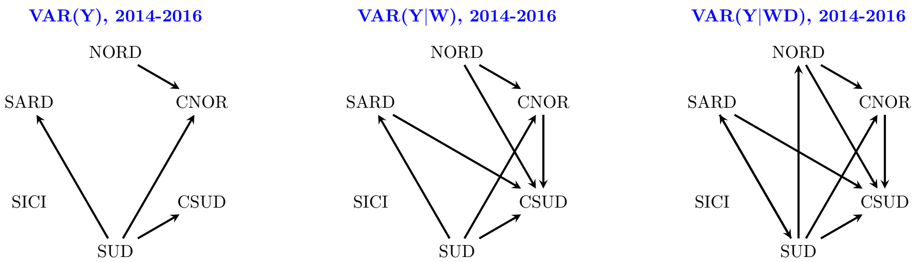

Figure 11: Inter-day average threshold networks.

From the table, it is evident that there are strong and persistent autoregressive effects (self-loop) in most of the zones with the exception of Central South. The autoregressive effect for Central South becomes significant only when conditioned on both forecast wind and demand (see, lower panel of Table 9). In terms of cross-lag connections, North affects Central North in the VAR(Y) model. The effect of North and Central North on Central South only persists when the VAR model is conditioned on forecast wind and demand. South has a persistent lagged effect on other zones except North and Sicily. The effect of South on North changes when conditioned on forecast wind and demand. Sardinia, on the other hand, had a fairly persistent lagged effect on Central South and South when forecast wind and demand are taken into account. Figure 11 shows the network structure of competing models when the average network matrix has a threshold of 0.5. In the three networks, the strongest links among the three models are NORD → CNOR, SUD → (SARD, CNOR, CSUD).

Rank	VAR(Y)		VAR(Y|W)		VAR(Y|W,D)	
	Hub Centrality					
1	SUD	(1)	SUD	(1)	SUD	(1)
2	NORD	(0.41)	NORD	(0.82)	NORD	(0.68)
3	CNOR	(0)	CNOR	(0.50)	SARD	(0.49)
4	CSUD	(0)	SARD	(0.50)	CNOR	(0.41)
5	SARD	(0)	CSUD	(0)	CSUD	(0)
6	SIC	(0)	SIC	(0)	SIC	(0)
	Authority Centrality					
1	CNOR	(1)	CSUD	(1)	CSUD	(1)
2	CSUD	(0.71)	CNOR	(0.65)	CNOR	(0.65)
3	SARD	(0.71)	SARD	(0.35)	NORD	(0.39)
4	SUD	(0)	SUD	(0)	SARD	(0.39)
5	NORD	(0)	NORD	(0)	SUD	(0.19)
6	SIC	(0)	SIC	(0)	SIC	(0)

Table 10: Ranking betweenness, Hub and Authority centrality for the intraday zonal power market network. Boldface indicates the most central zone for each metric.

The centrality of the average threshold inter-day network of the three models is shown over the sample period. Table 10 shows the ranking of the zones based on hub and authority centrality metrics. The South is the highest ranked zone in terms of hub centrality, i.e., it plays an influential role (source) in inter-day risk transmission. For authority centrality, Central North ranks highest in the VAR(Y) but is second highest in relation to Central South when account is taken of the impact of the penetration of renewable energy sources on volatility connectivity between the zones of the market.

5.5. Comparing Model Performance

With regard to the model performance, we compare the explanatory power of the estimated intraday and inter-day network models by employing the network BIC to analyze the contributions of the penetration of renewable energy sources.

	Min	Max	Median	Mean	Stdev
		intraday Network BIC			
SEM(Y)	2441.90	3839.68	3026.53	**3116.20**	356.49
SEM(Y|W)	2480.59	3897.87	3055.41	3150.69	367.67
SEM(Y|W,D)	2504.45	3937.89	3081.67	3197.81	379.08
		inter-day Network BIC			
VAR(Y)	2059.18	3286.31	2705.85	**2705.82**	265.39
VAR(Y|W)	2129.19	3326.76	2744.60	2746.28	262.73
VAR(Y|W,D)	2175.47	3393.37	2784.39	2805.83	278.11

Table 11: Summary Statistics of network BIC.

