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Impacts of oil volatility shocks on metal markets: A research note

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ABSTRACT

To the best of our knowledge, this is the initial study to investigate the predictive power of crude oil volatility index (OVX), a measure of oil market uncertainty, in explaining the return structure of industrial and precious metal markets. Applying different forms of the GARCH-jump model, we document the following major findings. First, we report a significant price spillover running from oil market to industrial metal sector. In addition, jumps do exist in the underlying metal market returns and such jumps are time-varying. Second, we do not find any evidence that oil volatility shocks impact the aggregate precious metal market. However, such effect is present at least in the silver market, if we disaggregate the data. Third, while examining the impact of global financial crisis on the association between oil and metal markets, we report that the effects of OVX hold for both crisis and post crisis periods. Finally, we document the existence of asymmetry in the linkages between oil and the industrial metal markets. To be specific, spillovers for the positive oil volatility shocks appear to be larger than that for the negative oil volatility shocks confirming the existence of uneven spillover effects.

1. Introduction

Metal manufacturing industries appear to be highly energy intensive (Hammoudeh et al., 2004). Since oil price is an important indicator of energy price,[1] fluctuations in global oil price could therefore account for significant variations in different metal prices. Zhang and Tu (2016), for instance, document that changes in oil prices will affect the costs of the production process directly, further resulting in the changes of metal prices. Besides, crude oil prices have substantial impacts on the metal industry due to transportation costs as well. It thus seems that metal industry is sensitive to variations in world oil price and hence oil price volatility embodies a vital role in the metal markets. It is also noteworthy that metals are widely used in various fields of national economy and therefore oil price volatility is likely to bring uncertainty to the overall economic growth through its impact on metal markets.

Considering the economic significance of the association between oil and metal markets, many studies attempt to examine the possible link between these two important commodity markets. For example, Chaudhuri (2001) shows that metal prices and oil prices are cointegrated over the sample period used and that the non-stationarity of metal prices can be attributed to non-stationarity of oil prices. While assessing the effect of crude oil prices on the prices of 35 internationally traded primary commodities for the 1960–2005 period, Baffes (2007) finds that metal prices exhibit a strong response to changes in crude oil price. Hammoudeh and Yuan (2008) employ a series of GARCH-type models to explore the volatility behavior of three strategic commodities: gold, silver, and copper, in the presence of crude oil and interest rate shocks. The empirical results indicate that past oil shock does not impact all three metals similarly. To be more specific, oil volatility mainly affects the precious metals. In addition, Soytas et al. (2009) examine the long- and short-run transmissions of information between the world oil price, Turkish interest rate, Turkish lira–US dollar exchange rate, and domestic spot gold and silver price. The authors show that the world oil price has no predictive power of the precious metal prices, the interest rate or the exchange rate market in Turkey. Sari et al. (2010) study the co-movements and information transmission among the spot prices of four precious metals (gold, silver, platinum, and palladium), oil price, and the US dollar/euro exchange rate. Although the authors report a weak long-run equilibrium relationship among the variables, the feedbacks are strong in the short run.

Besides, Ji and Fan (2012) study the effect of the crude oil market on metal and agricultural commodity markets before and after the 2008 financial crisis. To do so, the authors examine the price and volatility spillover between commodity markets by building a bivariate EGARCH model with time-varying correlation construction. The study reports that the crude oil market has significant volatility spillover effects on metal and food markets. Bakhat and Würzburg (2013) show that aluminum and nickel prices are threshold cointegrated with global oil prices. The Granger causality tests further indicate that the crude oil price leads the prices of aluminum and nickel. Ewing and Malik (2013) employ the univariate and bivariate GARCH models to assess the

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[1] Oil remains the world's leading fuel, accounting for 39.9% of global energy consumption. The information is sourced from “IEA Key World Energy Statistics-2016″.

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volatility of gold and oil futures incorporating structural breaks. The findings of their research indicate solid evidence of significant transmission of volatility between gold and oil returns when structural breaks in variance are taken into account in the model. Moreover, Jain and Ghosh (2012) apply ARDL bounds tests of cointegration and Toda–Yamamoto version of Granger causality to explore the dynamics of global oil prices, exchange rate and precious metal prices in India. The ARDL bounds tests establish cointegration among the variables when exchange rate and gold are dependent variables. Behmiri and Manera (2015) investigate the price volatility of metals using GARCH and GJR models. The authors consider daily spot prices for aluminum, copper, lead, nickel, tin, zinc, gold, silver, palladium and platinum. The study finds that returns have a high degree of volatility persistence before and after correcting for outliers, outliers bias the estimation of GARCH and GJR models, and removing outliers improves volatility modeling. Further, price volatility of metals reacts differently and asymmetrically to oil price shocks.

More recently, Zhang and Tu (2016) inspect the effects of global oil price shocks on the Chinese metal markets including whole metal, copper and aluminum markets. Adopting ARJI-GARCH models, the study reports that crude oil price shocks have significant impacts on China's metal markets and the impacts are symmetric. The authors further show that when compared with aluminum, copper is more easily affected by oil price shocks. Another recent study by Roboredo and Ugolini (2016) shows that large downward and upward oil price movements have spillover effects on several precious and industrial metals during the pre and post financial crisis periods.

