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## Method Article

# Risk management via contemporaneous and temporal dependence structures with applications



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## A B S T R A C T

This paper presents the estimation methods of the Bayesian Graphical Vector Auto-regression with and without innovations such as external regressors (BG-VAR(X)) and Bayesian Graphical Systems Equation Modelling with and without exogenous variables (BG-SEM(X)), which are developed to examine risk network structures embedded in multivariate time series. This methodical approach allows for the analysis of various dynamics and persistence in the multivariate time series in terms of risk propagation. For instance, both the BG-SEM(X) and BG-VAR(X) can reveal the within-day and across-day major risk transmitters as well as risk recipients from other univariate time series, which better explain risk contagion using complex network models. In addition, the procedures for models with and without exogenous variables have been explored, which shows that the former produce more network structures compared to the latter and therefore depict their influential role. This approach, therefore, provides a platform for future research in terms of extension of the method to encompass different types of multivariate data with additional innovations that might aid feasible analysis and the design of policy instruments and the implementation of relevant policy implications.

- Development and application of innovative network models that enhances the efficient analysis of multivariate time series data.
- Estimation of intra-day and inter-day interconnection from a daily multivariate time series data and their dynamics and persistence from contagion analysis viewpoint.

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## ARTICLE INFO

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Subject area	Economics and Finance
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Method name	Methods for Risk analysis, and Model performance using Bayesian Graphical Network Vector Autoregression with and without Exogenous Variables (BG-VAR(X) ) and Structural Equation Modelling with and without (BG-SEM (X)) coupled with real world applications.
Name and reference of original method	Modelling risk contagion in the Italian zonal electricity market.
Resource availability	Data source: Italian Electricity market data obtained at <a href="http://www.mercatoelettrico.org">www.mercatoelettrico.org</a> Software: R statistical software, MATLAB; Excel; Microsoft word; LATEX Hardware: Computers

## Introduction

The fundamental rationale behind network theory is that essential information, knowledge, data-driven insights and patterns about complex systems can be deduced by examining the underlying network structure. Some of these systems include the following: transportation, financial markets, power grids etc. Network theory, therefore, aids the discovery of hidden structures and provide unique understanding of the interactions between complex structures and their architectural network dynamics. The use of complex networks can therefore help to extract hidden information from various complex systems. From the viewpoint of network science, complex networks can be defined as a collection of nodes connected by edges that depicts various complex interaction among the nodes. It is worth noting that almost any large system whether natural or physical exhibits some form of interconnections. In terms of the energy market, one could think of, for instance, grid lines and their interconnections, energy prices and their linkages etc. In view of this, [6] use dynamic Granger-causality and network theory to analyze the interactions among 13 European electricity spot prices, by constructing 7651 dynamic multivariate networks, where the nodes correspond to different EU countries and the links weight the Granger-causality between the variations of the respective electricity prices. Other related works include: [14,16,19,20] and many more. Furthermore, accounting for linkages in electricity market zones that are rich in intermittent renewable energy sources, [15] explore volatility transmission patterns using VAR-GARCH estimation approach given ex-ante and ex-post the inauguration of a new cable. Specifically, the SAPEI cable offers two cyclical perspectives. On the one hand, it is able to accommodate stronger volatility transmissions towards Sardinia in the off-peak periods. On the other hand, it shows no significant transmissions during peak-load periods. However, this paper proposes and exploits risk network structures inherent in the Italian energy market by estimating the within-day and across-day market connections using a multivariate time series of hourly prices. Some recent papers that focus on the volatility spillover patterns include: [8,12,18,21] among many others.

In consequence, various network measures, such as network density, centrality of networks, etc. have been investigated to ascertain risk propagation in the market. Our findings are relevant for market participants such as policymakers, traders, investors and regulators to guard against sudden systemic failures, which can negatively have impact on many businesses and economies because of the significant socio-economic role played by energy in the global economy. Some related recent papers on systemic risk include the following: [2,4,5,7,9], 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<sup>1</sup>.