Figure 12 shows the time series of the network BIC for intraday and inter-day models. The plots show similar performance for the competing models. Table 11 summarizes statistics for the network BIC. On average, the SEM(Y) and VAR(Y) models record the minimum BICs,

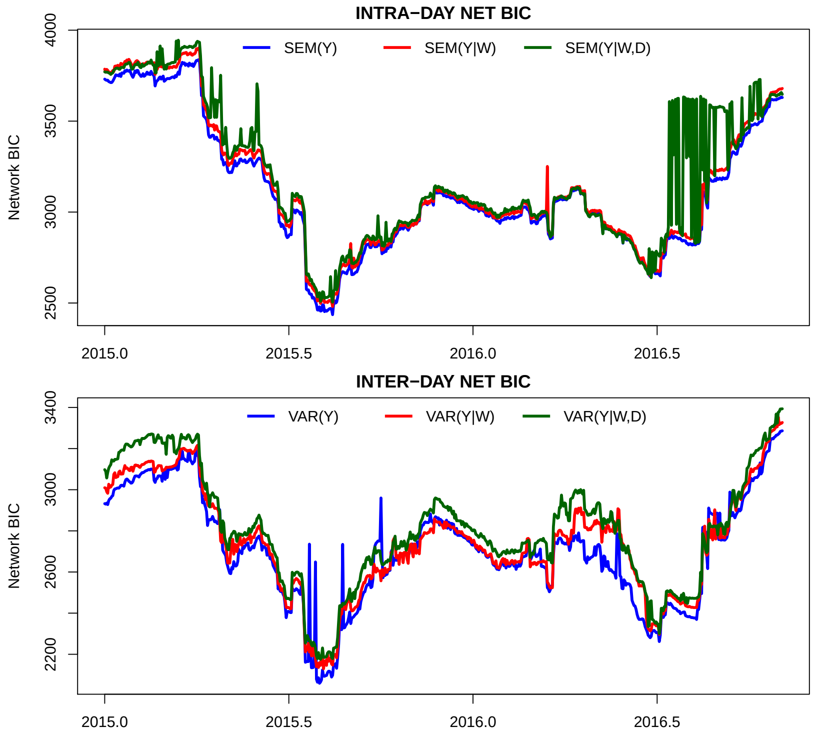

Figure 12: Time series plot of the network BIC.

which indicates that both models perform well accurately capturing the intraday and inter-day volatility linkages in the Italian zonal electricity market. Although the penetration of renewable sources helps explaining the volatility dynamics in some zones, the models with these variables are outperformed by the models without exogenous variables.

6. Conclusions

This paper innovatively and successfully uses the Bayesian graphical model to investigate risk propagation in the Italian electricity market, accounting for volatility interconnections between the physical zones in the electricity market. Our analysis provides a better understanding of and insight into the spread of risk among different zones in the market. For instance, imbalances of energy supply and demand due to operational failures, congestion and other causes of shocks such as the penetration of more renewables in these interconnections are likely to affect the stability and efficiency of the energy supply. In view of this, our framework includes two cases: modeling interdependencies with exogenous variables (forecast demand of electricity and forecast wind generation), and (ii) modeling interdependencies without exogenous variables. All in all, the modeling without exogenous variables via the graphical network model provides a better network structure based on network Bayesian information criteria. The fact that exogenous variables play no significant role in influencing the direction and spread of risks confirms the results of Bigerna et al. (2017), who empirically show that no changes occur in the interdependence mechanism. The NORD zone suffers no contagion effects due to the development of renewable energy sources in Italy.

These findings show that CNOR plays a dominant role in the spread of risk among the various interconnections in the period 2014-2016, whilst CSUD helps to mitigate risk propagation between the zones in the market by highlighting the various risk network structures present in the zones of the market. Indeed, this indicates that network analysis and its application to systemic risk is promising, providing a platform to meet current and future challenges and solutions to the problems of society and emerging risk. It may also indicate when a crisis is at its peak and when it ends. For instance, linkages between the spread of systemic risk in energy systems and the penetration of more renewable energy sources are extremely relevant, especially in an effort to create of a single European power market incorporating bidding zones.

