

Contents lists available at [ScienceDirect](#)

Finance Research Letters

journal homepage: [www.elsevier.com/locate/frl](http://www.elsevier.com/locate/frl)

## Dynamic spillovers between Shanghai and London nonferrous metal futures markets

Sang Hoon Kang<sup>a</sup>, Seong-Min Yoon<sup>b,\*</sup>

<sup>a</sup> Department of Business Administration, Pusan National University, Busan 609-735, Republic of Korea

<sup>b</sup> Department of Economics, Pusan National University, Jangjeon2-Dong, Geumjeong-Gu, Busan 609-735, Republic of Korea

### ARTICLE INFO

#### Article history:

Received 9 June 2016

Revised 23 July 2016

Accepted 25 July 2016

Available online xxx

#### JEL classification:

C58

F37

G14

G15

Q31

#### Keywords:

Dynamic spillovers

Financial crisis

Spillover index

Nonferrous metal futures

### ABSTRACT

This paper examines the dynamic return and volatility spillovers between the Shanghai Futures Exchange (SFE) and the London Metal Exchange (LME) from 2007 to 2016 using the new spillover index of Diebold and Yilmaz (2012). Our results indicate that the LME nonferrous metal futures have a greater impact on SFE nonferrous metal futures. In particular, these trends are more pronounced in the aftermath of the recent financial crises, indicating the strength of spillovers during periods of turmoil. The direction of spillovers significantly depends on time variation.

© 2016 Elsevier Inc. All rights reserved.

### 1. Introduction

The recent and ongoing financial crises and the attendant strength of commodity prices renew an interest in understanding the fundamental process of information transmission, through which returns and volatility among commodity markets have become more correlated with each other (Chng, 2009; Chan et al., 2011). This information transmission leads to another broad area of research in the contagion effect. Forbes and Rigobon (2002) described this effect as “significant increase in cross-market linkages after a shock to one country (or group of countries).” This effect can be intensified during financial crises, which further implies that both return and volatility persistently move together over time (Vivian and Wohar, 2012; Silvennoinen and Thorp, 2013; Sensoy et al., 2015; Yarovaya et al., 2016a). This deepens the interest of investors, portfolio and risk managers, manufacturers, and policy makers in better understanding the dynamics of commodity futures prices.

Over the past decade, the Chinese economy has experienced growth averaging 10% per annum, driven by rapid urbanization, heavy industrialization, and openness to global trade (Yue et al., 2015). The fundamental drivers of its economic growth accelerated the demand for nonferrous metals and import share of world trade.<sup>1</sup> As a result, Chinese economic ac-

\* Corresponding author. Fax: +82 515813143.

E-mail addresses: [sanghoonkang@pusan.ac.kr](mailto:sanghoonkang@pusan.ac.kr) (S.H. Kang), [smyoon@pusan.ac.kr](mailto:smyoon@pusan.ac.kr) (S.-M. Yoon).

<sup>1</sup> China is both the world's largest producer and largest consumer of aluminum (54%), and the largest consumer of most other commodities, i.e. copper (48%) and zinc (46%) (Source from World Bureau of Metal Statistics 2015).

tivities play an important role in determining world nonferrous metals prices. According to the Future Industry Association (in 2014), Chinese futures contracts were the top four most traded metals contracts in the world. The Shanghai Futures Exchange (SFE) has become the second largest nonferrous metal futures market in the world, after the London Metal Exchange (LME). With the rapid development of Chinese nonferrous metal futures market and the process of globalization of trading and competition among world commodity futures markets, it is worthwhile investigating the return and volatility spillovers between the Chinese and global leading nonferrous metal future markets.

Surprisingly, however, few studies have examined the Chinese nonferrous metal futures, not only its linkage with the global leading market. [Hua and Chen \(2007\)](#) used a vector error correction model (VECM) to examine the cointegration relationship between SFE and LME futures prices of copper and aluminum. [Li and Zhang \(2009\)](#) adopted a Markov switching VECM to investigate the long-run relationship between SFE and LME copper futures prices. By employing a structural vector autoregressive (VAR) model, [Li and Zhang \(2013\)](#) examined a causal relationship between SFE and LME copper futures prices. These prior studies have revealed the long-run or short-run price relationship with a mix of conclusions due to differing empirical methods and datasets.

