Abstract ampliado

RESUMEN AMPLIADO

Extreme risk co-movement in commodity markets: The global oil and food crises (2007-2008)

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Abstract

Commodities play a more and more central role in financial markets. There are currently around fifty major commodity markets where more than a hundred hard and soft primary commodities are traded. Financialization has made purchasing index funds one of the most popular ways to invest on commodities. Consequently, understanding the dynamics of commodity indexes and whether or not they co-move becomes crucial for investors, especially in distress periods, where risk sharply increases. In this short paper, we analyze the downside risk co-movement of a number of primary commodity indexes in a distress period known as the third oil crisis and food crisis, 2007-2008.The reason is that it is a recent distress period where at least two economic sectors were affected. For this purpose, we use the expected shortfall as a measure of downside risk, and multidimensional scaling as a technique to produce low-dimensional financial risk maps easy-to-interpret: indexes co-moving are those closely represented in such a map; the closer they are, the stronger the intensity of co-movement. In our empirical application, we deal with nine monthly commodity index time series for the period corresponding to the global oil and food crisis of 2007-2008: Energy, Metals and minerals, Beverages, Fats and oils, Fertilizers, Grains, Food, Row materials, and Timber. The results obtained are relevant for diversification purpose in the context of portfolio theory.

1. Introduction

There are currently about 50 major commodity markets where around one hundred of hard and soft commodities are traded. Today's commodity markets can be considered as mature and highly developed institutions, playing a very important role in the modern economy (Sieczka and Holyst, 2009).

In this article we focus on one of the open questions in these markets: the co-movement in commodity prices, and more specifically the co-movement in commodity indexes. However, we do not focus on co-movement in mean and/or volatility, as usual in the literature on the topic. We go beyond this point and deal with co-movement in tail or downside risk, which is more interesting for agents participating in commodity markets.

Co-movement (also spill-over processes and contagion) has been usually studied for returns and, less usually, for volatility. However, there exist only a few number of research on co-movement in the tail of the returns distribution (Algieri and Leccadeto, 2017; Pierret, 2013). We contribute to this stream of literature by analyzing the tail risk co-movement in commodity markets. To this purpose, we first estimate the expected shortfall (ES) as a downside risk measure. Then, ES is used as the input of a multidimensional scaling (MDS) procedure to constructing financial downside risk maps. One of the major advantages of this ES-MDS combined procedure is that it provides the representation of the objects under study (in our case ES commodity time series) as points in a map, so that highly correlated objects will be close each other in such a map and objects with a low correlation will be represented with very distant points in the map. To the best of our knowledge, this is the first study attempting to create financial risk maps using MDS. It is of note that this is a very easy-to-interpret technique whose results can serve as an input for further spatial (or spatio-temporal) statistical analysis of tail risk (geostatistics, spatial econometrics, local modelling, point patterns analysis, etc.).

For this purpose, in this short article we deal with nine major world commodity indexes listed in Table 1. More specifically, given the length limit of the short paper, we analyze the downside risk co-movement of such commodity indexes during the third oil crisis and food crisis, 2007-2008, a recent distress period of special interest because it affected more than one economic sector. During this distress period, world food prices increased dramatically in 2007 and the first and second quarter of 2008. Oil price increases also caused general escalations in the costs of fertilizers, food transportation, and industrial agriculture.

Table 1
Commodity indexes and their components.

Name	Index Components	Market
Energy	Coal, crude oil, natural gas	World
Metals and Minerals	Aluminum, copper, iron ore, lead, nickel, tin, zinc	World
Beverages	Cocoa, coffee, tea	World
Fats and Oils	Coconut, groundnut, palm, soybean oils	World
Grains	Barley, maize (corn), rice, wheat	World
Food	Bananas, beef, chicken, oranges, sugar	World
Timber	Tropical hard logs and sawn wood	World
Raw Materials	Cotton, rubber, tobacco	World
Fertilizers	Phosphates, potassium, nitrogenous products	World

[Aquí Table 1]

The remainder of the paper is organized as follows. Section 2 addresses methodological questions. Specifically, section 2.1 states the downside risk measure considered and section 2.2 describes our approach to creating financial risk maps using the MDS method. Section 3 presents the main results obtained. Finally, section 4 concludes.

2. Methodology

2.1 Selecting a downside risk measure

In order to create commodity financial risk maps, first, we have to choose an optimal measure of risk. We use ES because it is a coherent risk measure and takes into account extreme negative returns. Moreover, ES is comonotonic additive, robust and elicitable (see Emmer et al., 2013). In addition, the Basel Committee (BCBS, 2013) has also confirmed that ES will replace Value at Risk (VaR) for regulatory capital purposes in the trading book. ES was introduced by Artzner et al. (1999) and under the assumption of Student's t distributed losses, ES is calculated as:

$$ES_{\alpha,t} = \sqrt{\frac{v-2}{v}}\sigma_t \frac{g_v(\tau^{-1}_{\alpha,v})}{1-\alpha}\left(\frac{v+\left(\tau^{-1}_{\alpha,v}\right)^2}{v-1}\right), \tag{1}$$

where v is the degrees of freedom; g_v is the density function of the standardized t distribution and t −1 α,v is the α-quantile of such distribution. We use the parametric GJRGARCH (p,r,q) with t distribution in the updating process of the volatility estimates. From (1), it is clear that once the estimates of the volatility and the degrees of freedom have been obtained, the computation of ES estimates is straightforward.

