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Investigating dynamic conditional correlation between crude oil and fuels in non-linear framework: The financial and economic role of structural breaks

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ABSTRACT

To understand the crude oil volatility has been a challenge. The non-linear behavior, the skewed and leptokurtic returns, the presence of structural breaks and the constant political instability in suppliers' countries evidence the necessity of complex models to capture the market volatility. At the same time, crude oil is the raw material for several fuels such as jet fuel, gasoline, diesel and others, having a strong influence over their prices. Thus, this study aims to verify the presence of structural breaks in the volatility series and in the correlations between WTI return and the returns of Gasoline, Kerosene Jet Fuel, Diesel, Heating Oil, Propane and Natural Gas. To reach this objective, we identified which model presents the best fit to estimate the conditional mean between WTI and each fuel and we used a Copula–DCC–GARCH model to estimate the conditional volatility avoiding the frequently unrealistic presumptions of normality. Our main results indicate the necessity of a different model for each analyzed pair and the presence of at least one structural break in the conditional volatility and in the correlation between WTI and each fuel, usually preceded by a structural break in WTI return series.

1. Introduction

It is common knowledge that crude oil is raw material for several fuels such as jet fuel, gasoline, diesel and others. Thus its volatility can have an impact on transportation costs, life costs and even manufacturing costs. Due to its great importance, crude oil volatility behavior is significant to national economies and financial markets, given its capacity to generate economic shocks, such as those occurred in 1973, 1979 and 1990.

The relationship between crude oil, its derivatives and other fuels can change over time. Erdós (2012) applied vector error correction models showing that oil and natural gas prices had a long-term equilibrium before 2009, which is decoupled after that. This result evidences the instable relations between crude oil and other fuels. As highlighted by several researches, crude oil market is subjected to financial instability and political instability which are capable of generating regime changes and structural breaks (Salisu and Fasanya (2013); Ewing and Malik (2010)).

Presences of structural breaks in the correlation among assets have several implications. Investors can use information from oil market to trade or try to obtain extra information in fuel market. In fact, volatility spillover from oil to its derivatives, especially during supply originated crises. Thus, identifying these breaks can provide important information to investors and energy policy makers, which can understand that and adapt their strategies.

To determine the time point of structural breaks in volatility in crude oil prices has been a disagreement point of several studies. In this article we propose to identify which autoregressive model (VAR, TVAR, VEC or TVEC) presents the best fit to estimate the conditional mean, considering the linear or non-linear behavior of the WTI and fuel returns and to estimate the conditional volatility between WTI and each analyzed fuel via the Copula–DCC–GARCH model which presents a superior fit, since, as other financial assets, these returns are skewed, leptokurtic, and asymmetrically dependent. After that, we identified structural breaks in the volatility series and in the correlations between WTI return and the returns of Gasoline, Kerosene Jet Fuel, Diesel, Heating Oil, Propane and Natural Gas. This approach will

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contribute to literature by identifying the best models to analyze these relations, determining how it has changed through the years and completing a gap, since there are no recent studies about the presence of structural break in conditional volatility and correlation between crude oil and fuels.

This kind of information can supply investors with accurate information, contributing for their strategy choice, being especially useful to investors who desire to determine cross-hedge reasons among crude oil and different fuels. Furthermore, by determining models with better fit for energy assets, we can supply investors, policy makers and researchers with better tools, which provide more precise panoramas about the relations between crude oil and fuels volatilities.

2. Review of previous studies

The volatility series behavior has being the target of several researches. Ewing et al. (2002) estimated a BEKK Autoregressive Conditional Heteroscedasticity (GARCH) model for daily returns of natural gas and oil markets and verified that oil volatility depends on past volatility and not so much on specific events or economic news. In contrast, natural gas return volatility responds more to unanticipated events (e.g. supply interruptions, changes in reserves and stocks), regardless of which market they originated in.

Through a similar approach, Jin et al. (2012) analyzed the integration between future contracts of WTI, Dubai and Brent using the VAR–BEKK model. And observed that Dubai and Brent crude are highly responsive to market shocks and the WTI crude proved to be the least responsive of the three benchmarks. Simulating, they show that only large shocks will result in an increase in expected conditional volatilities.

However, a shortcoming of those approaches is that, even though models deal well with the clustering problem of volatility in data and mitigate the problems of fat tails, GARCH models commonly assume that no shift in volatility occurs, which means that the volatility oscillates within a constant range, being a stationary process. It is well known that volatility of asset prices is substantially affected by sudden changes or regime shifts, corresponding to domestic, global economics, and political events. To deal with this problem, Kang et al. (2011) analyzed the volatility considering structural breaks in the series, considering sub-periods of the changing volatility of crude oil returns and the BEKK–GARCH model was estimated. The results reveal five structural changes in the period from January 5, 1990 to March 27, 2009, reducing the degree of persistence in the conditional variance of both returns, concluding that ignoring structural changes may distort the direction of information inflow and volatility transmission between crude oil markets.

