Energy Economics 48 (2015) 46–60

Contents lists available at ScienceDirect

Energy Economics

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

Structural breaks, dynamic correlations, asymmetric volatility transmission, and hedging strategies for petroleum prices and USD exchange rate

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ARTICLE INFO

Article history:
Received 5 April 2014
Received in revised form 11 December 2014
Accepted 15 December 2014
Available online 23 December 2014

JEL classification:
G14
G15

Keywords:
Petroleum markets
USD/euro exchange rate
Asymmetric volatility spillovers
Dynamic hedge ratios
Multivariate-DCC–EGARCH
Structural breaks

ABSTRACT

This paper investigates the influence of structural changes on the asymmetry of volatility spillovers, asset allocation and portfolio diversification between the USD/euro exchange market and each of six major spot petroleum markets including WTI, Europe Brent, kerosene, gasoline and propane. Using the bivariate DCC–EGARCH model with and without structural change dummies, the results provide evidence of significant asymmetric volatility spillovers between the U.S. dollar exchange rate and the petroleum markets. Moreover, the model with the structural breaks reduces the degree of volatility persistence and leads to more appropriate hedging and asset allocation strategies for all pairs considered. Thus, the findings have important implications for financial risk management.

1. Introduction

Petroleum is arguably one of the most important commodities in terms of world trade and functioning of the global economy. This composite energy product is used in different economic activities and domains including industrial production, transportation, and agriculture, among other activities. Changes in international petroleum prices also have significant effects on the dynamics of non-energy and financial markets of the world's economy, particularly the foreign exchange markets. More importantly, the petroleum prices are denominated in U.S. dollars. This fact has important implications for the linkages between the exchange rate and the prices of petroleum products. Thus, variations in those prices when expressed in domestic currencies depend closely on changes in the dollar exchange rates with respect to those currencies. Traders make their buy and sell decisions based not only on the domestically available information in the petroleum markets but also in terms of the information disclosed by the foreign exchange markets. Therefore, the international petroleum prices and the U.S. dollar exchange rate are interrelated. A better understanding of the volatility interdependencies among those markets is therefore one of the most important tasks for investors and policy makers.

In the literature, less attention has been paid to the volatility interrelationships between the foreign exchange and commodity markets, particularly the international petroleum markets which include crude oil, gasoline, kerosene, and propane under consideration in this study. It is not well-known how the USD exchange rate interacts for example with gasoline and natural gas prices. Although these refined products have strong correlations with crude oil, they differ in terms of seasonality, contract liquidity and tradability, and stylized facts. They also have different linkages with real economic sectors due to their different uses. Hence, examining the volatility transmission between the foreign exchange and different petroleum markets is of great relevance for measuring volatility of petroleum futures prices (Kang and Yoon, 2013), value at risk (Aloui et al., 2013), risk management (Hammoudeh et al., 2010), out-of-sample forecasts (Mensi et al., 2014), asset allocation strategy (Wu et al., 2012), and monetary and fiscal policy operations (Kim et al., 2012), among other topics.

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http://dx.doi.org/10.1016/j.eneco.2014.12.004
0140-9883/

Moreover, the price dynamics of the petroleum and foreign exchange markets are extremely volatile and the interrelationships between them may be asymmetric in the sense that these markets respond differently to positive and negative shocks of the same magnitude. More precisely, the increase in volatility is greater when the returns are negative (a price fall due to bad news) than when they are positive (a price rise due to good news) of the same magnitude, indicating the presence of the 'leverage effect'. Furthermore, these markets have always been subjected to infrequent sudden changes and changes in dynamic correlations due to changes in business cycles and the occurrence of geo-political events (Kang et al., 2009).

More interestingly, the traditional GARCH models commonly assume that no shift in volatility occurs (Kang et al., 2011). However, ignoring structural breaks in those markets can lead to sizeable upward biases in the degree of volatility persistence.[1] By not accounting for the presence of structural breaks, the GARCH-family models do not accurately track changes in the unconditional variance, leading to forecasts that underestimate or overestimate volatility for long stretches, thus weakening the degree of integration among the markets.

The present research contributes to the existing literature in a number of ways. First, to our knowledge, this study is the first to incorporate structural breaks into the bivariate DCC–EGARCH approach and apply the revised model to volatility spillovers between the U.S. foreign exchange markets and the prices for the five international petroleum and propane products. We believe that this model is suitable to accommodate the abovementioned stylized facts in the volatility transmission mechanism. Second, given the fact that the United States is currently the world's second oil producer, producing more than 8.7 million barrels/day and moving to be the first producer, and that the euro-zone is a large importer of petroleum products, it is of great interest to consider the U.S. and Europe Brent petroleum products and the USD/euro exchange rate in this study when examining the spillovers between these variables.[2] Moreover, the euro area imports most of its petroleum products and settles most of its important transactions in U.S. dollars. Third, we analyze the dynamic conditional correlations among the US exchange rates and the major petroleum markets. Fourth, it is especially of interest to incorporate the structural breaks in the GARCH-family models when we examine the interrelations among the petroleum and foreign exchange markets to improve the model's performance. This consideration has implications for the persistence of volatility because the marginalization of the impact of structural breaks that change expectations and arbitrage activities leads to overestimation of the degree of volatility persistence, which has bearing on generating forecasts of future volatility. Finally, we examine the influence of the structural changes on the effectiveness of the dynamic hedging strategies by computing the optimal portfolio weights and dynamic hedge ratios to analyze the implications of these breaks for energy investors. More specifically, we investigate whether the consideration of structural breaks alters portfolio compositions and the variability of hedge ratios.

Motivated by the above considerations, we consider a bivariate DCC–EGARCH method to satisfy several purposes. First, it is less restrictive in terms of the number of variables included in the model, compared to other traditional multivariate GARCH models. Second, our model enables to understand the origins, directions and transmission intensities of shocks across markets, allowing investors to improve their asset allocation and better design their optimal hedging strategies. Third, it provides different responses to innovations regarding the quantity and quality of news, which is crucial for the degree of linkages or volatility transmission across markets. In fact, the multivariate DCC–EGARCH model is the best suited because it explicitly models potential asymmetry that may exist in the volatility transmission mechanism, allowing both own-market and cross-market innovations to exert asymmetric impacts on volatility in a given market. In other words, news generated in one market is assessed in terms of both size and sign by the other market. Interestingly, our econometric method allows for conditional correlations across asset return series to evolve over time. To overcome the overestimated persistence and the distortion of information inflows, we incorporate the sudden changes news into our volatility modeling. For this purpose, we use Inclán and Tiao's (1994) Iterated Cumulative Sum of Squares (ICSS) algorithm and identify multiple structural breaks for the markets.

Using daily data from December 15, 1998 to May 1, 2012, our main results provide strong evidence of significant asymmetric volatility transmission among the US exchange rate and petroleum markets. The conditional correlations among the considered markets evolve over time. More interestingly, the sudden changes are found to exert influence on the exchange rate–petroleum relationships as well as on the portfolio composition and to provide more accurate hedge ratios. These results have several important implications for investors and policymakers.

The remainder of this paper is organized as follows. Section 2 provides a brief review of the literature. Section 3 discusses the econometric framework, the data and the stochastic properties. Section 4 provides the empirical results. Section 5 analyzes the results. Section 6 draws conclusions and policy implications.

2. Literature review

The behavior of petroleum prices and its volatility should have significant effects on changing the conditions of the dollar exchange rates. The reverse may also be true (Kim et al., 2012). Chen and Chen (2007) examine the long-run links across real oil prices and real exchange rates for the G7 countries. They find that real oil prices may have been the dominant source of movements in real exchange rates and there is also a link between real oil prices and real exchange rates.

Various methods are used to test the interactions among energy and exchange rate markets. These methods can be broadly listed into two categories. The first category focuses on both the simultaneous and the causal relationship between oil prices and exchange rates. The studies in this category employ a range of econometric techniques, such as the vector autoregressive model, Granger-causality-in-mean and Granger causality-in-variance analysis, cointegration models, the vector error correction model, Markov-switching vector error-correction (MS–VECM) models, and multivariate ARCH and GARCH models, as discussed below.

