Energy Economics 62 (2017) 323–333

Contents lists available at ScienceDirect

Energy Economics

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

Oil shocks and stock markets revisited: Measuring connectedness from a global perspective

Dayong Zhang

Research Institute of Economics and Management, Southwestern University of Finance and Economics, 555 Liutai Avenue, Chengdu 611130, China

ARTICLE INFO

Article history:
Received 1 September 2016
Received in revised form 9 December 2016
Accepted 6 January 2017
Available online 21 January 2017

JEL classification:
G12
G15

Keywords:
Connectedness
Granger causality
Oil shocks
Stock markets
Variance decomposition

ABSTRACT

This paper contributes to the large volume of empirical studies on the relationship between oil shocks and stock markets from a new systemic perspective. The method of measuring connectedness proposed by Diebold and Yilmaz (2009, 2012, 2014) is adopted to study the relationship between oil shocks and returns at six major stock markets around the world. It is shown that the contribution of oil shocks to the world financial system is limited. Oil price changes, however, can be explained by information on the financial system. Furthermore, a rolling windows analysis finds that oil shocks can occasionally contribute significantly to stock markets, and it is also proved that only large shocks matter.

1. Introduction

Oil prices have been extremely volatile since the 2008 global financial crisis. For example, the Brent price dropped from the historical high of $132.72 per barrel in July 2008 to $43.32 per barrel in February 2009, a decline of almost two-thirds in just half a year.[1] As an important input factor in the modern economy, oil matters to the aggregate economy as well as individual firms. The volatility of oil price changes can act as one type of important fundamental risk. It will have adverse effects on the economy as well as financial markets. While the first part has been well established in the literature, oil shocks' role in financial markets has recently become a hot topic around the world.

Following early works by Jones and Kaul (1996) and Sadorsky (1999), who explored the link between international oil price shocks and stock market returns, intensive studies in the literature[2] have aimed to investigate the oil–stock relationship across almost all the major international stock markets.

Country-specific studies of developed countries and developing countries are too numerous to be listed here in full. Examples, such as Park and Ratti (2008), Kilian and Park (2009) and Kang et al. (2016) investigate the impact of oil shocks on US aggregate stock market returns. Cunado and de Gracia (2003), El-Sharif et al. (2005), and Abhyankar et al. (2013) study other developed countries, including Japan, the UK and other European countries. While most of these studies have found that oil shocks have a negative impact on the US stock market, Kilian and Park (2009) show that the impact differs significantly depending on whether they are demand shocks or supply shocks. Together, oil shocks contribute to 22% of the variation in US real stock returns, but only demand shocks matter.

Developing/emerging economies are becoming more involved in the international oil market and their stock markets are developing quickly, and interest in the link between oil shocks and emerging stock markets has grown (e.g., Basher and Sadorsky, 2006; Cong et al., 2008; Arouri and Rault, 2012; Asteriou and Bashmakova, 2013; Zhu et al., 2014; Fang and You, 2014; Ghosh and Kanjilal, 2016). Again, while most of the existing country-specific studies confirm the negative relationship between oil shocks and stock returns, Wang et al. (2013) and Filis and Chatziantoniou (2014), among others, divide stock markets into countries that import oil and countries that export it, and their empirical studies based on structural vector autoregressive models (VAR) find significant differences between

E-mail address: dzhang@swufe.edu.cn.

[1] US Energy Information Administration (www.eia.gov) monthly spot market prices.

[2] For a more detailed survey of related literature, see Broadstock et al. (2016 , Table 1).

http://dx.doi.org/10.1016/j.eneco.2017.01.009
0140-9883/

importers and exporters. This new evidence creates the need for further investigation.

One direction of research is to look at markets closely by considering industrial differences. For example, an early study by Huang et al. (1996) shows that oil companies' stock returns have been affected by oil shocks, while other industries tend not to be affected. Nandha and Faff (2008) study 35 global industry indices and find negative impacts except in mining, oil, and gas. Broadstock et al. (2014) show that the impact of oil shocks on the stock market can arise from two channels. Increasing oil prices can raise operational costs of firms in some industries, which consequentially reduce their profit and thus result in lower stock prices. This channel is called the direct effect from oil shocks. They also consider another indirect channel through the impact on systematic risk (in a typical asset pricing model). Other studies following the same logic and looking into industrial sectors or sub-indices include Elyasiani et al. (2011), Arouri (2011), Broadstock et al. (2012), Zhang and Cao (2013), Broadstock et al. (2014), Wen et al. (2014), and Zhu et al. (2016). The general consensus is that oil shocks matter to some industries but not all.

Some recent studies by Narayan and Sharma (2011, 2014) further break down the stock market response to oil shocks to the firm level. The common logic of these studies is to follow a bottom-up approach, which allows us to discover more granular information. Broadstock et al. (2016) study Chinese listed firms following the same logic. These studies also include the main stream financial models, such as the Capital Asset Pricing Model (CAPM) and the Fama–French three-factor model (Fama and French, 1993), in the empirical relationship. Broadstock et al. (2016) find that about 89% of listed firms in China react to oil price shocks, but the responses can be positive and negative even within the same industry.