Salisu and Fasanya (2013) employed the tests developed by Narayan and Popp (2010) and Liu and Narayan (2010) to detect structural breaks in oil price volatility. This approach permits shifts in the trend function to have a gradual effect on the oil price changes. This methodology allowed them to detect two structural breaks (1990 and 2008) in WTI and Brent series, referring to the Iraq/Kuwait conflict and the global financial crisis, respectively. After, they applied different GARCH models to estimate the oil price volatility, concluding that the EGARCH model presents the best fit. These evidences suggest that oil volatility is not uniform in time presenting persistence and leverage effects.

Following this line, Vivian and Wohar (2012) analyzed the presence of volatility breaks in energy commodities, among others. They employed GARCH (1,1) to model the volatility series and the ICSS algorithm to identify structural breaks in WTI, Brent, Fuel Oil, Heat Oil and Gas in the period between January 2nd 1985 and July 30th 2010. Their results aim for the presence of three breaks in Brent series, in 7/31/1990, 3/19/1991 and 1/8/1996, being the 2008 financial crises insufficient to generate a new break. The other fuels analyzed did not present any structural break. During the sub-periods, none of the commodities had a significant decline in short-term volatility persistence below unity. Those results are quite different to Ewing and Malik (2010) who found evidences of three structural breaks in WTI volatility series in August 29, 1994, January 8, 1996 and June 13, 2005.

However, these papers estimated volatility models under the assumption of multivariate normality – maximum likelihood (ML) – or based on a mixture of elliptical distributions — quasi maximum likelihood (QML). According to Cherubini et al. (2012), this assumption is unrealistic, as evidenced by numerous empirical studies, in which it has been shown that many financial asset returns are skewed, leptokurtic, and asymmetrically dependent. These difficulties can be treated as a problem of copulas.

The Copula–DCC–GARCH model was proposed with a financial application by Jondeau and Rockinger (2006). For oil and fuel markets, we follow the approach of Reboredo (2011) that examined the dependence structure between crude oil benchmark prices using copulas (for conceptual details see Sklar, 1959). Testing different copula models, he identified the best fit of Student-t copula and concluded the hypothesis that the oil market behaves like a common market.

Thus, the current studies diverge about the volatility of structural break time point and the investigations of this phenomenon in crude oil correlations with their derivatives are rare. Further, previous studies were based on the assumption of multivariate normality, a mixture of elliptical distributions, which are frequently unrealistic. Although some studies investigate the presence of structural breaks in crude oil, there are no researches about this phenomenon in the conditional volatility and correlations between crude oil and fuels. To solve this problem we propose the use of Copula–DCC–GARCH to model the volatility, believing that with a better modeling we are able to identify more accurate structural break points.

3. Methodology

3.1. Data

During this paper, we analyzed daily spot price log-returns of WTI crude oil, Gasoline, Kerosene Jet Fuel, Diesel, Heating Oil, Propane and Natural Gas. All data is available on the *U.S. Energy Administration* web site. In order to estimate the volatilities and to construct the correlation matrix between WTI and each fuel, the series were paired by date, following Table 1.

As Table 2 shows, WTI presents the lowest standard deviation, being less volatile than most fuels. Considering only fuels, Diesel presents the highest standard deviation, followed by Kerosene, Propane and Natural Gas, while Heating Oil is less volatile. The kurtosis analysis shows that WTI, Gasoline, Heating Oil and Natural Gas distributions present heavier tails, suggesting the copula model as a good approach.

3.2. Methodological procedures

We chose to use autoregressive models such as VAR, VEC, TVAR and TVEC for data relationships. It is common knowledge that cointegration is a presupposition for VEC and TVEC models, denoting a long-term relation between variables. We apply the two-step Engle–Granger approach to test for a cointegration relationship between each fuel

Table 1
Analyzed series paired with WTI by date.

Fuel	Period	Observations
Gasoline	June 2, 1986–February 20, 2013	6840
Kerosene Jet Fuel	April 02, 1990–February 20, 2013	5756
Diesel	April 17, 1996–February 20, 2013	4232
Heating Oil	June 2, 1986–February 20, 2013	6744
Propane	July 9, 1992–February 20, 2013	5173
Natural Gas	January 7, 1997–February 20, 2013	4035