This paper, therefore, contributes to various strands of methodological literature. First, we develop and employ an innovative Bayesian graphical network model that enhances and improves analysis of market interconnections using vector autoregression and system equation modeling with external regressors; BG-VARX and BG-SEMEX respectively. As a result, we provide both the within-day and across-day daily time series interconnection analysis, thereby exploring various risk network structures. On the other hand, we study the persistence of the interconnectedness in multivariate time series data. Finally, we examine the various risk network structures to identify and quantify individual univariate time series that play dominant role as well as those that are vulnerable to the spread of risk, for instance, among the multivariate time series data, thereby providing a unique understanding of risk management practices. Overall, modeling framework, details a methodology that is effective in designing policy and making actionable data-driven decision and thus applicable to risk management practices in various sector of the economy such as the financial markets, commodity markets, insurance markets, among many others.

## Method details

This section provides an overview of the model and estimation procedure adopted in this paper to analyze interdependencies in multivariate financial time series data. These interdependencies can be decoupled and broken down into two underlying network structure-inferred typologies: an intra-day (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. The intra-day and inter-day dependencies from multivariate time series are modeled using a simultaneous equation (SEM) and a vector autoregressive model (VAR). However, the aforementioned models also provide the possibility to incorporate exogenous variables; see [9] for further details. The subsequent sections discuss the modeling framework.

## Bayesian graphical network model estimation

In this section, we present the Bayesian graphical framework of multivariate analysis. The procedure for Bayesian Graphical Vector Autoregression and Bayesian Graphical Structural Equation modeling framework constitutes a special case of the [equation \(1\)](#). This implies that both methods can be represented by a system of equations framework given by:

$$Y_t = BX_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon) \quad (1)$$

where  $B = (B_{y|y}, B_{y|z})$ ,  $X_t = (Y'_t, Z'_t)'$  and  $\Sigma_\varepsilon = \Sigma_u$  in the case of the intra-day model; and  $B = (A_{1,y|y}, \dots, A_{p,y|y}, A_{y|z})$ ,  $X_t = (Y'_{t-1}, \dots, Y'_{t-p}, Z'_t)'$  and  $\Sigma_\varepsilon = \Sigma_v$  in the case of the inter-day model. The objective of the BG-SEMEX is to estimate  $(B_{y|y}, B_{y|z}, \Sigma_u)$ , while that of BG-VARX is to estimate  $(p, A_{y|y}, A_{y|z}, \Sigma_v)$  using the available data.

### Network models

Complex network analysis can be recognized as a tool for mining technological, social and financial data, among many others. The multiplexity of different network structures, if accurately inferred and elicited, can help provide unique understanding and insights into various naturally existing and man-made networks. As such, the introduction of networks in a typical multivariate multiple regressions model helps to interpret the relationships in the model. In the formalization of this representation, [equations \(1\)](#) can be specified from the viewpoint of networks by assigning to each coefficient  $B_{ij}$  a

<sup>1</sup> See [1] for a review of the state of the art for statistical inference and the application of network analysis to financial time series.

latent variable including indicator  $G_{ij} \in \{0, 1\}$ , such that for  $i, j = 1, \dots, n$ , we have the following:

$$B_{ij} = \begin{cases} 0 & \text{if } G_{ij} = 0 \Rightarrow Y_j \not\rightarrow Y_i \\ b_{ij} \in \mathbb{R} & \text{if } G_{ij} = 1 \Rightarrow Y_j \rightarrow Y_i \end{cases} \quad (2)$$

where  $Y_j \not\rightarrow Y_i$  means that  $Y_j$  does not influence  $Y_i$ . Modeling from the perspective of [equation \(1\)](#) and [equation \(2\)](#), a network model is specified by the parameters  $(G, B, \Sigma_\varepsilon)$ , where  $G$  is related to the latent network structure (often referred to as the adjacency matrix of a network graph).  $B$  denotes the coefficients, and  $\Sigma_\varepsilon$  is the residual covariance matrix.