Furthermore, these findings are relevant for policymakers because they provide a unique way of visualizing and quantifying the extent of exposure to risk and the spread of systemic risk in the zonal market. They also establish a platform for identifying the spread of systemic risk providing a support mechanism for the design of optimal environmental and energy policies by prudently including early warning and local investment signals. It is also useful for risk managers and other practitioners in their efforts to anticipate and prepare for a crisis in the electricity market as well as other commodity markets, increasing the resilience of the electricity market. Finally, given this amount of information, market participants are able to take prudent decisions in their trading and dealings in the zonal power market. In this light, our analysis could be extended to modeling other segmented commodity markets. however, it is not without shortcomings, which mostly lie in the lack of information on other sources of shock such as the increase in the penetration of renewable energy sources over the years. With more available data the analysis could be extended to accommodate calendar effects and their impacts and hence, provide a benchmark for future research.

References

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015). Systemic Risk and Stability in Financial Networks. *American Economic Review 105*(2), 564–608.

Ahelegbey, D. F. (2016). The Econometrics of Bayesian Graphical Models: A Review With Financial Application. *Journal of Network Theory in Finance 2*(2), 1–33.

Ahelegbey, D. F., M. Billio, and R. Casarin (2016a). Bayesian Graphical Models for Structural Vector Autoregressive Processes. *Journal of Applied Econometrics 31*(2), 357–386.

Ahelegbey, D. F., M. Billio, and R. Casarin (2016b). Sparse Graphical Vector Autoregression: A Bayesian Approach. *Annals of Economics and Statistics 123/124*, 333–361.

Ahelegbey, D. F. and P. Giudici (2014). Bayesian Selection of Systemic Risk Networks. *Advances in Econometrics: Bayesian Model Comparison 34*, 117–153.

Bigerna, S. and C. A. Bollino (2016). Ramsey Prices in the Italian Electricity Market. *Energy Policy 88*, 603–612.

Bigerna, S., C. A. Bollino, D. Ciferri, and P. Polinori (2017). Renewables diffusion and contagion effect in italian regional electricity markets: Assessment and policy implications. *Renewable and Sustainable Energy Reviews 68*, 199–211.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon (2012). Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors. *Journal of Financial Economics 104*(3), 535 – 559.

Boffa, F., V. Pingali, and D. Vannoni (2010). Increasing Market Interconnection: An Analysis of the Italian Electricity Spot Market. *International Journal of Industrial Organization 28*(3), 311–322.

Bollino, C. A., D. Ciferri, and P. Polinori (2012). Contagion in Electricity Markets: Empirical Evidences from Italian Markets. In *Electricity Markets and Reforms in Europe (Uvalic M., Ed.)*, pp. 49–59. FrancoAngeli.

Cappers, P., J. MacDonald, C. Goldman, and O. Ma (2013). An Assessment of Market and Policy Barriers for Demand Response Providing Ancillary Services in US Electricity Markets. *Energy Policy 62*, 1031–1039.

Creti, A. and F. Fontini (2019). *Economics of Electricity: Markets, Competition and Rules.* Cambridge University Press.

Creti, A., E. Fumagalli, and E. Fumagalli (2010). Integration of Electricity Markets in Europe: Relevant Issues for Italy. *Energy Policy 38*(11), 6966–6976.

Diebold, F. and K. Yilmaz (2014). On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms. *Journal of Econometrics 182*(1), 119–134.

Elliott, M., B. Golub, and M. O. Jackson (2014). Financial Networks and Contagion. *American Economic Review 104*(10), 3115–3153.

Fianu, E. S. (2015). Portfolio Optimization in Zonal Energy Markets: Evidence from Italy. *International Journal of Energy and Statistics 3*(2), 1550006.