In this first category, Sadorsky (2000) investigates the cointegration and causal relationships between energy futures prices of crude oil, heating oil and unleaded gasoline, and the U.S. dollar effective exchange rates and finds that the exchange rates transmit exogenous shocks to energy futures prices. In the same vein to Sadorsky (2000), Muñoz and Dickey (2009) show that the oil prices, Spanish electricity spot prices and the USD/euro exchange rate are cointegrated. The authors detect a transmission of volatility between the USD/euro exchange rate and oil prices to Spanish electricity prices. In a related study, Zhang et al. (2008) apply various econometric methods including cointegration, VAR model, ARCH type models, and the Granger causality-in-risk to test the mean, volatility and risk spillovers of changes in the U.S. dollar exchange rate on the global crude oil price. They find a significant effect of the U.S. dollar exchange rate on international oil prices in the long run, but short-run effects are limited. Using both linear and nonlinear causality tests, Wang and Wu (2012) examine the causal relationships between energy prices and the U.S. dollar exchange rates. They find evidence of significant unidirectional linear causality (bidirectional nonlinear causality) running from petroleum prices to exchange rates before (after) the recent financial crisis. As for Salisu and Mobolaji (2013), the authors support evidence of a bidirectional returns and spillover transmission between oil price and US–Nigeria exchange rate and hedging effectiveness involving oil and foreign exchange markets in Nigeria.

[1] For further information, see Aggarwal et al. (1999), Hammoudeh and Li (2008), Hillebrand (2005), Mikosh and Starica (2004) and Salisu and Fasanya (2013).

[2] Source: CIA World Factbook 2012.

Concerning Ding and Vo (2012), the authors use the multivariate stochastic volatility and the multivariate GARCH models to analyze the volatility interactions between the oil and the foreign exchange markets under the structural breaks. They support the presence of the bi-directional volatility interaction between the two variables during the 2007/2008 financial crisis. In a recent work on the volatility transmission between oil prices and the U.S. dollar exchange rates of emerging economies, Turhan et al. (2013) show that a rise in the oil price leads to a significant appreciation in those economies' currencies relative to the U.S. dollar. Basher et al. (2012) use the structural vector autoregression (SVAR) model and document that positive shocks to oil prices tend to depress emerging market stock prices and the U.S. dollar exchange rates in the short run. Beckmann and Czudaj (2013) employ a Markov-switching vector error correction (MS–VECM) model to analyze the causality between oil prices and nominal and real effective dollar exchange rates. They find evidence that supports the presence of different causalities, depending on the dataset under investigation.

The second strand of the empirical framework focuses on the dependence structure across markets and employs dynamic copula-based GARCH models and wavelet approaches. Aloui et al. (2013) apply a static copula-GARCH approach and find a significantly conditional dependence between oil prices and U.S. dollar exchange rates. Wu et al. (2012) use dynamic copula-based GARCH models to explore the dependence structure between the oil price and the U.S. dollar exchange rate. They find that an asset allocation strategy is implemented to evaluate the economic value and confirm the efficiency of the copula-based GARCH models. Moreover, in terms of out-of-sample forecasting performance, a dynamic strategy based on the copula-based GARCH model with the Student-t copula exhibits greater economic benefits than the static and other dynamic strategies. Similarly, Reboredo (2012) documents weak dependency between oil prices and the U.S. dollar exchange rate and also finds this dependency to be increasing substantially after the recent global financial crisis.

Chen et al. (2013) examine the volatility and tail dependence between the WTI oil prices and the US dollar exchange rate. Their results present evidence of asymmetric dependence structures between the oil price and the US dollar exchange rate, indicating that crude oil returns are more negatively linked with US dollar returns when the US dollar depreciates, as compared to when it appreciates. Furthermore, the authors examine the economic value of extreme-value information in oil and US dollar markets from the perspective of asset-allocation and show that the dynamic strategies based on the range-based volatility models outperform those based on the return-based volatility models. In this case, investors would be willing to pay substantial fees of between 72 and 713 annualized basis points to switch their strategies from return-based to range-based volatility models, and the less risk-averse investors would generate higher switching fees.

Using the wavelet method and a battery of linear and non-linear causality tests, Tiwari et al. (2013) uncover linear and nonlinear causal relationships between the oil price and the real effective exchange rate of the Indian rupee at higher time scales (lower frequency). The authors provide evidence of causality at higher time scales only. Using the same methodology, Benhmad (2013) studies the linear and nonlinear Granger causality between and finds a strong bidirectional causal relationship between the real oil price and the real effective U.S. dollar exchange rate for large time horizons. Reboredo and Rivera-Castro (2013) examine the relationship between oil prices and US dollar exchange rates using wavelet multi-resolution analysis for different time scales in order to disentangle the possible existence of contagion and interdependence during the global financial crisis. The authors conclude that oil prices and exchange rates are not dependent in the pre-crisis period but there is evidence of contagion and negative dependence after the onset of the crisis. Additionally, they find that oil prices lead exchange rates and vice versa in the crisis period but not in the pre-crisis period.

Our study extends the work of Salisu and Mobolaji (2013) and addresses the volatility transmission between petroleum prices and US dollar exchange rate. In contrast to Salisu and Mobolaji (2013), our model is significantly more flexible since it allows for time-varying conditional correlations and asymmetric responsiveness to changes in volatility, permitting the asset allocation and the hedge ratio to be adjusted to account for the most recent information. Additionally, we examine the influence of the sudden changes on the spillovers effects in the returns and volatility between the petroleum and foreign exchange markets as well as on the dynamic hedging strategies.

3. Empirical methods and data

3.1. Bivariate DCC–EGARCH model

In this paper, we use the bivariate DCC–EGARCH model of Nelson (1991) combined with the DCC model to examine the significance of potential asymmetry and structural breaks in the relationship between the petroleum and the foreign exchange markets. As pointed out earlier, one of the main advantages of this model is that it allows one to capture the potential asymmetric effect of shock transmissions, the dynamics of volatility, the volatility spillovers, and the time-varying conditional correlations between series.[3] Moreover, modeling volatility without incorporating structural breaks may generate spurious regressions due to resulting overestimated volatilities.

3.1.1. Mean spillover equation

We propose that the mean spillover effect is captured by the following bivariate relationship between the returns of the U.S. dollar/euro exchange rate and petroleum/propane prices:

$$\begin{pmatrix} r_{EX,t} \\ r_{PET,t} \end{pmatrix} = \begin{pmatrix} C_{EX,0} \\ C_{PET,0} \end{pmatrix} + \begin{pmatrix} \beta_{EX,1} & \beta_{EX,2} \\ \beta_{PET,1} & \beta_{PET,2} \end{pmatrix} \begin{pmatrix} r_{EX,t-1} \\ r_{PET,t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{EX,t} \\ \varepsilon_{PET,t} \end{pmatrix}, \tag{1}$$

where

$$\begin{pmatrix} \varepsilon_{EX,t} \\ \varepsilon_{PET,t} \end{pmatrix} \Bigg| \ \Omega_{t-1} \sim N(0, H_t),$$

$r_{EX,t}$ represents the return of the U.S. dollar/euro exchange rate, $r_{PET,t}$ is the return for each of the international petroleum and propane prices measured in U.S. dollars of West Texas Intermediate (WTI), Europe Brent (Brent), kerosene, gasoline, and propane, Ω_{t-1} denotes all relevant information set known at time $t-1$, and H_t is the conditional variance–covariance matrix as defined below. Here, $\sigma^2_{EX,t}$, $\sigma^2_{PET,t}$, and $\sigma_{EX,PET,t}$ represent the variance of the U.S. dollar exchange rate return, the variance of each of the petroleum and propane returns, and the covariance between them, respectively. Moreover, $\beta_{PET,1}$ and $\beta_{EX,2}$ represent the mean spillover effects of each of the petroleum prices and the U.S. dollar exchange rate returns, respectively. Finally, $\beta_{EX,1}$ and $\beta_{PET,2}$ capture the effect of the own lagged returns for the exchange rate and each of the respective petroleum prices, respectively.

