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GLASSO Estimation of Commodity Risks
Stima GLASSO dei Rischi delle Commodities

Beatrice Foroni and Saverio Mazza and Giacomo Morelli and Lea Petrella

Abstract In this paper we apply the Graphical LASSO (GLASSO) procedure to estimate the network of twenty-four commodities divided in energy, agricultural and metal sector. We follow a risk management perspective. We use GARCH and Markov-Switching GARCH classes of models with different specifications for the error terms, and we select those that best estimate Value-at-Risk for each commodity. We achieve GLASSO estimation exploring the precision matrix of the multivariate Gaussian distribution obtained from a Gaussian Copula, with marginals given by the residuals of the models, selected via backtesting procedure. The analysis of interdependences in the resulting network is carried out by using the eigenvector centrality metric.

Abstract *In questo articolo applichiamo la procedura GLASSO per stimare il network di ventiquatto commodities divise nei settori dell'energia, agricoltura e metalli. Seguiamo un approccio di valutazione del rischio. Usiamo modelli GARCH e Markov-Switching GARCH con differenti specificazioni per il termine di errore, scegliendo il modello che meglio stima il Value-at-Risk. Effettuiamo la stima GLASSO analizzando la matrice di precisione di una distribuzione Normale ottenuta a partire da una Copula Gaussiana, le cui marginali sono date dai residui*

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dei modelli selezionati attraverso la procedura di backtesting. L'analisi delle interdipendenze nel network viene effettuata usando la metrica di centralità dell'autovettore.

Key words: Value at Risk, GARCH, Energy Commodities, Gaussian Copula

1 Introduction

Over the last two decades, financial markets have recorded an increase of investments in commodities, a feature known as *financialization of commodities*. In particular, investments in commodity futures have tripled making their prices more vulnerable to fluctuations originated in, e.g., volatility. During stress periods, such price swings together with the strong interconnections of commodity markets create alerts for contagion effects. In this paper, we investigate interdependences among and within twenty-four time series of commodity returns representative of the energy, agriculture and metals sectors. We use GARCH and Markov-Switching GARCH (MSGARCH) models with different error term distributions to forecast the Value-at-Risk (VaR) of each commodity. For a given time horizon t and a confidence level p, the VaR is the loss in market value that is exceeded with probability 1-p thus, evaluating the quality of its estimates is of utmost importance. To do this in the context of risk management, backtesting is the most recognized test procedure. We use three different backtesting methodologies that allow us to quantify the quality of the forecasts from a risk perspective. These are the Unconditional Coverage (UC) test of [15], the Conditional Coverage (CC) test of [6] and the Dynamic Quantile (DQ) test of [9]. The residuals of the models, selected through VaR backtesting procedures, are then used as marginals in a Gaussian copula. The Gaussianity achieved allows to exploit Graphical LASSO (GLASSO) estimation of the Gaussian Graphical model in order to identify the underneath co-dependence structure in the network of commodities, where vertices represent the commodities and their dependence is visualized by edges. We carry out the analysis of the network using the eigenvector centrality metric that provides indications on which are the most geographically central and important nodes in the graph. A recent study of within and between interdependences among commodities is in [4]. We differentiate from their analysis in that we operate in a risk management perspective and obtain i) model selection of GARCH and MSGARCH according to backtesting procedures of VaR forecasts and ii) a sparse Gaussian Graphical representation of the commodities achieved via GLASSO estimation. Co-movements in commodity markets are addressed in [7] to examine the relation between Gold and Silver in the metal sector. The seminal paper of [17] detects inter-sectorial co-movements between oil price and metals finding short and long-run equilibrium relationships whereas dependence between oil and agriculture are studied in e.g.,[16].Gold (GC1)[1], Silver (SI1), Palladium (PA1), Copper (HG1), and Zinc (LX1) are representative of the metals sector; WTI Crude

[1] Bloomberg tickers

Oil (CL1), Heating Oil (HO1), Gasoline (XB1), Low Sulfur Gasoline (QS1), Natural Gas (NG1), Natural Gas UK (FN1), and Ethanol (DL1) are representative of the energy sector; Corn (C1), Oats (O1), Rough Rice (RR1), Soybeans (S1), Wheat (W1), Cocoa (CC1), Cotton (CT1), Coffee (KC1), Sugar (SB1), Soybean Oil (BO1), Soybean Meal (SM1), and Orange Juice (JO1) are representative of the agricultural sector. The results show a prevalence of the two-regime models over the single regime ones and Soybean Oil (BO1) for the agriculture sector, Natural Gas (NG1) for energy and Copper (HG1) and Palladium (PA1) for the metal sector seem to be the most central node in the estimated graph. The rest of the paper is organized as follows. In Section 2 we describe the approach and the models used whereas in Section 3 we discuss the main results regarding the model selection, the dependence structure in the Graphical model, the network metrics and conclude.

