Time-frequency co-movements between the largest nonferrous metal futures markets☆

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1 China is both the world's largest producer and largest consumer of aluminium (54%), as well as the largest consumer of most other commodities, such as copper (48%) and zinc (46%); World Bureau of Metal Statistics, 2015).

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ABSTRACT

This study contributes to the literature on metal commodity market co-movement by studying its dynamics in the time-frequency domain. The novelty of our approach lies in the application of wavelet coherence analysis to nonferrous metal futures markets in Shanghai and London. We show that London's nonferrous futures market generally leads Shanghai's market, especially in the medium-run. In addition, Shanghai's market leads London's market in the case of aluminium and zinc in the long-run, with implications for long-term investors. In particular, we observe strong causal effects for 2008–2014, indicating that market turmoil intensifies the causality between the markets.

1. Introduction

Nonferrous metals (such as aluminium, zinc, and copper) play an important role in industrial production and economic activity, as their prices affect a wide range of industries and a variety of industrial manufacturers operating in these markets (Todorova et al., 2014). The demand for nonferrous metals is growing rapidly, and the price dynamics of nonferrous metal markets are extremely volatile due to the imbalances in global production and consumption along with rapid urbanization and industrialization (Gil-Alana and Tripathy, 2014; Wu and Hu, 2016). Nonferrous metal futures feature increasing demand among market participants including banks, investment funds, hedgers, and speculators.

For more than 10 years, the fundamental drivers of Chinese economic growth have accelerated the demand for nonferrous metals and China’s import share of world trade. Chinese economic activities play an important role in determining world nonferrous metals prices. According to the Future Industry Association, Chinese futures contracts were the top four most-traded metals contracts globally in 2014. The Shanghai Futures Exchange (SFE) has become the world’s second-largest nonferrous metal futures market after the London Metal Exchange (LME). Given the rapid development of the Chinese nonferrous metal futures market and the global trade and competition in commodity futures markets, it is worthwhile investigating the co-movement between the Chinese and global nonferrous metal future markets.

Despite the importance of nonferrous metal markets, research is limited relative on other commodities, such as energy commodities and precious metals (see for example Singhal and Ghosh, 2016). Most empirical studies on the co-movement and causality between the SFE and LME have employed standard time-series approaches that include vector autoregressive (VAR) and vector error correction models (VECM). Hua and Chen (2007) showed evidence of a bi-cointegration relationship between SFE and LME futures prices of copper and aluminium. Li and Zhang (2009) found that the influence of the LME on the SFE is stronger than that of the SFE on the LME. Li and Zhang (2013) also found that the price impact of SFE copper on LME copper has been increasing since 2007, while the impact of LME copper on SFE copper has been decreasing. More recently, Yue et al. (2015) used the

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multivariate generalized autoregressive conditional heteroscedastic (VAR-MGARCH) model to explore the dynamic volatility correlation across the three nonferrous metals market prices. They found that LME nonferrous metals prices had a greater impact on Chinese nonferrous metals prices, while the impact of Chinese nonferrous metals prices on LME nonferrous metals prices remained weak. Kang and Yoon (2016) applied the spillover index of Diebold and Yilmaz (2012) to examine the return and volatility directional spillover between the two markets, finding evidence of directional spillover from the LME to the SFE. These studies revealed co-movement and casual relationships but offer differing conclusions due to the differing empirical methods and datasets used. Moreover, these studies ignore the distinction between short- and long-term frequencies in co-movement analysis. Investors, such as speculators, are interested in co-movement at higher frequencies (e.g. short-term movement), while others, such as hedgers and arbitragers, are focused on lower frequencies (e.g. long-term movements; Aloui and Hkiri, 2014; Pal and Mitra, 2017). Wavelet coherence analysis, which examines the multi-scale dynamics of time series, enables market participants to quickly assess their investment horizons at various frequency band scales when making portfolio decisions (Vacha and Barunik, 2012).

Our study contributes to the literature on financial markets co-movement and employs the wavelet coherence technique of Rua (2010) as well as a new approach to causality employing a time-frequency framework proposed by Olayeni (2016), which is much easier to interpret. The application of wavelets enables us to explore the interdependence of nonferrous metals in time as well as frequency domains, enhancing our understanding of possible dependencies. We focus on co-movement based on wavelet coherence between the SFE and LME markets and investigate the causal relationships between aluminium, zinc, and copper in both the SFE and LME markets using a continuous wavelet transform proposed by Olayeni (2016). Therefore, differing from previous works on SFE and LME co-movement (e.g. Yue et al., 2015), our paper provides additional insights to international investors and risk managers. Classical tools such as dynamic conditional correlation (DCC) models do not allow the estimation of continuous changes in the lead–lag relationship between variables, nor allow for the interaction of short- and long-term investment strategies (Rua and Nunes, 2009). Using wavelets, we are able to investigate nonlinearities, structural breaks, and different lead–lag situations between nonferrous metal markets.