3.1.2. Variance equation

To explore the joint evolution of the conditional variances of the dollar exchange rate and each of the petroleum price returns, we first build the variance equations that include both the asymmetric and the lagged variance terms. The time-series dynamics of the diagonal elements of the (2×2) variance–covariance matrix are modeled as follows:

$$\begin{cases} \ln\left(\sigma^2_{EX,t}\right) = \alpha_{EX,0} + \alpha_{EX,1} f_1\left(z_{EX,t-1}\right) + \alpha_{EX,2} f_2\left(z_{PET,t-1}\right) + \gamma_{EX} \ln\left(\sigma^2_{EX,t-1}\right) \\ \ln\left(\sigma^2_{PET,t}\right) = \alpha_{PET,0} + \alpha_{PET,1} f_1\left(z_{EX,t-1}\right) + \alpha_{PET,2} f_2\left(z_{PET,t-1}\right) + \gamma_{PET} \ln\left(\sigma^2_{PET,t-1}\right) \end{cases}. \tag{2}$$

[3] Abraham and Seyyed (2006), Zhang et al. (2008), Bhar and Nikolova (2009), and Ji and Fan (2012) have used the bivariate EGARCH model but without test-based structural breaks.

In Eq. (2), f_1 and f_2 are functions of the lagged standardized innovations defined at time t as $z_{EX,t} = \varepsilon_{EX,t}/\sigma_{EX,t}$ and $z_{PET,t} = \varepsilon_{PET,t}/\sigma_{PET,t}$, while γ_{EX} and γ_{PET} measure the degree of volatility persistence for the U.S. dollar exchange rate and each of the petroleum price returns, respectively. The functions f_1 and f_2 capture the effects of the lagged innovations for the exchange rate and petroleum return variables in the above bivariate EGARCH (1,1) model, respectively, as follows:

$$f_1\left(z_{EX,t-1}\right) = \left|z_{EX,t-1}\right| - E\left(\left|z_{EX,t-1}\right|\right) + \delta_{EX} z_{EX,t-1}, \quad (3)$$

$$f_2\left(z_{PET,t-1}\right) = \left|z_{PET,t-1}\right| - E\left(\left|z_{PET,t-1}\right|\right) + \delta_{PET} z_{PET,t-1}. \quad (4)$$

The term $|z_{i,t-1}| - E(|z_{i,t-1}|)$ represents the magnitude effect, and $\delta_i z_{i,t-1}$ captures the sign effect ($i = EX, PET$). If $\delta_i < 0$, then a negative innovation for $z_{i,t}$ would tend to increase the volatility by more than a positive innovation of equal magnitude would. Similarly, if the past absolute value of $z_{i,t}$ is greater than its expected value, then the current volatility will rise. The asymmetric effect of the standardized innovations on volatility at time t can be measured as the derivatives of Eqs. (3) and (4):

$$\frac{\partial f_i\left(z_{i,t}\right)}{\partial z_{i,t}} = \begin{cases} 1+\delta_i & z_{i,t} > 0 \\ -1+\delta_i & z_{i,t} < 0 \end{cases}, \quad (5)$$

where the relative asymmetry is defined as $RA = |-1+\delta_i|/(1+\delta_i)$. This ratio is greater than, equal to, or less than 1 for negative asymmetry, symmetry, and positive asymmetry, respectively. The persistence of volatility can also be measured by an examination of the half-life (HL), which indicates the time period required for the shocks to decline to one half of their original size. That is, $HL = \ln(0.5)/\ln|\gamma_i|$. However, the correlation between the exchange rate and petroleum markets can reflect the degree or the extent to which their returns move together in different periods. Knowledge of the co-movement between these markets is of crucial importance for global investors because of its relevance to portfolio diversification and hedging strategies.

To estimate the time-varying conditional correlations between the U.S. dollar exchange rate and each of the petroleum market returns, $\rho_{EX,PET,t}$, we follow the method developed by Darbar and Deb (2002) and Skintzi and Refenes (2006) by using the index function $\xi_{EX,PET,t}$.[4] This function is assumed to depend on the cross-market standardized innovations and its lagged values, as defined below. The conditional correlation that falls in the range $[-1, +1]$ can be expressed as a logistic transformation of the index function. That is,

$$\sigma_{EX,PET,t} = \rho_{EX,PET,t}\sigma_{EX,t}\sigma_{PET,t}, \quad (6)$$

$$\rho_{EX,PET,t} = 2\left(\frac{1}{1+\exp\left(-\xi_{EX,PET,t}\right)}\right) - 1, \quad (7)$$

$$\xi_{EX,PET,t} = C_0 + C_1 z_{EX,t-1} z_{PET,t-1} + C_2 \xi_{EX,PET,t-1}. \quad (8)$$

The parameters of the bivariate EGARCH model are estimated by using the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992).

3.2. Identification of structural breaks

We use Inclán and Tiao's (1994) ICSS algorithm to capture the structural breaks in both the petroleum returns and the U.S. dollar exchange rate data series. Considering several structural break tests, this algorithm has been extensively used by several studies, including by Andreou and Ghysels (2002), Hammoudeh and Li (2008), Kang et al. (2011), Kumar and Maheswaran (2013), Mensi et al. (2014) and Vivian and Wohar (2012), among others, to identify the points of shocks/sudden changes in the volatility of return series.[5]

The Inclán and Tiao's (1994) test assumes that the data display a stationary variance over an initial period until a sudden change occurs, resulting from a sequence of events. Then the variance reverts to stationary again until another change occurs. This process is repeated through time, generating a time series of observations with an unknown number of changes in the variance. The sudden change points in variance are endogenously detected.

3.3. Data and stochastic properties

3.3.1. Data

We use daily data for the U.S. dollar/euro exchange rate and the closing spot prices for the WTI and Brent crude oil prices expressed in U.S. dollars per barrel, and the kerosene, gasoline and propane prices in U.S. dollars per gallon for the period ranging from December 15, 1998 to May 1, 2012. This period has been characterized by high levels of volatility and an upward trend in prices and also covers all episodes of sharp fluctuations in crude oil markets. It also includes several episodes of wide instabilities and crises (e.g., the 2001 U.S. terrorist attacks, the 2001 Dot-com bubble, the 2003 Gulf wars, the 2011 Libyan revolution, the food price surge of 2007–2008, the 2008–2009 global financial crisis and the 2009–2012 Eurozone debt crisis).

Several reasons have motivated us to select the USD/euro exchange rate. The U.S. dollar is considered as the exchange rate currency because it is used as the invoicing currency in international crude oil trading, the most important reserve currency in the world, and the currency in which the most international commercial transactions are made. The choice of the USD/euro exchange rate is also highlighted by the fact that Europe, and in particular the Eurozone, is very sensitive to changes in oil prices. The European region imports the majority of its petroleum and propane product needs and pay for them in dollars. Moreover, the USD and euro currencies are the most actively traded pair on the foreign exchange market. Zhang et al. (2008) argue that the exchange rate of the euro against the US dollar accounts for the largest market trades in the total international exchange. During our sample period, the most dramatic losses of the dollar have occurred against the euro.[6]

As for the petroleum commodities, both the WTI, the reference crude oil for the United States, and Europe Brent, the reference crude for the North Sea, are among the most important fossil fuels and their prices serve as the benchmarks for pricing numerous financial instruments and oil-related products. Gasoline and kerosene are among the most important products refined from crude oil. Gasoline contracts are also heavily traded on the commodity exchanges. Kerosene is widely used to power jet engines of aircraft and some rocket engines. Propane is an energy-rich gas and is one of the liquefied petroleum gases that are found mixed with natural gas and oil. It thus captures the effects of changes in natural gas prices on the dollar/euro exchange rate. Given the strong 'financialization' of commodities in the energy sector, we include the crude oil and the related oil and natural gas products in this analysis. Additionally, the presence of different correlations between the US dollar exchange rate and the petroleum assets has also motivated us to investigate the relevance of these products in conjunction with the U.S. dollar exchange rate for the investors and traders. In fact, we find positive correlations between the USD/euro exchange rate and kerosene but negative correlation with the rest of refined oil products. Moreover, although these refined products have strong correlations with crude oil

[4] $\xi_{EX,PET,t} \in (-\infty, +\infty)$.