This paper attempts to extend the empirical studies, with the intensity and direction of return and volatility spillovers between SFE and LME from 2007 to 2016. First, we apply the spillover index model of [Diebold and Yilmaz \(2012\)](#) to measure the return and volatility spillover indexes across three nonferrous metals, namely aluminum, copper and zinc, in both SFE and LME. To our best knowledge, this is first study to apply this method to address the spillover effect between SFE and LME nonferrous metal markets. Second, we also use a rolling window approach to detect the dynamics of the return and volatility spillovers, to the extent that the two recent crises, i.e., the 2008–2009 global financial crisis (GFC) and the 2010–2012 European debt crisis (EDC), may directly affect return and volatility structures across nonferrous metal futures. Finally, we calculate the net spillover impact to identify the pure ‘source’ or ‘recipient’ of spillovers during the recent financial crises ([Wang et al., 2016; Yarovaya et al., 2016b](#)).

The remainder of this study is organized as follows. [Section 2](#) explains the study methodology. [Section 3](#) describes the data and conducts some preliminary analyzes. [Section 4](#) discusses the empirical results. [Section 5](#) provides concluding remarks.

## 2. Econometric modeling framework

We apply the generalized VAR (GVAR) methodology, variance decomposition and the generalized spillover index of [Diebold and Yilmaz \(2012\)](#), to analyze the directional spillovers across commodity futures markets. Following [Diebold and Yilmaz \(2012\)](#), we assume a covariance stationary VAR ( $p$ ) as:

$$y_t = \sum_{i=1}^p \psi_i y_{t-i} + \varepsilon_t \quad (1)$$

where  $y_t$  is  $N \times 1$  vector of endogenous variables,  $\Phi_i$  are  $N \times N$  autoregressive coefficient matrices and  $\varepsilon_t$  is a vector of error terms that are assumed to be serially uncorrelated. As the above VAR process is assumed to be a covariance stationary, a moving average representation can be written as  $y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$ , where the  $N \times N$  coefficient matrices  $A_j$  obey a recursion of the form  $A_j = \psi_1 A_{j-1} + \psi_2 A_{j-2} + \dots + \psi_p A_{j-p}$ , with  $A_0$  being the  $N \times N$  identity matrix and  $A_j = 0$  for  $j < 0$ .

Using the GVAR framework, the  $H$ -step-ahead generalized forecast-error variance decomposition is expressed as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \quad (2)$$

where  $\Sigma$  denotes the variance matrix of the vector of errors  $\varepsilon$ , and  $\sigma_{jj}$  denotes the standard deviation of the error term of the  $j$ th equation. Finally,  $e_i$  is an  $N \times 1$  vector with one on the  $i$ th element, and zero otherwise. The spillover index composes an  $N \times N$  matrix  $\theta(H) = [\theta_{ij}(H)]$ , where each entry gives the contribution of variable  $j$  to the forecast-error variance of variable  $i$ .

Since the own- and cross-variable variance contribution shares do not sum to one under the generalized decomposition, each entry of the variance decomposition matrix is normalized by its row sum, as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^N \theta_{ij}(H)}, \quad (3)$$

with  $\sum_{j=1}^N \tilde{\theta}_{ij}(H) = 1$  and  $\sum_{j=1}^N \tilde{\theta}_{ij}(H) = N$  by construction.

Thus, a total spillover index can be defined as:

$$TS(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{N} \times 100. \quad (4)$$

This index measures the average contribution of spillovers from shocks to all (other) commodities to the total forecast-error variance. The total spillover matrix consists of two parts: the diagonal elements reflecting own spillovers, and the off-diagonal elements reflecting cross spillovers.

Download English Version:

<https://daneshyari.com/en/article/5069500>

Download Persian Version:

<https://daneshyari.com/article/5069500>

[Daneshyari.com](https://daneshyari.com)