Resources Policy 39 (2014) 32–41

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

An improved wavelet–ARIMA approach for forecasting metal prices

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ARTICLE INFO

Article history:
Received 11 January 2013
Received in revised form
6 September 2013
Accepted 24 October 2013
Available online 25 November 2013

Keywords:
Forecast
Wavelet analysis
Multiresolution analysis
Metal prices

ABSTRACT

Metal price forecasts support estimates of future profits from metal exploration and mining and inform purchasing, selling and other day-to-day activities in the metals industry. Past research has shown that cyclical behaviour is a dominant characteristic of metal prices. Wavelet analysis enables to capture this cyclicality by decomposing a time series into its frequency and time domain. This study assesses the usefulness of an improved combined wavelet-autoregressive integrated moving average (ARIMA) approach for forecasting monthly prices of aluminium, copper, lead and zinc. The performance of ARIMA models in forecasting metal prices is demonstrated to be increased substantially through a wavelet-based multiresolution analysis (MRA) prior to ARIMA model fitting. The approach demonstrated in this paper is novel because it identifies the optimal combination of the wavelet transform type, wavelet function and the number of decomposition levels used in the MRA and thereby increases the forecast accuracy significantly. The results showed that, on average, the proposed framework has the potential to increase the accuracy of one month ahead forecasts by \$53/t for aluminium, \$126/t for copper, \$50/t for lead and \$51/t for zinc, relative to classic ARIMA models. This highlights the importance of taking into account cyclicality when forecasting metal prices.

Introduction

Metal price forecasts support forward planning and investment decisions in metal producing and processing industries, such as mining, refining and fabrication (Watkins and McAleer, 2004). Dooley and Lenihan (2005) argued that metal price tends to be the major factor causing variability in revenues from mining operations. Therefore, accurate price forecasts are essential to assess the economic viability of metal exploration and mining activities. Moreover, the volatile and cyclical behaviour of international metal prices strongly affects the economic stability of nations whose exports are dominated by metals (Labys et al., 2000; Radetzki, 2008; Watkins and McAleer, 2004). To give some examples, aluminium accounts for almost 40% of the total value of exports from Mozambique and Tajikistan, and copper has a share of almost 70% of the total value of exports from Zambia (United Nations Conference on Trade and Development (UNCTAD), 2011). The ability to accurately forecast primary commodity prices can support budgetary planning (Dehn, 2000) and the development of stabilisation policies in these countries (Cashin et al., 2002; Deaton, 1999; Deaton and Miller, 1995).

Metal prices are the result of complex market dynamics and stochastic economic processes, which makes price forecasting difficult (Labys, 2006). Dooley and Lenihan (2005) used autoregressive integrated moving average (ARIMA) and lagged forward price models to forecast monthly lead and zinc cash prices. They found that ARIMA models perform marginally better and they are a useful tool for mining companies to predict metal prices. Labys (2006) used a structural time series model to forecast monthly prices of copper, lead, tin, zinc and other primary commodities. He emphasised the importance of correctly accounting for cyclicality in modelling and forecasting primary commodity prices. Much evidence suggests that cyclical behaviour is a dominant characteristic of metal prices (Cashin et al., 2002; Davutyan and Roberts, 1994; Labys et al., 1998; Roberts, 2009). Labys et al. (1998) found short-term cycles of durations of less than 12 months in monthly prices of aluminium, copper, lead, zinc and other metals and encouraged producers, consumers and traders to re-examine their price forecasting methods based on this finding.

A relatively novel technique to capture cyclicality in time series is wavelet analysis. In contrast to the traditional Fourier analysis, which transforms a time series into its frequency domain, the wavelet transform decomposes a time series into its frequency and time domain. Thereby, variations of different frequencies in a time series are not only identified but also localised. This feature has been used for several purposes in resource economics, for instance, to identify cycles in primary commodity prices (Davidson et al., 1998; Naccache, 2011), to examine co-movement between primary commodity prices (Conner and Rossiter, 2005; Tonn et al., 2010) and

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http://dx.doi.org/10.1016/j.resourpol.2013.10.005

to analyse the relationship between crude oil prices and a range of macroeconomic variables (Aguiar-Conraria and Soares, 2011; Jammazi and Aloui, 2010; Naccache, 2011). Davidson et al. (1998) argued that wavelet analysis may help to forecast commodity price movements. Also Ramsey (1999) found that wavelets have the potential to increase the predictive power of time series methods. These findings and the above mentioned results of Dooley and Lenihan (2005) provide the motivation for combining wavelets with ARIMA models to forecast monthly base metal prices.

Schlüter and Deuschle (2010) identified and tested several ways that wavelets could support time series forecasting. For crude oil spot price predictions one week ahead, they found that the highest forecast accuracy is achieved if wavelets are used in a multiresolution analysis (MRA) that decomposes the time series into a smooth series representing a trend and a number of detail series describing fluctuations of known approximate frequency around this trend. In a second step, these subseries are extended using time series methods and, third, summed to obtain the forecast of the original time series. The wavelet–ARIMA model applied in this study follows this approach. This technique can be more accurate than directly forecasting the original series, since the subseries tend to have a more stable variance and typically no outliers (Shafie-khah et al., 2011).