2 Model Specification

We define y_t the log-return of a financial asset at time t. We follow [14] for the general specification of the MSGARCH model:

$$y_t|(s_t = k, \mathscr{I}_{t-1}) \sim \mathscr{D}(0, h_{k,t}, \xi_k) \tag{1}$$

$$h_{k,t} \equiv \alpha_{k,0} + \alpha_{k,1}\varepsilon_{t-1}^2 + \beta_k h_{k,t-1} \tag{2}$$

where $\mathscr{D}(0, h_{k,t}, \xi_k)$ is a continuous distribution with zero mean, time-varying variance equal to $h_{k,t}$ and additional shape parameters gathered in the vector ξ_k and $\mathscr{F}_{t-1}$ the information set up to time $t-1$. We assume that the latent variable s_t, defined on a discrete space $\{1, \ldots, K\}$, evolves according to an unobserved first order ergodic homogeneous Markov chain with transition probability $\mathbf{P} \equiv \left\{p_{ij}\right\}_{i,j=1}^K$, where $p_{ij} = P[s_t = j|s_{t-1} = i]$. When $k = 1$ we obtain the GARCH(1,1) specification. To ensure positivity of $h_{k,t}$ it is required that $\alpha_{k,0} > 0$, $\alpha_{k,1} > 0$, and $\beta_k \geq 0$. Covariance-stationarity in each regime is obtained by requiring that $\alpha_{k,1} + \beta_k < 1$. For each commodity, we choose the model that best predicts its VaR accurately and replicates the well known stylized facts using backtesting procedures. We use the residuals of the models selected via backtesting procedure as marginal of a Gaussian copula function. This way, the Graphical LASSO (GLASSO) procedure introduced in [11] that relies on the gaussianity assumption can be applied to estimate the sparse inverse covariance matrix $\Omega = K^{-1}$. GLASSO builds on a linear regression model to shrink to zero some coefficient, that results in a maximum likelihood problem using a L_1-norm penalty term. It solves the following problem:

$$\max_{\Omega} \log\det\Omega - tr(\Sigma\Omega) - \rho\left\|\Omega\right\|_1 \tag{3}$$

where tr indicates the trace of the matrix and $\|\Omega\|_1$ the L_1-norm that can be calculated as the sum of the absolute values of the elements of Ω. The parameter ρ controls the size of the penalty and it determines the number of zeros in the sparse precision matrix Ω: a higher (lower) value is responsible for a more (less) sparse matrix. Like most of the shrinking methodologies, to get a reliable selection it is fundamental the right choice of the penalization parameter ρ. We follow [12], in selecting $\rho = \hat{\rho}$ such that $\hat{\rho}$ minimizes the cross-validation estimator of the risk. We use the K-fold cross-validation with $K = 10$, which allows the tuning parameter in the GLASSO to remain persistent. In the following Section we emphasize the fundamental results obtained with the techniques described above.

3 Main Results and Conclusion

We study the returns of three different commodity sectors: agriculture, energy and metals. We estimate the models described in Section 2 for $K = 1$ (i.e. GARCH(1,1) models) and for $K = 2$ (i.e. MSGARCH(1,1) models) where we assume several distributions for the error term in (1) to account for well known stylized facts. In particular we use the standard Normal (”norm”), the Student-t (”std”) and the Generalized Normal (”ged”) distributions, as well as their skewed version (see e.g [3] and [10]) labeled ”snorm”, ”sstd”, and ”sged”, respectively. In Table 1 we show all the models considered for the application. It is worth noting that for the MS-GARCH models we fix $K = 2$ apriori where the two states idendify a low and a high volatility regime. The estimation procedure has been conducted using the maximum likelihood estimation as described in [3]. For each time series, we perform model selection by testing the forecast performance of two specific estimated quantiles, the 95-th and the 99-th, thus offering a risk management perspective of the analysis. Among the models available after the backtesting, we select those that succeeds in at least two out of three tests. We compute network metrics that quantify the position of the nodes in the Gaussian Graphical model obtained. In particular, we focus on the *eigenvector centrality*, which provides indications on which are the most geographically central and important nodes [13]. In a risk management framework, eigenvector centrality is a measure used to capture the capacity of a node (a single commodity) to cause systemic risk, that is, a contagion of risks on other nodes [5]. Table 1 shows the outcome of the backtesting procedure. On the one hand, we observe that there is a considerable prevalence of the Markov-Switching specification in the selected models: 18 selected models present a Markov-Switching specification. This confirms what is pointed out in [2] that is, the two-regime specification better captures the jumps in the dynamic of the volatility in financial returns. On the other hand, we find that there is no prevalence for the asymmetric distributions over the symmetric ones. In Figure 1 we show the graph representation of the adjacency matrix obtained from the estimation of the sparse covariance matrix through the GLASSO algorithm. The dimension of the nodes is proportional to the eigenvector centrality score. According to such metric, we observe the most important nodes in