2.2 Constructing financial downside risk maps with MDS

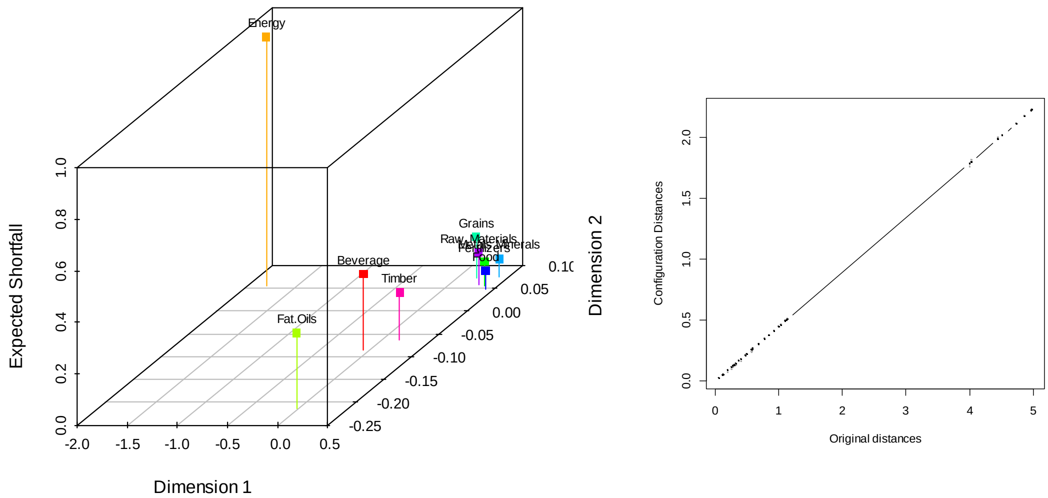
Financial downside risk maps are constructed applying MDS to the ES series of the commodity indexes listed in Table 1.

MDS is a body of exploratory data analysis techniques whose birth is closely linked to the studies on experimental psychology in the 1950s to determine the similarity between the stimuli applied to different individuals. Its current development is due to the investigations by Torgerson, Shepard, Kruskal and Gower (Peña, 2002, and the references therein), among others, and has been applied, above all, in the social sciences. The MDS approach has the advantage of reproducing the main features of the data in the form of maps that not only lead themselves to intuitive interpretation but also provide the set of financial risk distances. The main aim of MDS is to discover structures in multidimensional data. Based on a proximity matrix, typically derived from variables measured on objects as input entity, these dissimilarities are mapped on a low-dimensional spatial representation (Mair et. al 2015). More in detail, given a matrix of measured or perceived similarities among various items (in our study, ES commodity indexes time series), MDS plots the items on a map (a financial risk map) such that those which are perceived to be similar are placed near one another. Technical details can be seen in Jobson (1992) and Peña (2002).

3. Results

Figure 1 shows, in left side, the downside financial risk map of the nine commodity indexes considered in the analysis in during the global oil and food crisis in 2007-2008. As can be seen, Energy is the most risky commodity index and do not co-move with any other index; it exhibits a specific dynamics. The second most risky index is Fat and oils, related with oil crisis as soybean was used as biofuel. It is also far from co-moving with any other index. Beverage and Timber exhibit a certain co-movement. Metals and minerals, Raw materials, Grains, Food, and Fertilizers, the least risky indexes, show the highest degree of co-movement. Right side of Figure 1 shows the Shepard plot, which depicts a good distribution of points around the 45 line. Moreover, the Kruskals stress-1 indicates a god fit (0.0092).

Figure 1. Extreme risk map for the global oil and food crises (2007-2008)



4. Conclusion

In this short paper we study whether or not the downside risk of a number of major commodity indexes co-move. We use a combined expected shortfall/multidimensional scaling approach which provides intuitive and easy-to-interpret low dimensional downside risk maps.

During the third oil and food crisis, 2007-2008, the distress period under study, Metals and minerals, Raw materials, Grains, Food, and Fertilizers, the least risky indexes, exhibit a high degree of downside risk co-movement, whereas Energy, the riskiest index, shows a particular dynamics that has nothing to do with the dynamics exhibited by the rest of indexes. Fat and oils, the second most risky index, is also far from co-moving with the other indexes, and Beverage and Timber exhibit a certain co-movement, but not of the intensity of the co-movement in Metals and minerals, Raw materials, Grains, Food, and Fertilizers.

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