*Prior specification*

The joint estimation of the BG-SEMIX and BG-VARX or the simplified regression model in [equation \(1\)](#) is a challenging and computationally expensive problem. To this extent, the Bayesian formulation with prior specification and posterior approximation for the inference of the model parameters are carried out by specifying the prior distributions as follows:

$$[B_{ij}|G_{ij} = 1] \sim \mathcal{N}(0, \eta), \quad G_{ij} \sim \text{Ber}(\pi_{ij}), \quad \Sigma_\varepsilon^2 \sim \mathcal{W}(\delta, \Lambda_0)$$

where  $\eta, \pi_{ij}, \delta$ , and  $\Lambda_0$  are hyper-parameters. The specification for  $B_{ij}$  conditioned on  $G_{ij}$  follows a normal distribution with zero mean and variance  $\eta$ . Therefore, the relevant explanatory variables with significant information to predict a response variable are associated with coefficients different from zero and the rest (representing not-relevant variables) are restricted to zero. We consider  $G_{ij}$  as Bernoulli distributed with  $\pi_{ij}$  as the prior probability. Closely related to our specification for  $B$  and  $G$ , is the stochastic search variables selection [[SSVS, 11](#)] that assumes an indicator matrix underlying  $B$  and employs the spike and slab prior on the elements in  $B$  [see also [13](#)]. The SSVS and the Bayesian graphical VAR [[BGVAR, 3](#)] have proven efficient in selecting relevant variables in over-parameterized VAR models. The difference between the two methods is that the estimated SSVS coefficient matrix often consists of elements with values significantly different from zero, whereas the rest concentrate around zero but are not ignored. Parsimony is, therefore, not guaranteed.

Finally, we assume  $\Sigma_\varepsilon^{-1}$  is Wishart distributed with prior expectation  $\frac{1}{\delta} \Lambda_0$  and  $\delta > n$  as the degrees of freedom parameter.

*Posterior approximation*

Let  $Y_t$  be the vector of log volatilities of the zones and  $X_t$  the vector of explanatory variables at time  $t$ . In addition, let  $Y = (Y_1, \dots, Y_T)$  and  $X = (X_1, \dots, X_T)$  denote a collection of  $Y_t$  and  $X_t$  over a fixed window of length  $T$ . Following the Bayesian framework of [[10](#)], the structural parameters can be integrated out analytically to obtain a marginal likelihood function over the graphs. This allows for the application of an efficient Gibbs sampling algorithm to sample the graph structure and the model parameters in blocks. In order to approximate the graph and parameters posterior distribution, we consider a collapsed Gibbs sampler that proceeds as follows:

1. Sample via a Metropolis-within-Gibbs  $[G|Y, X]$  (see [3.1](#) for an overview)
2. Sample from  $[B, \Sigma_\varepsilon|Y, X]$  by iterating the following steps:
  - (a) Sample  $[B_{i,\pi_i}|Y, X, \hat{G}, \Sigma_\varepsilon] \sim \mathcal{N}(\hat{B}_{i,\pi_i}, Q_{\pi_i})$  where

$$\hat{B}_{i,\pi_i} = \sigma_{\varepsilon,i}^{-2} Q_{\pi_i} X'_{\pi_i} Y_i, \quad Q_{\pi_i} = (\eta^{-1} I_{d_x} + \sigma_{\varepsilon,i}^{-2} X'_{\pi_i} X_{\pi_i})^{-1} \quad (3)$$

where  $X_{\pi_i} \in X$  is the set of predictors of  $Y_i$  that corresponds to  $(\hat{G}_{y_i, x_{\pi_i}} = 1)$ ,  $\sigma_{\varepsilon,i}^2$  is the  $i$ -th diagonal element of  $\hat{\Sigma}_\varepsilon$ , and  $d_x$  is the number of covariates in  $X_{\pi_i}$ .