[5] The CUSUM test does not disclose the exact number of breaks and their corresponding dates of occurrence, while the Bai and Perron (2003) test has a size-distortion problem when heteroscedasticity is present in the data.

[6] One of the authors of this paper undertook an experiment with his MBA student to figure out which of the different types of the dollar exchange rate has the highest correlation with petroleum products and found that the dollar/euro exchange rate is the one.

(Tong et al., 2013), they differ among themselves in terms of seasonality, contract liquidity and tradability, stylized facts and economic uses, as indicated earlier.

The daily closing prices for the petroleum products are accessed from the U.S. Energy Information Administration (EIA) database, and the exchange rate is sourced from the Oanda website.[7] The continuously compounded daily returns are computed by taking the difference in the logarithm of two consecutive prices.

Fig. 1 displays the daily evolution of the petroleum prices of WTI, Europe Brent, kerosene, gasoline and propane and the U.S. dollar/euro exchange rate over the sample period. For a clear comparison, the evolution of these variables is shown in different multiples. The petroleum and propane prices exhibit similar trends, suggesting that they are highly correlated. In 2008, we can easily observe sharp movements in those prices, corresponding to the subprime mortgage crisis, while concurrently the U.S. dollar exchange rate generally shows reverse movements. This is not a surprise because gasoline and kerosene are downstream products of crude oil and their prices are highly correlated with oil prices. On the other hand, the time paths of the return series over the study period are plotted in Fig. 2. Considering this figure, we can see that the daily returns exhibit stylized facts. Indeed, the marginal distributions of the exchange rate and petroleum price return series appear leptokurtic, and a number of volatility clusters are clearly visible. The asymmetric GARCH-family models are designed for the parameterization of this phenomenon.

3.3.2. Stochastic properties

The statistical properties of the return behaviors for the exchange rate and the petroleum markets are formally shown in Table 1. The daily averages of these return series vary between −0.02 and 0.074, with Brent oil having the highest mean. On the other hand, the propane returns yield the lowest mean during the sample period, which is likely has to do with low natural gas prices. Furthermore, gasoline has the highest risk, as is evident by its standard deviation which amounts to 2.91%, followed by kerosene (2.76%) and propane (2.58%).

The coefficient of variation is negative for the USD/euro exchange rates but positive for the petroleum return series, indicating that the relative dispersion is greater for the petroleum markets than for the foreign exchange markets. The skewness value is a negative number for all return series, except for the gasoline asset, indicating that the series are left skewed (i.e., asymmetric). The kurtosis values of all return series are more than three times the value of a normal distribution, indicating the presence of peaked distributions and fat tails. The Jarque–Bera normality test also indicates that the returns for the petroleum prices and the exchange rate are not normally distributed. Also, the results of the Ljung–Box test statistics of the residuals ($Q(14)$) fail to support the null hypothesis of white noise process (i.e., an i.i.d. process), underlying the presence of temporal dependence for all return series. Therefore, the use of a GARCH-based approach is appropriate for modeling some stylized facts such as fat-tails, clustering volatility, persistence and asymmetry for the foreign exchange and petroleum returns. Additionally, we find that the exchange rate returns are positively correlated with the petroleum assets, whereas they are negatively correlated with propane assets.

To initially establish that we are dealing with nonstationary time series, we implement two types of unit root tests and one type of stationary tests. The two unit root tests are the augmented Dickey and Fuller (ADF; 1979) and the Phillips and Perron (PP; 1988) tests, and the stationary test is the Kwiatkowski et al. (KPSS; 1992) test. The results of the unit root and the stationarity test strongly suggest that all return series are stationary processes at the conventional levels. Finally, both the LM- and the F-statistics are very significant, confirming the presence of ARCH effects in the petroleum price and exchange rate returns. This implies that the use of a GARCH-family model is appropriate.[8]

4. Results

In this section, we present the estimation results obtained from the bivariate DCC–EGARCH model for the exchange rate and petroleum returns, and the potential effect of structural breaks on the transmission of volatility. We will provide the discussion of the portfolio management with petroleum risk hedging strategies with and without the presence of structural breaks in the following section.

4.1. Return and volatility spillovers without structural breaks

As mentioned earlier, there are six markets under investigation in this study. We proceed with the estimation of the five bivariate DCC–EGARCH models, where each model contains the daily U.S. dollar exchange rate return and the daily return for one of each of the five petroleum/propane prices. The estimation results of the bivariate DCC–EGARCH (1,1) models are reported in Table 2. Examining the return-generating process (see Panel A), the estimation results show that the one-period lagged values of the U.S. dollar exchange rate (represented by $\beta_{EX,1}$) and each of the petroleum markets ($\beta_{PET,2}$) largely influence their current values at the 1% significance level, showing persistence in returns and contradicting the weak-form market efficiency. This influence suggests that the past price returns be used to forecast future price returns, indicating short-term predictability in these markets. However, only the returns of the propane market are affected by the U.S. dollar exchange rate returns. The coefficient of one day of the past returns of the U.S. dollar exchange rate is significant and positive for this market, with an estimated coefficient of 0.068, suggesting that investors should consider the news in the foreign exchange markets to determine the propane returns. Thus, we conclude that depreciation of the dollar can cause higher volatility in the propane market and raise its returns. The changes in the USD/euro exchange rate signal considerable information about future propane market movements.

Meanwhile, the U.S. dollar exchange rate returns are not affected by the information about any of the petroleum market returns (see the coefficient $\beta_{EX,2}$), implying that the formation of the U.S. dollar returns is not explained by the fluctuations of the past returns of these petroleum products. On the whole, the results reject the hypothesis of significant cross-market mean spillovers among the considered markets (with the exception of the propane returns which respond to the information from the U.S. dollar exchange market). The return innovation or shock in any of the petroleum markets also does not affect the mean returns for the U.S. exchange rate market.

Regarding the conditional variance equations (see Panel B), the sensitivity to the past own conditional variance (γ_{PET}) appears to be significant for the petroleum markets, implying strong volatility persistence for these markets. The persistence of these petroleum markets is generally high and close to one, indicating a long memory process and implying that a shock in current volatility has an impact on future volatility over the long term. This result is similar to that reported by Chang et al. (2011). More precisely, Brent is the most volatile petroleum price (where $\gamma_{PET} = 0.931$), followed by kerosene (0.919), WTI (0.913) and propane (0.872). In contrast, gasoline shows the lowest past volatility effect (0.854). This finding suggests that past volatility values for these markets can be employed to forecast future volatility and also indicates that the bivariate DCC–EGARCH (1,1) model is adequate for capturing any persistence in the volatility of the petroleum markets, as relatively large volatility is often followed by large volatility in the same direction.

[7] The EIA website for the petroleum prices is http://www.eia.gov, and the Oanda website is http://www.oanda.com.

[8] The estimation results for the unit root tests, the ARCH-LM test of Engle (1982) and the unconditional correlations for the returns of the exchange rate and the petroleum prices are not presented here, but are available under request addressed to corresponding author.