Attempts to improve the predictive power of MRA-based forecasting have focused primarily on the choice of a technique to forecast the detail and smooth series. Several statistical forecasting techniques have been tried to this end, such as ARIMA models (Conejo et al., 2005; Fernandez, 2007, 2008), a combination of ARIMA and generalized autoregressive conditional heteroskedasticity (GARCH) models (Tan et al., 2010), spline and trigonometric extrapolation (Yousefi et al., 2005) or support vector machines (Pahasa and Theera-Umpon, 2007). Much research has also concentrated on the combination of artificial neural networks with wavelets (e.g. Amina et al., 2012; Amjady and Keynia, 2008; Aussem and Murtagh, 1997; Bashir and El-Hawary, 2009; Catalão et al., 2011; Chen et al., 2010; Jammazi and Aloui, 2012). However, in the vast majority of studies on MRA-based forecasting, the configuration of the MRA has been either neglected or chosen based on assumptions rather than on empirical evidence.

The MRA involves the choice of a wavelet transform type, a wavelet function and the number of decomposition levels taken into account. With few exceptions (Jammazi and Aloui, 2012; Murtagh et al., 2004; Nguyen and Nabney, 2010), the discrete wavelet transform (DWT) is the most frequently used wavelet transform type in wavelet-based forecasting, especially in the context of resource and energy economics (Amjady and Keynia, 2008; Bashir and El-Hawary, 2009; Catalão et al., 2011; Conejo et al., 2005; Fernandez, 2007, 2008; Mandal et al., in press; Nowotarski et al., 2013; Shafie-khah et al., 2011; Tan et al., 2010; Voronin and Partanen, in press; Zhang and Tan, 2013). Most authors do not discuss this choice or the possibility of using other transform types, such as the maximum overlap DWT (MODWT). Also the wavelet function choice is rarely discussed if wavelets are used for forecasting. Several authors state that they chose a specific wavelet function because it offers "an appropriate trade-off between wave-length and smoothness" without further specifying how the choice relates to the time series characteristics or how it affects the forecast accuracy (Amjady and Keynia, 2008; Conejo et al., 2005; Shafie-khah et al., 2011; Tan et al., 2010, Voronin and Partanen, in press). A few authors assessed a limited selection of wavelet functions and chose the best performing alternative (Aggarwal et al., 2008; Rocha Reis and Alves da Silva, 2005; Yousefi et al., 2005, Nowotarski et al., 2013).

In the context of electricity price forecasting, Conejo et al. (2005) recommended the use of short wavelets because the larger support interval of longer wavelet functions might corrupt the prediction. On the other hand, Gencay et al. (2001) found that longer wavelets approximate an ideal band-pass filter better than short wavelet functions. Moreover, they suggested that the shape of the wavelet function should resemble that of the time series to be decomposed, for example the Haar wavelet function is suitable for decomposing data appearing to be constructed of piecewise constant functions, while wavelet functions of higher order should be used for smoother time series. In practice, this recommendation can only roughly guide the choice of a wavelet function as the number of wavelet functions is high and many wavelets are similar in shape. According to Crowley (2007), the choice of a wavelet function and the number of decomposition levels depends on the type and frequency of the variations that the analyst aims to capture in a time series. Different numbers of decomposition levels have found application in MRA-based forecasting, for example three levels (Conejo et al., 2005), five levels (Yousefi et al., 2005) and up to seven levels of decomposition (Fernandez, 2007). However, it is unclear which combination of wavelet transform, wavelet function and number of decomposition levels performs best for a specific time series and whether these decisions have a significant effect on the accuracy of MRA-based forecasting.

The aim of this paper is to contribute to the improvement of metal price forecasting by assessing the usefulness of a combined wavelet–ARIMA model for predicting monthly base metal prices. The objectives are to:

- assess the effect of the wavelet transform type, namely the DWT and the MODWT, the wavelet function and the number of decomposition levels on the predictive power of the wavelet–ARIMA forecasting technique;
- calibrate the wavelet–ARIMA model by identifying the combination of these choices that achieves the highest predictive power for forecasting monthly cash prices of aluminium, copper, lead and zinc up to 12 months ahead; and
- quantify the predictive power of the proposed forecasting technique and compare it with that achieved with normal ARIMA models without prior MRA and a naïve modelling approach.

To the authors' best knowledge, this is the first study to statistically test the effect of the MRA configuration on time series forecasts considering a large set of more than 400 different configurations and a large number of simulated forecasts to enable accurate quantification of the forecast error and robust statistical testing. Moreover, this is the first study that applies MRA-based forecasting to metal prices.

Methods

Data

This study forecast time series of the monthly nominal cash prices of aluminium, copper, lead and zinc traded on the London Metal Exchange (LME) in US$/t. Following Dooley and Lenihan (2005) and Labys (2006), monthly data were chosen to capture the timespans relevant for short-term planning of companies in the metals industry. The LME was favoured over other metal exchanges as it is the major market for pricing non-ferrous metals worldwide (Watkins and McAleer, 2004). The data were provided by the United Nations Conference on Trade and Development (United Nations Conference on Trade and Development (UNCTAD), 2012). Each time series analysed comprised 628 observations that cover the period from January 1960 to April 2012. Prior to forecasting, the natural logarithm of the prices was taken. This led to a more stable variance throughout the sample, thus could be assumed to increase the accuracy of the forecasts (Lütkepohl and Xu, 2012).