- (b) Sample  $[\Sigma_\varepsilon^{-1}|Y, X, \hat{G}, B] \sim \mathcal{W}(\delta + N, \Lambda_T)$  where

$$\Lambda_T = \Lambda_0 + (Y - X\hat{B})'(Y - X\hat{B}) \quad (4)$$

For further details concerning the network sampling algorithm and convergence diagnostics, refer to [3.1](#) for an overview.

**Lasso regularization method**

We apply the Lasso regularization method by [17] as a benchmark model for our empirical analysis. This approach estimates the coefficients of (1) by solving:

$$\hat{B}_{ij} = \min_{B_{ij}} \left\{ \sum_{t=1}^T \left( Y_{i,t} - \sum_{j=1}^q B_{ij} X_{j,t} \right)^2 + \lambda \sum_{j=1}^q |B_{ij}| \right\} \tag{5}$$

where  $T$  is the number of observations,  $q$  the number of covariates, and  $\lambda$  is the penalty term, such that large values of  $\lambda$  shrinks a large number of the coefficients towards zero. In the empirical analysis, we select the regularization parameter using ten-fold cross-validation on a grid of  $\lambda$  values for the penalized logistic regression problem. We select the regularization parameter that corresponds to one standard error from the minimum mean square cross-validated errors, i.e.,  $\lambda.1se$ .

**Network sampling algorithms**

The Bayesian inference of a network graph underlying a system of linear equations is made feasible by integrating out other parameters analytically to obtain a marginal likelihood function over graphs [see 2,10]. Let  $V_y = (y_1, \dots, y_n)$  be the vector of indices of response variables, and  $V_x = (x_1, \dots, x_q)$  the indices of the predictor variables in  $X$ . The network relationship from  $x_{\psi} \in V_x$  to  $y_i \in V_y$  can be represented by  $(G_{y_i, x_{\psi}} = 1)$ . Following [10], the closed-form expression of the local marginal likelihood is given by

$$P(Y|G_{y_i, x_{\psi}}) = \frac{\pi^{-\frac{1}{2}N} \nu_0^{\frac{1}{2}\nu_0} \Gamma\left(\frac{\nu_0 + N - n_r}{2}\right)}{\nu_n^{\frac{1}{2}\nu_n} \Gamma\left(\frac{\nu_0 - n_r}{2}\right)} \left( \frac{|X'_{\psi} X_{\psi} + \nu_0 I_{n_{\psi}}|}{|R'_i R_i + \nu_0 I_{n_r}|} \right)^{\frac{1}{2}\nu_n} \tag{6}$$

where  $\Gamma(\cdot)$  is the gamma function,  $R_i = (Y_i, X_{\psi})$ ,  $I_d$  is a  $d$ -dimensional identity matrix,  $n_{\psi}$  is the number of covariates in  $X_{\psi}$ ,  $n_r = n_{\psi} + 1$ . In addition,  $\nu_0 > n_r$  is a degree of freedom hyper-parameter of the prior precision matrix of  $(Y, X)$ , and  $\nu_n = \nu_0 + N$ . Equation (6) shows that only the ratio of the posterior sum of squares depends on the data. Thus, we reduce computational time by pre-computing the part of equation (6) that is independent of the data, for different values of  $n_r \in [1, m]$  and for fixed  $\nu_0 = m + 2$  and  $N$ . We also pre-compute the posterior of the full sum of squares matrix and extract the sub-matrices that relate to  $\{X_{\psi}\}$  and  $\{(Y_i, X_{\psi})\}$ . For computational details of the score function [see 2].

The algorithm presented for sampling  $G$  is a Metropolis-within-Gibbs sampler with random walk proposal distribution. In the Monte Carlo Markov chain (MCMC) search algorithms, the space exploration crucially depends on the choice of the starting point of the MCMC chain. Usually, a set of burn-in iterations is conducted to obtain a good starting point. In this application, we adopt an initialization scheme that provides a good starting point for the MCMC algorithm.