Our analysis of co-movement between nonferrous metal futures markets in a time-frequency framework appears to be the first. Albulescu et al. (2017) investigated stock index futures markets’ co-movement using wavelets, but ours is the first attempt to explore the time-frequency co-movement between the largest metal exchange market (LME) and the second-largest futures exchange market (SFE). Furthermore, the focus on futures and not on spot markets allows us to provide international investors with valuable information. On the one hand, the price discovery takes place in futures markets (Kawaller et al., 1993). On the other hand, the amount of noise in those markets is constant and independent of data frequencies. In addition, the non-synchronous issue between LME and SFE markets is avoided by focusing on futures contracts. Finally, different from previous works investigating SFE and LME relationship, we consider the role of macroeconomic fundamentals in explaining co-movement. More precisely, we try to explain how the nonferrous futures market co-movement is influenced by latent variables, as the co-movement between exchange rates, interest rates and stock price representative indexes of China and UK.

The remainder of this study is organized as follows: Section 2 details the methodology used in this study. Section 3 describes the data and the preliminary analysis. Section 4 discusses the empirical results. Section 5 analyses the role of macroeconomic fundamentals in explaining nonferrous futures market co-movement. Finally, Section 6 provides concluding remarks.

2. Econometric modelling framework

2.1. Wavelet coherence

The wavelet transformation technique promotes understanding of the evolution of a signal or time series across time as well as over frequency. It adjusts the time resolution to the frequency, narrows the window width on high frequencies, and widens when dealing with low frequencies. This technique uses local base functions that can be translated and stretched into both time and frequency. Moreover, the wavelets are characterized by finite energy such that they grow and die out within a period. The wavelets are defined as:

$$\psi_{\tau s}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t - \tau}{s}\right),$$

(1) where, $\tau$ is the translation parameter, $s$ is the dilation parameter, $\frac{1}{\sqrt{s}}$ is a normalization factor and $\psi_{\tau s}(t)$ are elementary functions obtained via the decomposition of a time series through wavelet transform and derived from a time-localized mother wavelet $\psi(t)$.2

The convolution of continuous wavelet transform (CWT) of a time series $x(t)$ with respect to $\psi(t)$ is given by:

$$W_s(t, s) = \int_{-\infty}^{+\infty} x(t)\psi^*_s(t)dt = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t - \tau}{s}\right)dt,$$

(2)

where $^*$ denotes the complex conjugate.

Moreover, several interesting quantities can be captured within the wavelet domain. The measure of the wavelet power spectrum that captures the relative contribution at each time and at each scale to the time series’ variance is defined as $|W_s(t, s)|^2$. The measure of the cross-wavelet spectrum that captures the covariance between two time series $x(t)$ and $y(t)$ in the time-frequency space $|W_s(t, s)|^2$ is given as $W_s^*(t, s) = W_s(t, s)W^*_s(t, s)$.

Following Croux et al. (2001), the cross-wavelet spectrum can be decomposed into real and imaginary components, defined as:

$$\rho_{\psi_0}(t, s) = \frac{\Re(W_s(t, s))}{\sqrt{|W_s(t, s)|^2|W^*_s(t, s)|^2}},$$

(3)

where $\Re$ measures the contemporaneous variance and corresponds to the real part of the cross-wavelet spectrum. The wavelet $\rho_{\psi_0}(t, s)$ quantifies the co-movement in the time-frequency space and identifies the time-frequency period over which the co-movement is higher. The cross-wavelet spectrum acts as a contemporaneous correlation coefficient around each moment in time and for each frequency (Rua, 2010). The striking feature of the cross-wavelet spectrum is its ability to provide information about co-movement both at the frequency as well as over time. Moreover, assessing the contour plot of the wavelet cross spectrum allows us to identify the time-frequency regions over which the two series co-move as well as to assess the features of the time and frequency variations of the co-movement. The suggested wavelet-based measure thus enriches the analysis of co-movement between a set of variables.

2.2. Causality in continuous wavelet transform

As an alternative to the discrete wavelet transform (DWT) for the Granger (1969) causality test above, we employ the continuous wavelet transform (CWT) for the Granger causality proposed by Olayeni (2016), which extends the CWT-based correlation measure in Rua (2013). It is given by:

$$C_{\psi_0}(t, s) = \frac{\zeta{s^{-1}\Re(W_s^*(x, s))}I_{\psi_0}(x, s)}}{\zeta{s^{-1}\|W^*_s(x, s)\|^2} + \zeta{s^{-1}\|W_s(x, s)\|^2}},$$

(4)

\[2\] For more details, see Percival and Walden (2000).
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