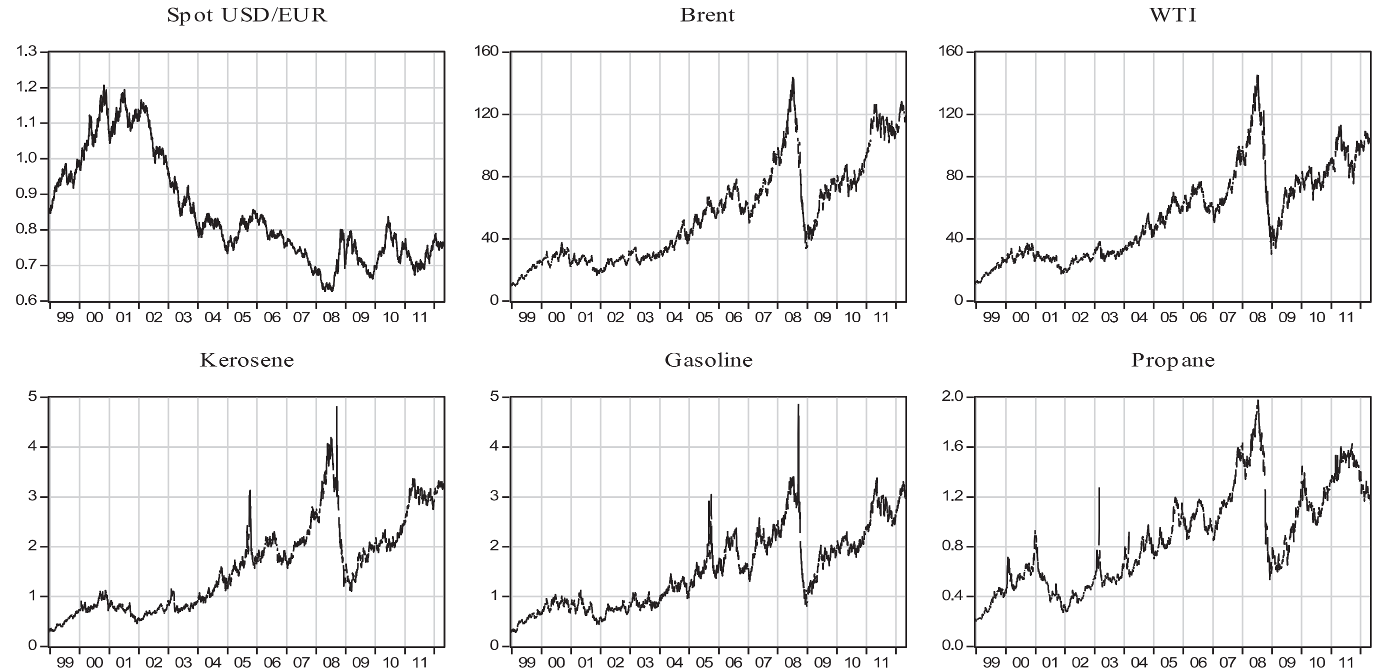

Fig. 1. Daily price behavior for the exchange rate and the petroleum markets.

As reported in Panel B, the volatility equation parameters $\alpha_{EX,2}$ and $\alpha_{PET,1}$ capture the cross-market volatility spillover effects between the U.S. dollar exchange rate and each of the petroleum market returns. The results reveal that the past U.S. dollar exchange rate innovations have significant and positive effects on the five petroleum market volatility (see the coefficient $\alpha_{PET,1}$). Meanwhile, the volatility of the U.S. dollar exchange rate is influenced by the past innovations of all the petroleum volatility, except for gasoline (see the coefficient $\alpha_{EX,2}$). Our results indicate that significant volatility spillover takes place between the U.S. dollar exchange rate and the petroleum markets. However, the effect of the U.S. dollar exchange rate innovations on the volatility of the petroleum markets is positive, which implies a positive relationship between the past period innovations in the U.S. dollar exchange rate and these markets.

Clearly, we can say that the depreciation risk of the U.S. dollar may increase the petroleum demand, which in turn generates a dramatic increase in the petroleum prices. On the other hand, as noted in Wang and Wu (2012), lower petroleum demand reduces the demand for the U.S. dollar, resulting in its depreciation. The half-life (*HL*) is used to evaluate the persistence of volatility shocks. As shown in Table 2—Panel C, the findings suggest that the Brent market take the most days to cut the impact of volatility persistence by half (that is, $HL = 9.70$ days), followed by kerosene (8.23 days) and WTI (7.65 days). In contrast, the propane and gasoline prices have the shortest persistence, 5.07 days and 4.40 days, respectively. This result suggests that the propane and the gasoline markets have a lower level of volatility persistence than do other petroleum markets. It is advisable that decision makers monitor the trajectories and behavior of volatility persistence in the petroleum/propane markets in order to make better decisions (i.e., to buy or sell commodity assets) and maximize benefits. Investors may use this information to determine how long they need to wait to ride out or take advantage of volatility. The parameters $\alpha_{EX,1}$ and $\alpha_{PET,2}$ (own past shocks), which capture the impacts of the markets' own lagged standardized innovations on the volatility of the U.S. dollar exchange rate and each of the petroleum markets, respectively, are significant for all markets at the 1% level. This means that the volatility in these markets depends on their respective lagged standardized innovations, suggesting that past news can be used to determine current volatility.

Furthermore, Table 2—Panel C shows the presence of asymmetric volatility in the U.S. dollar exchange rate and each of the petroleum markets. The relative asymmetry (*RA*) is greater than one for the Brent market, indicating that this phenomenon which implies that negative innovations in the previous period in the Brent market would lead to greater volatility in the current period, substantiating the presence of the leverage effect for this crude oil market. Kerosene prices deliver symmetry, as seen in the value of the relative asymmetry coefficient, which is equal to unity. Meanwhile, the relative asymmetries of the WTI, propane, and gasoline markets and the U.S. dollar exchange rate are less than one. This result indicates that negative innovations in the previous period would result in a lower volatility in the current period for these markets than positive shocks do. Therefore, the results do not suggest the presence of symmetry for any of the variables, with the exception of kerosene. The leverage effect is thus present in five markets.

All in all, we find evidence of a bidirectional or feedback volatility spillover effect between the petroleum markets and the U.S. dollar exchange market. These results are consistent with those of Zhang et al. (2008).

4.2. Dynamic conditional correlations

To further analyze the time-varying characteristics of the correlations between the U.S. dollar exchange rate and each of the petroleum and propane price returns, we estimate their dynamic conditional correlation coefficients. The results are displayed in Table 2—Panel C. The values of the dynamic conditional correlation parameter, C_2 in Eq. (8), are significant and close to one (with the exception of the value for the gasoline market). Thus, the correlations between the U.S. dollar exchange market and each of the petroleum markets reveal strong persistence over time. This is consistent with the strong volatility persistence of the U.S. dollar exchange rate and each of the petroleum markets. In contrast, the coefficient of the time-varying correlation for gasoline is about 0.75, indicating lower and less significant persistence for the gasoline market, probably because the price of this surface fuel is the most watched by the public on a daily basis, and gasoline also has a very low price elasticity of demand. More importantly, as illustrated in Fig. 3, the plots of the dynamic conditional correlations