**Sampling SEMX network**

Let  $X_t = (Y'_t, Z'_t)'$  be the vector of possible explanation variables for the SEMX model.

1. Initialization: Set  $G^{(0)}$  as  $(n \times n)$  null matrix.
  - Set  $V_y = (y_1, \dots, y_n)$  - vector of indices of response variables in  $Y$
  - Set  $V_x = (x_1, \dots, x_q)$  - vector of indices of predictor variables in  $X$ .
  - Note that  $V_y \subseteq V_x$
2. Iterate  $h = 1, \dots, H$  by performing a local network update
  - Pick at random  $y_i \in V_y$  and set  $G_{y_i}^{(*)} = G_{y_i}^{(h-1)}$  and  $V_{x_i} = V_x \setminus \{y_i\}$ 
    - (a) Randomly draw a candidate explanatory variable  $x_k \sim V_{x_i}$
    - (b) **If**  $G_{y_i, x_k}^{(h-1)} = 0$  and  $G_{x_k, y_i}^{(h-1)} = 1$  **then** Consider a reverse move:  $G_{y_i, x_k}^{(*)} = 1$  and  $G_{x_k, y_i}^{(*)} = 0$  **else** Add/remove edge between  $x_k$  and  $y_i$ :  $G_{y_i, x_k}^{(*)} = 1 - G_{y_i, x_k}^{(h-1)}$
    - (c) **If**  $G^*$  is acyclic **then**
      - (i) Compute  $\log P(Y|G^{(*)}) = \sum_{i=1}^n \log P(Y_i|G_i^{(*)})$

- (ii) Compute  $\phi_i = \exp [ \log P(Y|G^{(*)}) - \log P(Y|G^{(h-1)}) ]$
- (iii) Draw  $u \sim \mathcal{U}(0, 1)$ . **If**  $u < \min\{1, \phi\}$  **then** Set  $G^{(h)} = G^{(*)}$  **else** Set  $G^{(h)} = G^{(h-1)}$
- (d) **else if**  $G^*$  is not acyclic Set  $G^{(h)} = G^{(h-1)}$

**Sampling VARX network**

Let  $X_t = (Y'_{t-1}, \dots, Y'_{t-p}, Z'_t)'$  be the vector of possible explanation variables for the VARX model. Assume  $X_t$  is a  $q$ -dimensional vector. Following standard application, we determine the lag length  $p$  by minimizing the BIC:

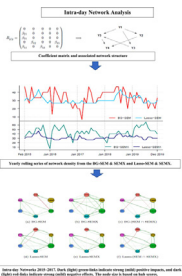
$$BIC(p) = \log |\hat{\Sigma}_{y|x}(p)| + n^2 p \frac{\log M}{M}, \quad \underline{p} \leq p \leq \bar{p} \tag{7}$$

where  $\hat{\Sigma}_{y|x}(p) = \Sigma_{yy} - \Sigma_{yx} \Sigma_{xx}^{-1} \Sigma'_{yx}$ ,  $\Sigma_{yx}$  is the covariance between  $Y$  and  $X$ ,  $M = N - p$  is the number of observations, and  $|\hat{\Sigma}_{y|x}(p)|$  is the determinant of  $\hat{\Sigma}_{y|x}(p)$ . Given some lag length  $\hat{p}$ , we proceed with the VAR network sampling as follows:

1. Initialization: Set  $G_{\hat{p}}^{(1)}$  as  $(n \times q)$  null matrix  
 Set  $V_x = (x_1, \dots, x_q)$  - vector of indices of predictor variables in  $X$   
 Set  $V_y = (y_1, \dots, y_n)$  - vector of indices of response variables in  $Y$   
 For each  $y_i \in V_y$ , compute a reference score:  $Pr(Y|G_{y_i|\hat{p}}^{(1)})$ 
  - (a) For each  $x_j \in V_x$ , compute the marginal score:  $Pr(Y|G_{y_i, x_j}^{(1)})$
  - (b) Compute  $BF = \log Pr(Y|G_{y_i, x_j|\hat{p}}^{(1)}) - \log Pr(Y|G_{y_i|\hat{p}}^{(1)})$
  - (c) **If**  $BF > 0$  **then** set  $G_{y_i, x_j|\hat{p}}^{(1)} = 1$  **else** set  $G_{y_i, x_j|\hat{p}}^{(1)} = 0$
2. Iterate in  $h = 2, \dots, H$  by performing a local network update  
 For each  $y_i \in V_y$ , set  $G_{y_i|\hat{p}}^{(*)} = G_{y_i|\hat{p}}^{(h-1)}$ 
  - (a) Randomly draw a candidate explanatory variable  $x_k \sim V_x$
  - (b) Add/remove edge between  $x_k$  and  $y_i$ :  $G_{y_i, x_k|\hat{p}}^{(*)} = 1 - G_{y_i, x_k|\hat{p}}^{(h-1)}$
  - (c) Compute  $\phi = \exp [ \log P(Y|G_{y_i|\hat{p}}^{(*)}) - \log P(Y|G_{y_i|\hat{p}}^{(h-1)}) ]$  and draw  $u \sim \mathcal{U}(0, 1)$ .
  - (d) **If**  $u < \min\{1, \phi\}$  **then** set  $G_{y_i|\hat{p}}^{(h)} = G_{y_i|\hat{p}}^{(*)}$  **else** set  $G_{y_i|\hat{p}}^{(h)} = G_{y_i|\hat{p}}^{(h-1)}$

**Graphical abstractions of modeling framework**

This section presents the graphical abstract of our modelling framework. In effect, it summarizes some of the stages of our procedures and thus provide a unique understanding for readers with diverse interest. As earlier on mentioned, the network structures are deduced from the adjacency matrix. In our approach, the sub-periods are selected based on the evolution of the network density plots, which depict unique features of peaks and troughs. Furthermore, the network structures are deduced based on these sub-periods for detailed analysis. A graphical display of these procedures are demonstrated below.



## Conclusion

In this paper, methodologies based on network theory and econometrics have been presented. Specifically, we have developed and proposed the BG-VARX and BG-SEM, which are able to account for and accommodate both the intra-day and inter-day analysis, respectively. In the proposed model, multivariate time series data has been utilized to study complex dynamic network structures embedded in the data. The analysis has been achieved using, Microsoft Excel, MATLAB and R software. MATLAB recorded a maximum computational speed of BG-SEM at 9.63 secs; and the of BG-SEM is 12.07 secs; BG-VAR is 2.67 secs; and BG-VARX is 2.80 secs.

On the one hand, for the Lasso method, we observed the following computational speed using MATLAB, that is, Lasso-SEM 2.15, Lasso-SEM 3.38, Lasso-VAR 3.89, and for Lasso-VARX a computation speed of 6.06. These differences in the computational speed for both the BG-VAR(X) and BG-SEM(X) accounts for the constraints used in the Bayesian graphical method. On the other hand, the Lasso-SEM and Lasso-VARX show a relatively higher computational time because of the additional covariates (or exogenous variables) and the self-looping nature of the Lasso method respectively. In this light, both intra-day and inter-day dependencies structures inherent in the data have been examined. For each case, the overall time series have been divided into sub-periods to accommodate short-term variability due to the nature of electricity time series data. The methodologies help to identify major risk transmitters and risk receivers based on the within-day and across-day dependencies, respectively, which is relevant for market participants to effectively and efficiently identify and manage changing trends in the markets with various underlying scenarios.