In terms of methodology, the literature on oil shocks and stock returns has evolved quickly to incorporate the most advanced techniques. Following Ciner (2001), Hamilton (2003) and Zhang (2008), nonlinearity in the relationship has been included in the empirical studies. Aloui and Jammazi (2009) use a two-state Markov-switching EGARCH model to study oil shocks and stock market returns in the UK, France and Japan. They find evidence that the relationship changes between regimes. Filis et al. (2011) and Broadstock et al. (2012) allow correlations between oil price changes and stock returns to be dynamic. Their multivariate GARCH type models show that the relationship is actually time varying. Antonakakis and Filis (2013) also use a time-varying approach to study the relationship. Wen et al. (2012) study the time-varying relationship between West Texas Intermediate (WTI) prices, S&P 500 returns, and the Chinese stock market indices with a copula approach (also used by Nguyen and Bhatti, 2012) and they find that the dependence between oil shocks and stock markets increases after the 2008 global financial crisis, which is also consistent with the study by Broadstock et al. (2012).

Although the increasing studies have enriched this strand of the literature, a couple of issues have been generally missing. The first is that since the 2008 global financial crisis, the global financial market has become increasingly interconnected. Given the existing evidence that oil shocks matter to almost all stock markets, globalization and inter-market links introduce another indirect effect (Broadstock et al., 2014) that can complicate the results. Most current studies paired oil shocks (either Brent or WTI) with individual stock market/sectors without considering the inter-market linkages. The second is that when the oil–stock relationship is studied, oil shocks are normally assumed to be exogenous. Earlier, it might have been a reasonable assumption and valid for some small markets. But now, oil prices have gradually shown characteristics that are similar to those of financial products, so it is no longer true that oil prices are independent from changes in financial markets (Creti and Nguyen, 2015). Both issues have become more relevant since the 2008 global financial crisis.

This study, therefore, aims to fill the gap and explicitly incorporate these issues into a newly developed systemic framework. The multivariate time-series approach proposed by Diebold and Yilmaz (2009, 2012, 2014) is adopted to revisit the oil–stock relationship from a global perspective. Using returns data for six major international stock markets and oil price shocks measured by the changes of Brent spot price, this paper aims to answer the following questions: Do oil shocks really matter? If so, how important are oil shocks to global financial markets? If the global financial markets and oil shocks are directly linked, what is the transmission mechanism? Are oil price shocks really exogenous? Do oil and stock markets have time-varying relationships?

The remainder of this paper is structured as follows: the next section (Section 2) introduces the methodology. Section 3 describes the data used in this paper with some preliminary analysis. Section 4 reports empirical findings and discusses the results in light of the aforementioned research questions. The last section (Section 5) concludes.

2. Methodology

The core method used in this paper is essentially a multivariate time-series approach developed by Diebold and Yilmaz (2009). They introduce a simple measure of connectedness to explicitly account for interdependence in financial markets. This measure is then used to look at spillover effects in the global financial market as it has been shown to be a very simple but successful idea. This method has been widely expanded to study systems in many areas of the economy. The methodology is based on VAR and the well-understood variance decomposition procedure.

Consider a K variable $VAR(p)$ model in the form:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1 y_{t-1} + \mathbf{A}_2 y_{t-2} + \cdots + \mathbf{A}_p y_{t-p} + \mathbf{u}_t \tag{1}$$

where $\mathbf{y}$ is a $(K \times 1)$vector of variables at date t, $\mathbf{c}$ is a $(K \times 1)$ vectors of constants and $\mathbf{u}$ is a $(K \times 1)$ vector of error terms at date t; $\mathbf{A}$s are $(K \times K)$dimensional matrices of coefficients. The model can be written in a compact form such as:

$$\mathbf{Y}_t = \mathbf{C} + \mathbf{A}\mathbf{Y}_{t-1} + \mathbf{U}_t. \tag{2}$$

$\mathbf{A}$ is a $(Kp \times Kp)$ dimensional matrix and $\mathbf{Y}$, $\mathbf{C}$, $\mathbf{U}$ are $(Kp \times 1)$ vectors:

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_p \end{bmatrix}, \mathbf{C} = \begin{bmatrix} \mathbf{c} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}, \mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 & \cdots & \mathbf{A}_{p-1} & \mathbf{A}_p \\ \mathbf{I}_K & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_K & \mathbf{0} & \mathbf{0} & \\ \vdots & \ddots & \vdots & \vdots & \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I}_K & \mathbf{0} \end{bmatrix}, \mathbf{U} = \begin{bmatrix} \mathbf{u}_t \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}.$$

After estimating the VAR model, variance decomposition is often used to show how much each variable contributes to the explanation of other variables. It starts with the mean squared error of the H-step forecast of variable y_i:

$$\mathbf{MSE}[y_{i,t}(H)] = \sum_{j=0}^{H-1} \sum_{k=1}^{K} (e_i' \Theta_j e_k)^2. \tag{3}$$

e_i is the ith column of $\mathbf{I}_K$, $\Theta_j = \Phi_j P$, and P is a lower triangular matrix through a Cholesky decomposition of the variance covariance