Geiger, D. and D. Heckerman (2002). Parameter Priors for Directed Acyclic Graphical Models and the Characterization of Several Probability Distributions. *Annals of Statistics 30*(5), 1412–1440.

Glasserman, P. and H. P. Young (2016). Contagion in Financial Networks. *Journal of Economic Literature 54*(3), 779–831.

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica 37*(3), 424–438.

Ignatieva, K. and S. Trueck (2016). Modeling spot price dependence in australian electricity markets with applications to risk management. *Computers & Operations Research 66*, 415 – 433.

Klos, M., K. Wawrzyniak, and M. Jakubek (2015). Decomposition of Power Flow Used for Optimizing Zonal Configurations of Energy Market. In *European Energy Market, 2015 International Conference*, pp. 1–5. IEEE.

Lamadrid, A. J. and T. Mount (2012). Ancillary Services in Systems with High Penetrations of Renewable Energy Sources, The Case of Ramping. *Energy Economics 34*(6), 1959–1971.

Lautier, D. and F. Raynaud (2012). Systemic Risk in Energy Derivative Markets: A Graph-Theory Analysis. *Energy Journal 33*(6), 215–239.

Martens, M. and D. Van Dijk (2007). Measuring Volatility with the Realized Range. *Journal of Econometrics 138*(1), 181–207.

Phan, S. and F. Roques (2015). Is the Depressive Effect of Renewables on Power Prices Contagious? A Cross Border Econometric Analysis. Working Paper 1527, Faculty of Economics, University of Cambridge.

Pierret, D. (2013). The Systemic Risk of Energy Markets. Working paper, Université Catholique de Louvain, Center for Operations Research and Econometrics (CORE).

Sapio, A. and N. Spagnolo (2018). Volatility import effects of a new cable linking sardinia with mainland italy. *in conference proceedings; Energy Finance conference*.

Schwartz, D. L. (2012). *The Energy Regulation and Markets Review*. The Law Business Research Limited.

Appendix A. Network Analysis

This section briefly describes the network analysis measures considered in the paper.

Network Density

The density of a network measures the number of estimated links in the network divided by the total number of possible links. For n number of zones and given that out estimate network is a directed network, there are $n(n-1)$ possible links (without self-loops). Standard applications indicate that the higher the network density, the higher the degree of interconnectedness of the markets. Denser networks have been shown to provide risk sharing mechanisms among institutions as well as shock propagation and spill-over into markets (Acemoglu et al., 2015; Elliott et al., 2014; Glasserman and Young, 2016).

In/Out-Degree

The concept of in/out-degree in network analysis is crucial to understand the most connected zone in terms of risk transmission. The *In-degree* of say zone$_i$ measures the total number of links directed toward zone$_i$, while the *Out-degree* measures the total number of links from zone$_i$ to the others. The higher the out-degree (in-degree), the higher the influence (vulnerability) of a zone in the network.

Link Stability

We conduct a stability analysis to investigate the survival/persistence of links in the estimated networks. This is carried out by averaging the estimated network over the rolling windows which produces a weighted adjacency matrix where the weights represent probabilities. In this application, we threshold the average network matrix by considering a link to be stable (or persistent) when the edge probability is over 0.5.

Node Centrality

In network analysis, node centrality measures the importance of a node in the network. In our analysis, we focus on two main centrality measures, i.e., hub and authority. Hub and authority centrality distinguishes between prominent senders and receivers of risk in the zonal volatility network. These centrality measures assign a score to each zone in a way that is proportional to the scores for importance of neighbors. Given an adjacency matrix A where links are directed from column to row labels, the hub and authority score require the following problem to be solved:

$$(A'A)\ h_v = \lambda_h h_v, \qquad\qquad (AA')\ a_v = \lambda_a a_v, \tag{A.1}$$

where h_v and a_v are the hub score and authority score vectors, respectively, and λ_h and λ_a are the largest eigenvalue of $A'A$ and AA', respectively. A zone with a high hub score is well connected and a prominent sender of risk in the network, whereas a zone with a high authority score is heavily dependent on the hub and very vulnerable in the case of a negative shock on hub counterparties.