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## Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.mex.2021.101587](https://doi.org/10.1016/j.mex.2021.101587)

## References

- [1] D.F. Ahelegbey, *The Econometrics of Bayesian Graphical Models: A Review With Financial Application*, *Journal of Network Theory in Finance* 2 (2) (2016) 1–33.
- [2] D.F. Ahelegbey, M. Billio, R. Casarin, *Bayesian graphical models for structural vector autoregressive processes*, *Journal of Applied Econometrics* 31 (2) (2016a) 357–386.
- [3] D.F. Ahelegbey, M. Billio, R. Casarin, *Sparse graphical vector autoregression: A Bayesian approach*, *Annals of Economics and Statistics* 123/124 (2016b) 333–361.
- [4] D.F. Ahelegbey, P. Giudici, *Bayesian Selection of Systemic Risk Networks*, *Advances in Econometrics: Bayesian Model Comparison* 34 (2014) 117–153.
- [5] M. Billio, M. Getmansky, A.W. Lo, L. Pelizzon, *Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors*, *Journal of Financial Economics* 104 (3) (2012) 535–559.
- [6] G. Castagneto-Gissey, M. Chavez, F.D.V. Fallani, *Dynamic granger-causal networks of electricity spot prices: A novel approach to market integration*, *Energy Economics* 44 (2014) 422–432.
- [7] F. Diebold, K. Yilmaz, *On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms*, *Journal of Econometrics* 182 (1) (2014) 119–134.
- [8] S. Farid, G.M. Kayani, M.A. Naeem, S.J.H. Shahzad, *Intraday volatility transmission among precious metals, energy and stocks during the covid-19 pandemic*, *Resources Policy* 72 (2021) 102101.
- [9] E.S. Fianu, D.F. Ahelegbey, L. Grossi, *Modeling risk contagion in the italian zonal electricity market*, *European Journal of Operational Research* (2021).
- [10] D. Geiger, D. Heckerman, *Parameter Priors for Directed Acyclic Graphical Models and the Characterization of Several Probability Distributions*, *Annals of Statistics* 30 (5) (2002) 1412–1440.

- [11] E.I. George, D. Sun, S. Ni, Bayesian Stochastic Search for VAR Model Restrictions, *Journal of Econometrics* 142 (2008) 553–580.
- [12] N.T. Hung, X.V. Vo, Directional spillover effects and time-frequency nexus between oil, gold and stock markets: Evidence from pre and during covid-19 outbreak, *International Review of Financial Analysis* 76 (2021) 101730.
- [13] H. Ishwaran, J.S. Rao, Spike and slab variable selection: Frequentist and bayesian strategies, *Ann. Statist.* 33 (2) (2005) 730–773, doi:10.1214/009053604000001147.
- [14] L. Margaritella, M. Friedrich, S. Smeeke, High-dimensional granger causality for climatic attribution, in: *EGU General Assembly Conference Abstracts*, 2021, pp. EGU21–8020.
- [15] A. Sapio, N. Spagnolo, Volatility import effects of a new cable linking Sardinia with mainland Italy, in *conference proceedings; Energy Finance conference* (2018).
- [16] E. Siggiridou, C. Koutlis, A. Tsimpiris, D. Kugiumtzis, Evaluation of granger causality measures for constructing networks from multivariate time series, *Entropy* 21 (11) (2019) 1080.
- [17] R. Tibshirani, Regression Shrinkage and Selection via the LASSO, *Journal of the Royal Statistical Society. Series B (Methodological)* 58 (1) (1996) 267–288.
- [18] L.H. Vo, T.-H. Le, Eatery, energy, environment and economic system, 1970–2017: Understanding volatility spillover patterns in a global sample, *Energy Economics* (2021) 105391.
- [19] D. Wang, W.-Q. Huang, Forecasting macroeconomy using granger-causality network connectedness, *Applied Economics Letters* 28 (16) (2021) 1363–1370.
- [20] G.-J. Wang, H.-B. Si, Y.-Y. Chen, C. Xie, J. Chevallier, Time domain and frequency domain granger causality networks: Application to china's financial institutions, *Finance Research Letters* 39 (2021) 101662.
- [21] T. Wu, X. Gao, S. An, S. Liu, Time-varying pattern causality inference in global stock markets, *International Review of Financial Analysis* (2021) 101806.