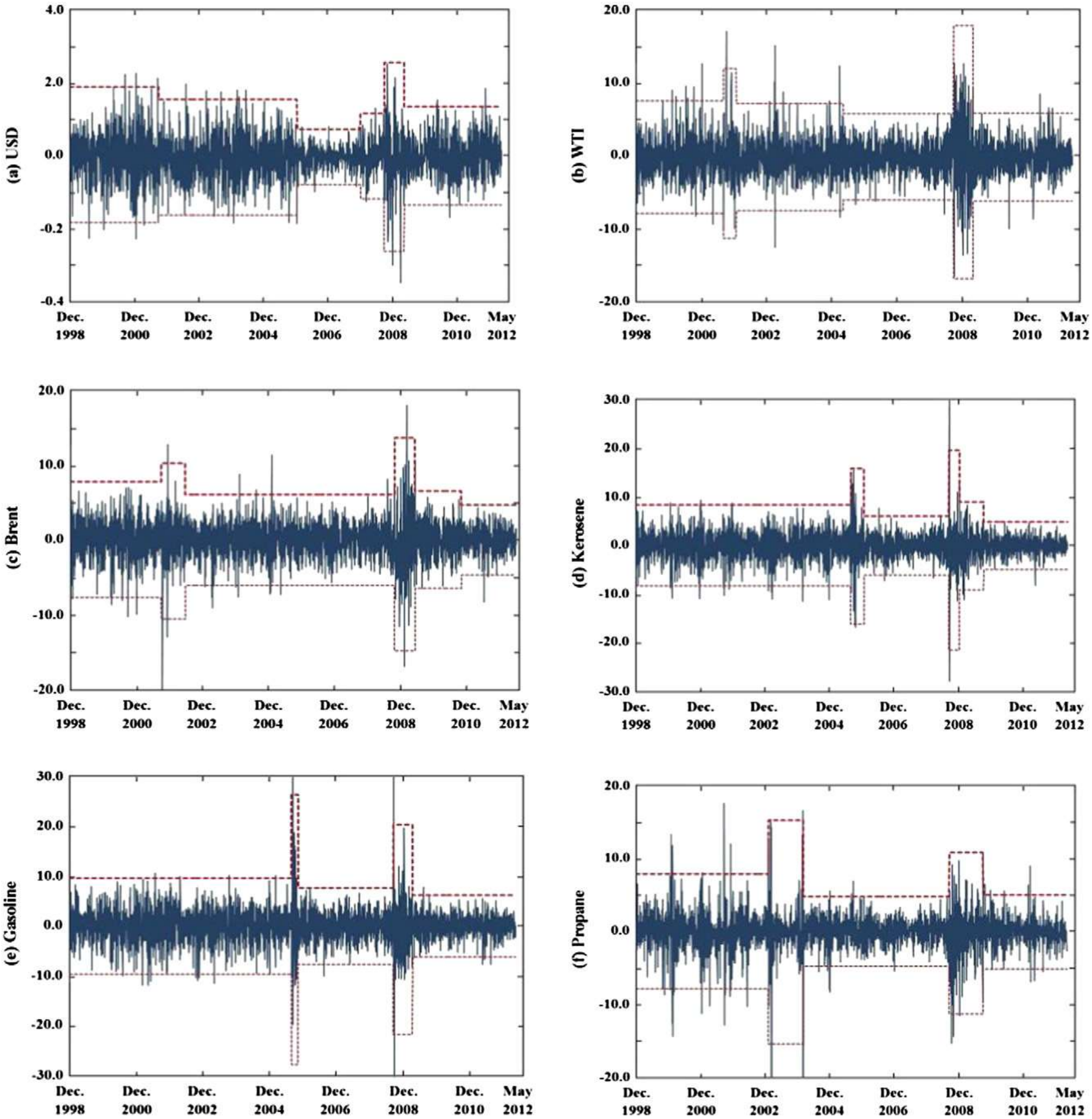

Fig. 2. Daily returns behavior for the exchange rate and petroleum markets. Notes: (a) USD, (b) WTI, (c) Brent, (d) kerosene, (e) gasoline, and (f) propane. Note that the dotted lines define the ±3 standard deviation bands around the structural break points estimated by the ICSS algorithm.

Table 1
Descriptive statistics for the returns of the five petroleum prices and the exchange rate.

	USD/euro	WTI	Brent	Kerosene	Gasoline	Propane
Mean	−0.002	0.065	0.074	0.068	0.067	0.049
Median	0.000	0.139	0.123	0.124	0.156	0.000
Maximum	2.524	16.413	18.129	32.642	23.505	17.673
Minimum	−3.460	−17.091	−19.890	−27.749	−17.889	−49.913
Std. dev.	0. 509	2.573	2.415	2.763	2.913	2.589
CV	−254.500	39.585	32.635	40.632	43.478	52.837
Skewness	−0.051	−0.288	−0.246	−0.097	0.021	−3.112
Kurtosis	5.881	7.294	7.887	14.76	6.818	65.406
JB	1692***	2624***	3373***	19,346***	2038***	549,908***
Q (14)	64.05***	31.94***	38.78***	35.65***	34.00***	47.81***

Notes: CV denotes the coefficient of variation which is the ratio of the standard deviation to the mean. JB and Q (14) refer to the results of the Jarque–Bera test for normality and the Ljung–Box test for autocorrelation, respectively. The asterisk *** denotes statistical significance at the 1% level.

Table 2
Estimation results of the bivariate DCC–EGARCH model for the U.S. dollar exchange rate and petroleum prices returns without structural breaks.

Variables		WTI		Brent		Kerosene		Gasoline		Propane	
EX	*PET*	*EX*	*PET*	*EX*	*PET*	*EX*	*PET*	*EX*	*PET*	*EX*	*PET*
Panel A: Mean equation											
$C_{EX,0}$	$C_{PET,0}$	−0.001	−0.093**	0.002	0.089**	−0.001	0.150***	−0.003	0.164***	0.001	0.105***
		(0.007)	(0.040)	(0.007)	(0.037)	(0.007)	(0.041)	(0.007)	(0.048)	(0.007)	(0.033)
$\beta_{EX,1}$	$\beta_{EX,2}$	0.111***	−0.033	0.109***	−0.103	0.109***	0.049	0.108***	0.024	0.102***	−0.046
		(0.018)	(0.078)	(0.017)	(0.072)	(0.018)	(0.084)	(0.018)	(0.091)	(0.017)	(0.061)
$\beta_{PET,1}$	$\beta_{PET,2}$	−0.025	0.024***	0.022	−0.027***	−0.015	−0.016***	0.002	−0.010***	0.068***	−0.019***
		(0.017)	(0.003)	(0.018)	(0.003)	(0.019)	(0.002)	(0.018)	(0.002)	(0.016)	(0.003)
Panel B: Variance equation											
$\alpha_{EX,0}$	$\alpha_{PET,0}$	−0.007***	0.159***	−0.005**	0.119***	−0.006***	0.165***	−0.004**	0.341***	−0.007***	0.241***
		(0.002)	(0.016)	(0.002)	(0.010)	(0.002)	(0.013)	(0.002)	(0.022)	(0.002)	(0.011)
$\alpha_{EX,1}$	$\alpha_{EX,2}$	0.077***	0.051***	0.076***	0.025**	0.077***	0.053***	0.074***	0.006	0.074***	0.096***
		(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.009)	(0.006)	(0.014)	(0.007)	(0.009)
$\alpha_{PET,1}$	$\alpha_{PET,2}$	0.013***	0.129***	0.011***	0.112***	0.017***	0.157***	0.015***	0.254***	0.019***	0.257***
		(0.003)	(0.013)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.014)	(0.003)	(0.011)
γ_{EX}	γ_{PET}	0.992***	0.913***	0.993***	0.931***	0.991***	0.919***	0.993***	0.854***	0.989***	0.872***
		(0.001)	(0.009)	(0.001)	(0.006)	(0.001)	(0.007)	(0.001)	(0.010)	(0.001)	(0.006)
δ_{EX}	δ_{PET}	0.195***	0.384***	0.260***	−0.503***	0.309***	−0.001	0.243***	0.149***	0.290***	0.171***
		(0.061)	(0.077)	(0.066)	(0.087)	(0.062)	(0.051)	(0.065)	(0.044)	(0.061)	(0.028)
Panel C: Correlation parameters											
C_0		0.000 (0.000)		−0.000 (0.000)		−0.000 (0.004)		−0.001 (0.009)		−0.000 (0.002)	
C_1		−0.005 (0.004)		0.001 (0.003)		0.004 (0.018)		0.025 (0.035)		0.009 (0.015)	
C_2		1.004 (0.004)***		0.999 (0.005)***		0.932 (0.476)*		0.750 (0.475)		0.954 (0.103)***	
Half-life		83.29	7.65	96.56	9.70	78.89	8.23	96.31	4.40	64.11	5.07
Relative asymmetry		0.67	0.45	0.59	3.02	0.53	1.00	0.61	0.74	0.55	0.71
Panel D: Diagnostic checking											
Log likelihood		−9866.43		−9781.07		−10,025.59		−10,642.13		−9377.61	
AIC		19,766.87		19,596.13		20,085.18		21,318.27		18,789.23	
SBIC		19,870.87		19,700.13		20,189.18		21,422.27		18,893.23	

Notes: We find the VAR(1) model to be suitable as a mean equation. The number of lags in the VAR model is selected by the Bayesian information criterion (also called the Schwarz criterion; SBIC). The figures in parentheses are the standard errors. The asterisks *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

for the US dollar exchange rate and each of the petroleum market pairs exhibit significant variability in the conditional correlations along the sample period, with important phases of decreases and increases. The rise of the conditional correlations across the markets is more apparent with the occurrence of major events, particularly during the 2007–2009 global financial crisis that was generated by the U.S. mortgage subprime crisis and spread to the other markets. The exception in this case is the propane product where the conditional correlation decreases over this period. The 'financialization' of the commodities in the energy sector strongly explains this result.

