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Oil price and stock market co-movement: What can we learn from time-scale approaches?

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ABSTRACT

This paper study the relationship between oil and stock markets in G7 countries, by distinguishing between interactions based on fundamentals (long-term interdependence: high memory impact) and contagion (short-term interaction: transitory contamination). To do this, we propose in the first time two complementary frequency approaches based: the evolutionary co-spectral analysis and the wavelet approach allowing a time-varying measure of the dynamic correlation between the oil and stock markets over time and across time horizons. We find that interdependence between oil price and the stock market is more pronounced in the short and medium terms than in the long term. In addition, we prove that stock markets are more sensitive to oil shocks originating from demand shocks. These findings provide important policy implications for both policymakers, in terms of taking relevant actions regarding oil shocks originating from the demand side, and investors, in terms of a policy of diversification that depends on horizons.

1. Introduction

Since 2000, different peaks have been observed in the movement of oil prices. The oil price movements have an impact on the real economy. Indeed, oil price increases lead to higher production costs, which translate into lower profits, since oil is considered a primary input in the production process. Therefore, oil price differentials have a significant impact on stock markets. Several studies have documented the impact of oil price movements on the economy, especially on stock markets, and highlight the main transmission mechanisms. Barsky and Kilian (2004) and Kilian and Park (2009) present a transmission channel between the oil price and the stock market based on the principle that the price of a share is equal to its discounted cash flow. They highlight that an increase in the oil price can lead to an increase in interest rates in attempts by central banks to limit inflation pressure and decrease costs of doing business. This puts pressure on output prices, and therefore, profits decrease. In line with this reasoning, Chittedi (2012) suggests that a high interest rate favors bond investments rather than stock investments.

The previous literature has produced conflicting results for oil and stock market interrelationships. Most studies support a negative oil price impact on stock markets (Basher, Haug, & Sadorsky, 2010; Chen, 2009; Creti, Ftiti, & Guesmi, 2014; Elder & Serletis, 2010; Guesmi & Fattoum, 2014; Jones & Kaul, 1996; Kilian & Park, 2009; Masih, Peters, & Mello, 2011; Wei, 2003). Other studies conclude that the relationship is ambiguous (Miller & Ratti, 2009). Some other studies reject the hypothesis of a link between the oil market and the stock market (Al Janabi et al., 2010; Wang, Wu, & Yang, 2013). These previous works are based on time domains, such as, generalized autoregressive conditional heteroskedasticity (GARCH) models, time-varying correlation, and vector autoregressive (VAR) models. However, recently, more attention has been given to measuring co-movements between financial and economic indicators. A growing number of empirical studies can be found in the recent literature dealing with this aspect and based on a frequency approach (Camacho, Perez-Quiros, & Saiz, 2006; Eickmeier & Breitung, 2006; Ftiti, 2010; Gençay, Selçuk, & Whitcher, 2001, 2005; Lemmens, Croux, & Dekimpe, 2008; Ramsey, Uskinov, & Zaslavsky, 1995; Ramsey & Zhang, 1996; Rua & Nunes, 2005). Co-movement in the frequency domain is different from and more advantageous than co-movement in the time domain.

The main objective of this study is to tackle the issue of linkage between the oil market and stock market returns for industrialized countries. For Group of 7 (G7) leading industrialized countries, we examine the S&P 500 (United States, US), NIKKEI 225 (Japan), DAX 30 (Germany), CAC 40 (France), FTSE 100 (United Kingdom, UK), FTSE MIB (Italy), and S&P/TSX Composite (Canada) during the period

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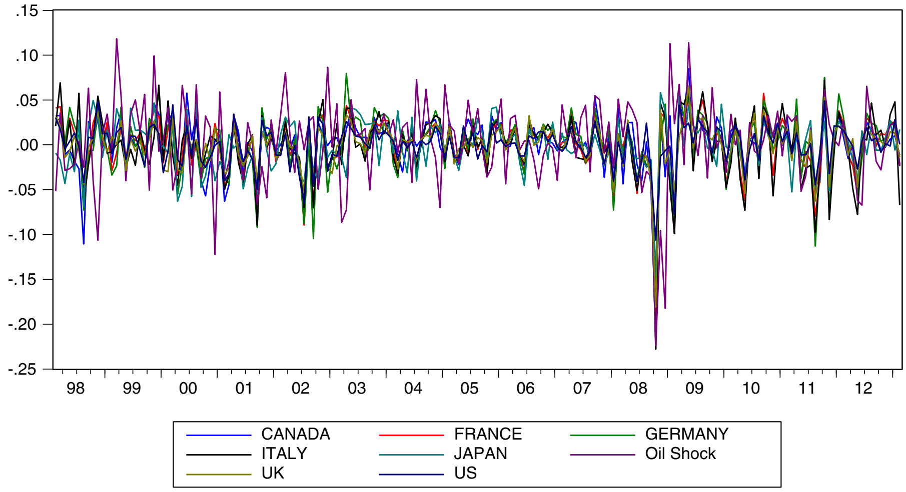

Fig. 1. Stock returns and oil price differential in G7 countries.