Commodity sector					
Energy		Metals		Agricolture	
Commodity	Model	Commodity	Model	Commodity	Model
Heating Oil	GARCHged	**Gold**	MSGARCHstd	**Oats**	GARCHsstd
Gasoline	GARCHsged	**Silver**	MSGARCHged	**Wheat**	MSGARCHsged
Low Sulfur Gasolio	GARCHsged	**Copper**	MSGARCHsnorm	**Soybeans**	MSGARCHsnorm
Natural Gas	MSGARCHged	**Palladium**	MSGARCHsstd	**Coffee**	MSGARCHnorm
Ethanol	MSGARCHsstd	**Zinc**	MSGARCHged	**Cocoa**	GARCHsstd
WTI Crude Oil	MSGARCHsstd			**Cotton**	MSGARCHnorm
Natural Gas UK	GARCHsged			**Corn**	MSGARCHged
				Rough Rice	GARCHged
				Sugar	MSGARCHsged
				Soybean Oil	MSGARCHnorm
				Soybean Meal	MSGARCHstd
				Orange Juice	MSGARCHnorm

Table 1 Best models selected

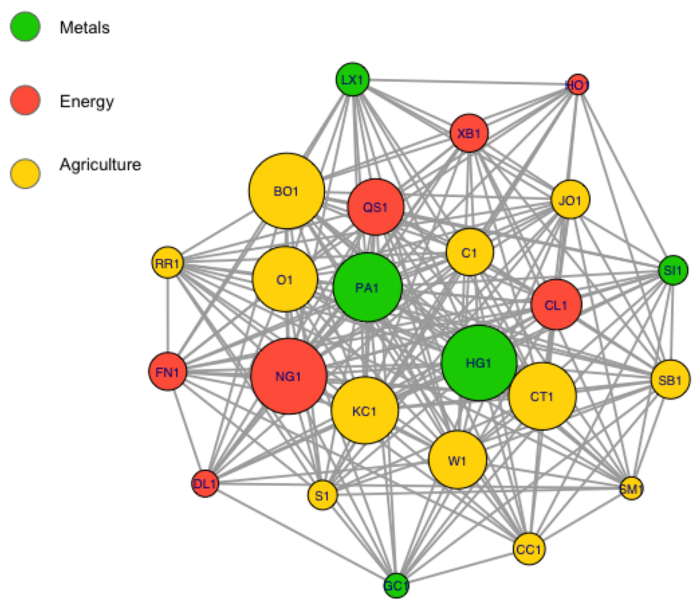

Fig. 1 Graphical model of the commodity futures obtained with GLASSO. The size of the nodes is proportional to their centrality.

the graph: Soybean Oil (BO1) for the agriculture sector, Natural Gas (NG1) for the energy sector and Copper (HG1) and Palladium (PA1) for the metal sector.

Regarding Soybean Oil (B01), the fact that it presents the maximum connection rate with the energy sector can also be found in and [8]; indeed it is known that Biodiesel production in the USA is based predominantly on Soybean Oil, precisely for the 82% [1]. Among the least central commodities we find the Gold (GC1) with a position in the dependence structure that highlights its nature of refuge commodity: showing a marginal role this commodity can be a good investment in anticipation of high volatility periods. Concluding, the application of VaR backtesting procedure for the set of commodity returns studied has allowed to extend the literature on the model selection with GARCH and MSGARCH dynamics, in a risk management framework. The structure of interdependences in the commodity network has been detected in a Gaussian Graphical model. The choice of exploiting network metrics in a risk oriented framework could bring relevant informations both in terms of effects of risk contagion and for improvements of policy formulation in developing and developed countries.

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