4.3. Structural breaks in variance

Fig. 2 illustrates the return behavior for the foreign exchange and petroleum markets with the structural break points and the ± 3 standard deviation bands. Additionally, Table 3 displays the results for the number of jumps in the variance of the series and the time point of each shift using the ICSS algorithm. As can be seen, all return series exhibit at least five structural breaks in their variances over the full sample period. Indeed, we detect six breaks for the U.S. dollar exchange rate, WTI, Brent, and kerosene returns and five breaks for both gasoline and propane return series. These identified breaks are linked to major extreme global events such as the 2007 Great Recession, the summer 2008 financial meltdown in the United States, and the 2009/2012 euro-zone debt crisis. More specifically, both the WTI and Brent crude oil returns show structural breaks in volatility at similar time points which coincide with global economic and political events.

The first major structural break is associated with the 9/11 New York attack in 2001. Moreover, the increases in the second volatility during the period 2008–2009 are correlated with the U.S. recession which started in 2007 and the U.S. sub-prime mortgage crisis that occurred in 2008, with the subsequent volatility change being consistent with the euro-zone debt crisis. These results are consistent with those given in Kang et al. (2011). The first sudden change in the propane market is associated with the 2003 Iraq war. After this short war, propane prices entered a period of steady decline, which persisted to the end of 2003.

The second volatility increases for propane during the period 2008–2009 are correlated with the recent financial crisis. When it comes to the U.S. exchange rate market, one can identify two volatility increases: the first increase is during the period December 2007–September 2008 which marks the Great Recession period, and the second increase is in September 2008–April 2009. Thus, we conclude that the observed regime changes in the variance could be attributed largely to major extreme events, as documented by Hammoudeh and Yuan (2008) and Hammoudeh and Li (2008).

4.4. Return and volatility spillovers with structural breaks

Modeling volatility without incorporating structural breaks may generate spurious regressions due to the obtained over-estimated volatilities (Lamoureux and Lastrapes, 1990). We reiterate that the main purpose of the present research is to investigate volatility transmission among the petroleum and foreign exchange markets under consideration. To get an accurate measure of volatility, we include the dummy variables corresponding to the structural breaks in the bivariate DCC–EGARCH (1,1) model.

Table 4 presents the estimates of the bivariate DCC–EGARCH model for the U.S. dollar exchange rate and each of the petroleum markets within the structural break framework. Upon examining the estimates of the mean equations, one can recognize that the results are very similar to those in Table 2. Thus, we will not interpret them here.

However, upon a careful inspection of the variance equation under structural breaks (see Table 4—Panel B), one can discern from the significance of $\alpha_{PET,1}$ that all five petroleum markets absorb the shocks produced in the foreign exchange markets. However, news in both the

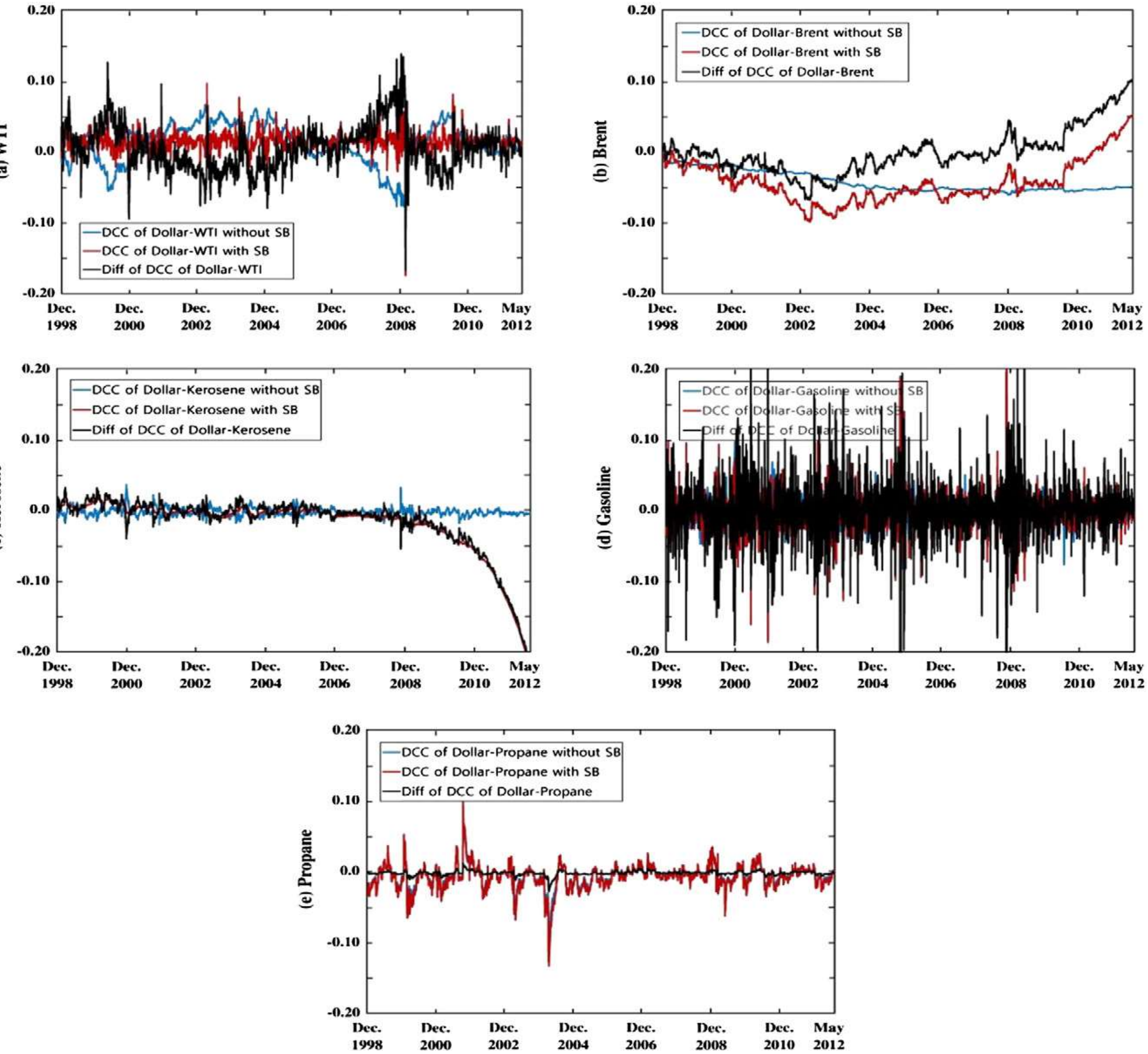

Fig. 3. Time-paths of the DCC with and without structural breaks and the differences between them.

Brent and gasoline markets, among the petroleum markets, does not affect conditional variance in the U.S. dollar exchange rate in this new framework because $\alpha_{EX,2}$ is not significant. Brent is benchmarked for Europe, which is dominated by the euro which is a good measure of scarcity in the oil markets, whereas the gasoline market has many regional fundamentals and special factors.

Controlling for sudden changes, we also find a significant decrease in the degree of volatility persistence for all markets, compared with the case with no structural breaks. With regard to the two crude oil markets, for example, the persistence of volatility for WTI drops from 0.913 to 0.747, and for Brent falls from 0.931 to 0.817 (see γ_{PET} in Panel B of Tables 2 and 4). This result implies that ignoring these changes in the volatility models may distort the degree of persistence of volatility in each of the considered markets and the volatility spillovers between the U.S. exchange rate and both Brent and propane markets. This finding is consistent with those of Hammoudeh and Li (2008), Kang et al. (2011), Kang et al. (2009) and Ewing and Malik (2013), among others.