February 1998 to February 2013. Contrary to previous works, we aim to distinguish between permanent interdependence, explained by long-term co-movements based on fundamentals, and contagion produced by short-term excess co-movement explained by market shocks. This study tackles this issue for the first time in the literature on the oil–financial markets relationship.

To deal with the limits of interdependence measures in the time-domain approaches, which are discussed later (Section 3), we propose two advantageous frequency approaches in this study: evolutionary spectral analysis (ESA) and wavelet analysis. To the best of our knowledge, this is the first time that such approaches have been used. The advantages of the ESA are as follows. First, it does not require any pre-treatment of the data.[1] Second, it does not require any band-pass or trend projection methods. Third, the ESA proposes robust modeling of a non-stationary process, avoiding information loss. Finally, the ESA provides additional information about the time horizon of the relationship: whether the studied variables present short-, medium-, or long-term interdependence. This is the main advantage of frequency analysis: it allows understanding of any permanent interdependence[2] (co-movement based on fundamentals) or transitory interdependence[3] (contagion based on excess co-movement explained by shocks). The monthly frequency of our data prevents us from obtaining long-term dependence through the spectral approach, which allows the study of short-term (10 months in our study) and medium-term dependence (three years and one quarter).[4] In order to compare our results to other frequency approaches and for robustness, we adopt wavelet analysis. This is a relatively new process in signal processing that decomposes data into different frequency components. This decomposition of different scales makes it easy to distinguish between seasonality, structural breaks, volatility clusters, and the identification of the local and global dynamic properties of the variables. In addition, the wavelet method provides a best alternative to investigate the interconnection between oil and stock markets, as it does not impose parametric restrictions on the dynamics of the stock market and oil price fluctuations. Finally, the wavelet process adapts different features of the time series in general (as equity market, and oil price series) such as, time-varying variance–covariance matrix and eventual structural breaks. This property is useful in our analysis to discriminate between interdependence (long-term co-movement) and contagion (short-term co-movement) in the relationship between oil and financial markets.

Our empirical results show that the co-movement of an oil price increase and stock return is confined to the short- to medium-term time-scale (high frequency to medium frequency) fluctuations and is relatively weak for the long-term time-scale (low frequency) fluctuations. In addition, the evidence suggests that global oil price variations influence stock return co-movement at different times and frequencies.

This study contributes to the literature in three ways. First, our analysis is related to new recent literature in finance based on trade noise. In other words, contrary to previous studies, we attempt to explain the relationship between oil and stocks without fundamental drivers. Second, our work is related to a few studies (e.g., Jammazi, 2012; Madaleno & Pinho, 2014; Reboredo & River-Castro, 2014) that have used the frequency approach in order to analyze the relationship between oil and stock markets. We extend these studies by using two comparative frequency approaches for robustness and by analyzing several countries. Third, in our analysis we cover 2 decades (1998–2013). Our choice is motivated by several economic crises and periods of financial turmoil having occurred during the study period, which allows us to draw relevant conclusions regarding co-movements of most dynamic international financial markets.

The remainder of the paper is structured as follows. Section 2 provides a brief literature review. Section 3 presents the data and stochastic properties. Section 4 describes the study's empirical methodologies. Section 5 discusses the empirical results. Finally, Section 6 summarizes the major findings and concludes.

2. Related literature

A significant number of studies in recent years have examined the link between oil price movements and stock market returns, at both the market and sectorial levels. A pioneering study by Jones and Kaul

[1] In the case of time domain approaches, some pre-treatments are indispensable. In the cases of the VAR model and the GARCH model, the econometric procedure requires data to be stationary. The co-integration techniques apply only under the condition of same-order integration of all data.

[2] Permanent interdependence is long-run co-movement. Thus, it is associated with low frequency.

[3] Transitory interdependence or contagion is based on excess co-movement. Thus, it is associated with a high frequency component.

[4] The frequency approach allows for the study of seven frequencies: $\pi/20$, $4\pi/20$, $7\pi/20$, $10\pi/20$, $13/20$, $16\pi/20$, and $19\pi/20$. The shift from the frequency domain to the time domain occurs through the following formula: $2\pi/\lambda$, where λ is the frequency. A smaller frequency gives us information about the bigger time span relationship. In other words, the frequency $\pi/20$ corresponds to $(2\pi/(\pi/20))$ months $= 3$ years and 1 quarter, whereas $10\pi/20$ refers to a 10-month timeframe. With monthly data, we cannot go beyond the 3 year and 1 quarter limit.