The present study differs from the existing literature in several aspects. First, unlike the earlier papers, we have considered the use of crude oil volatility index (OVX) rather than using the traditional oil price series to examine the oil-metal link. Several researchers discuss the importance of utilizing the information content of OVX. Liu et al. (2013), for instance, argue that the application of oil volatility index, as a measure of oil market uncertainty, could reveal more information than the historical oil price series. Luo and Qin (2016) also contend that OVX contains both the information of historical volatility of oil spot prices and the investors' expectations on future volatility. Our study thus makes a novel extension to the previous studies by investigating the impact of implied oil volatilities on the return structure of precious and industrial metal markets. Second, we adopt an adjusted GARCH-jump model, originally developed by Chan and Maheu (2002), to explore whether time-varying jumps occur in the returns of the underlying metal markets due to the fluctuations in oil implied volatility. This could be considered as an important contribution, since the jump model, contrasting the traditional GARCH models, can capture the effects of extreme news or abnormal information arising from earnings surprises, crashes, terrorist attacks and similar other events (Fowowe, 2013; Dutta et al., 2017). Moreover, in addition to accounting for smooth persistent changes in volatility, the model also captures the discrete jumps in asset returns. Finally, we assess whether oil price uncertainty has asymmetric effects on the metal markets by splitting oil volatility shocks into positive and negative components. We use the likelihood ratio test to examine if such asymmetry exists.

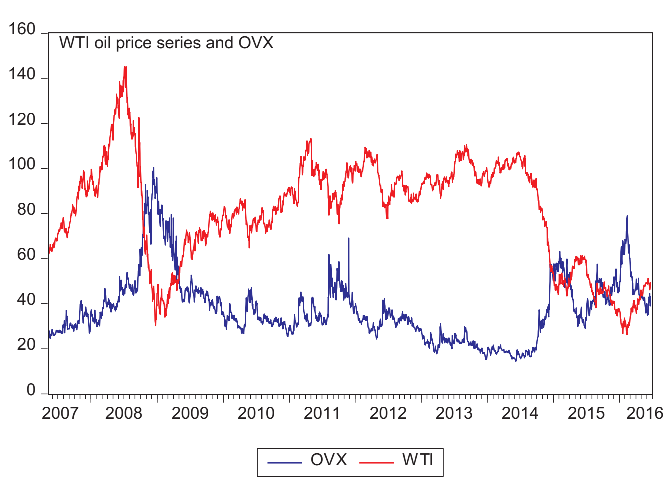

Fig. 1. OVX and WTI oil price from 10/05/2007-30/06/2016. Notes: The horizontal axis indicates the sample period, while the WTI oil price series and crude oil volatility index (OVX) are shown in the vertical axis.

The rest of the paper will proceed as follows. The next section describes the data used in this study. Section 3 outlines the adopted GARCH-jump approach. Results are discussed in Section 4. We conclude in Section 5.

2. Data

The crude oil volatility index, an important tool for trading oil price volatility, is published by the Chicago Board Options Exchange (CBOE) from the middle of 2007. The OVX considers real-time bid/ask quotes of nearby and second nearby options with at least 8 days to expiration, and weights these options to derive a constant, a 30-day estimate of the expected volatility of crude oil prices (Liu et al., 2013).

The metal market data are obtained from S & P GSCI. The industrial metal series consists of aluminum, copper, lead, nickel and zinc, while the precious metal index comprises gold and silver. We consider using the S & P GSCI data, since this index is designed as a benchmark for investment in the metal markets and as a measure of industrial metals price movements within the commodity markets. In addition, it is one of the most widely recognized benchmarks in the metal market and is designed as a tradable index that is readily accessible to market participants. The Index is not equally weighted and it is calculated primarily on a world production-weighted basis. The weights of the relevant commodities in the Index which are represented by the relevant commodity futures contracts for such commodities are rebalanced in January each year. The weights in the Index will change depending on the performance of the price of each commodity reflected by it and changes in the contract production weighting of each such commodity.[2]

In this study, we utilize daily data and our sample period starts in 10 May 2007 and ends in 30 June 2016, yielding a total of 2386 observations. All the information is collected from the Thomson Reuters DataStream database.

Fig. 1 depicts the crude oil volatility index along with the WTI oil price series for the whole sample period. The figure reveals several major spikes in OVX during the sample period considered. It is noteworthy that these hikes are the consequences of either economic or political events (see Liu et al. (2013) and Dutta et al. (2017) for further details). Moreover, according to Fig. 1, there is an inverse relationship between the OVX and WTI oil prices. The oil volatility index usually tends to be upwards as WTI prices drop.

3. Methodology

At the empirical stage, we use the following GARCH-jump specification[3]:

$$R_t = \pi + \mu_1 R_{t-1} + \mu_2 R_{t-2} + \delta \Delta OVX_t + \epsilon_t \quad (1)$$

where R_t is the log return of metal price at time t, $\Delta OVX_t = OVX_t - OVX_{t-1}$ and ϵ_t refers to the error term at time t which has two components as follows:

[2] Source: Standard & Poor's website.

[3] Selection of the mean and variance equations is based on the Akaike Information criterion (AIC) and likelihood ratio test results. We first estimate the AR(1)-GARCH(1,1) model. In addition, several alternative models are also tested. These include AR(2)-GARCH(1,1), AR(3)-GARCH(1,1), AR(2)-GARCH(2,1), AR(2)-GARCH(2,2) amongst others. But, on the basis of AIC statistics and likelihood ratio test results, we finally select the AR(2)-GARCH(1,1) model as it produces the lowest AIC value.