Comparing the values in Panel C of Tables 2 and 4, we can find that Half Life *HL* is evidently reduced for all markets when we consider the structural breaks. For the crude oil markets, for example, *HL* declines by about 5.28 days for the WTI market (from 7.65 to 2.37 days, the values of HL for the models without and with structural breaks, respectively) and by 6.28 (9.70 to 3.42) days for Brent. The relative asymmetry *RA* also declines under the structural breaks for all petroleum markets with the exception of the gasoline and kerosene markets, thereby reducing the difference in the effects of bad vs. good news on volatility. Moreover, *RA* also declines for the U.S. exchange rate market when we control for the structural breaks. This decrease varies from 0.11 ($\Delta RA = 0.59 - 0.48$) for the Brent market to 0.22 ($\Delta RA = 0.53 - 0.31$) for the kerosene market.

The conditional correlation between the U.S. dollar exchange rate and each of the petroleum markets' volatilities is not constant over time. This time-varying nature of the conditional correlations of the petroleum markets with the foreign exchange market can be beneficial to traders and hedgers in terms of managing the risks of their portfolios. Energy investors should be aware that the correlations are dynamic and evolve over time, which implies that portfolios should be rebalanced over time. Thus, the amount of portfolio diversification within a given asset allocation should be changed over time.

Interestingly, the diagnostic tests allow us to check whether the bivariate DCC–EGARCH model with the structural break dummies outperforms the bivariate DCC–EGARCH model for each petroleum/

Table 3
Structural breaks in volatility as detected by the ICSS algorithm by series.

Series	Number of change points	Time period	Standard deviation
USD/euro	1	16 December 1998–13 September 2001	0.619
	2	14 September 2001–6 January 2006	0.528
	3	9 January 2006–27 December 2007	0.253
	4	28 December 2007–18 September 2008	0.390
	5	19 September 2008–30 April 2009	0.861
	6	1 May 2009–1 May 2012	0.449
WTI	1	16 December 1998–22 August 2001	2.581
	2	23 August 2001–14 January 2002	3.883
	3	15 January 2002–3 May 2005	2.442
	4	4 May 2005–12 September 2008	1.960
	5	15 September 2008–20 April 2009	5.775
	6	21 April 2009–1 May 2012	2.010
Brent	1	16 December 1998–10 September 2001	2.585
	2	11 September 2001–28 May 2002	3.468
	3	29 May 2002–20 August 2008	2.042
	4	21 August 2008–2 April 2009	4.752
	5	3 April 2009–26 August 2010	2.169
	6	27 August 2010–1 May 2012	1.567
Kerosene	1	16 December 1998–26 August 2005	2.766
	2	29 August 2005–25 January 2006	5.348
	3	26 January 2006–8 September 2008	2.005
	4	9 September 2008–5 January 2009	6.853
	5	6 January 2009–30 September 2009	3.006
	6	1 October 2009–1 May 2012	1.633
Gasoline	1	16 December 1998–16 August 2005	3.225
	2	17 August 2005–26 October 2005	8.999
	3	27 October 2005–5 September 2008	2.552
	4	8 September 2008–2 April 2009	6.994
	5	3 April 2009–1 May 2012	2.066
Propane	1	16 December 1998–27 January 2003	2.624
	2	28 January 2003–3 March 2004	5.112
	3	4 March 2004–12 September 2008	1.592
	4	15 September 2008–28 September 2009	3.688
	5	29 September 2009–1 May 2012	1.688

Note: Time break periods are detected by the ICSS algorithm.

Table 4
Estimation results of the bivariate DCC–EGARCH model for U.S. dollar exchange rate and each petroleum price returns with structural breaks.

Variables		WTI		Brent		Kerosene		Gasoline		Propane	
EX	*PET*	*EX*	*PET*	*EX*	*PET*	*EX*	*PET*	*EX*	*PET*	*EX*	*PET*
Panel A: Mean equation											
$C_{EX,0}$	$C_{PET,0}$	−0.003	−0.113***	−0.001	0.103***	−0.003	0.113***	−0.004	0.130***	−0.001	0.105***
		(0.007)	(0.039)	(0.007)	(0.036)	(0.007)	(0.039)	(0.007)	(0.047)	(0.007)	(0.032)
$\beta_{EX,1}$	$\beta_{EX,2}$	0.112***	−0.059	0.109***	−0.040	0.114***	−0.051	0.111***	−0.034	0.107***	−0.009
		(0.018)	(0.081)	(0.018)	(0.071)	(0.018)	(0.088)	(0.018)	(0.099)	(0.018)	(0.064)
$\beta_{PET,1}$	$\beta_{PET,2}$	−0.031*	0.025***	0.018	−0.028***	−0.010	−0.017***	−0.003	−0.010***	0.069***	−0.020***
		(0.018)	(0.003)	(0.016)	(0.003)	(0.019)	(0.003)	(0.018)	(0.002)	(0.017)	(0.003)
Panel B: Variance equation											
$\alpha_{EX,0}$	$\alpha_{PET,0}$	−0.027***	0.483***	−0.030***	0.336***	−0.045***	0.801***	−0.031***	1.001***	−0.023***	0.371***
		(0.007)	(0.061)	(0.008)	(0.048)	(0.011)	(0.077)	(0.008)	(0.109)	(0.006)	(0.022)
$\alpha_{EX,1}$	$\alpha_{EX,2}$	0.058***	0.037**	0.062***	0.014	0.056***	0.071***	0.061***	0.018	0.060***	0.052***
		(0.010)	(0.017)	(0.010)	(0.016)	(0.010)	(0.023)	(0.010)	(0.025)	(0.009)	(0.011)
$\alpha_{PET,1}$	$\alpha_{PET,2}$	0.020***	0.159***	0.009**	0.084***	0.025***	0.218***	0.018***	0.215***	0.017***	0.279***
		(0.006)	(0.021)	(0.004)	(0.019)	(0.006)	(0.029)	(0.006)	(0.027)	(0.004)	(0.015)
γ_{EX}	γ_{PET}	0.969***	0.747***	0.966***	0.817***	0.951***	0.601***	0.964***	0.573***	0.973***	0.816***
		(0.007)	(0.031)	(0.008)	(0.026)	(0.011)	(0.037)	(0.008)	(0.046)	(0.006)	(0.011)
δ_{EX}	δ_{PET}	0.305***	0.486***	0.354***	−1.202***	0.525***	−0.189***	0.304***	0.063	0.395***	0.186***
		(0.110)	(0.098)	(0.116)	(0.294)	(0.138)	(0.080)	(0.112)	(0.088)	(0.103)	(0.036)
Panel C: Correlation parameters											
C_0		0.006 (0.014)		0.000 (0.000)		0.000 (0.000)		−0.009 (0.064)		−0.000 (0.002)	
C_1		0.016 (0.024)		−0.003 (0.003)		−0.001 (0.005)		−0.040 (0.036)		0.010 (0.016)	
C_2		0.784 (0.435)*		1.003 (0.005)***		1.004 (0.004)***		−0.770 (0.276)***		0.955 (0.087)***	
Half-life		21.67	2.37	19.99	3.42	13.74	1.36	18.92	1.24	25.47	3.40
Relative asymmetry		0.53	0.35	0.48	−10.93	0.31	1.46	0.53	0.88	0.43	0.69
Panel D: Diagnostic checking											
Log likelihood		−9814.37		−9742.32		−9958.39		−10,588.69		−9313.20	
AIC		19,682.75		19,538.64		19,970.78		21,231.37		18,880.39	
SBIC		19,847.92		19,703.81		20,135.96		21,396.55		19,657.33	

Note: See the notes of Table 2.

propane–exchange rate pair. A model that fits our data should satisfy the various diagnostic tests for model selection. Those diagnostic tests include the log likelihood, the Akaike information criterion (AIC) and Schwarz Bayesian information criterion (SBIC). Panel D of Tables 2 and 4 displays the statistics of the above diagnostic tests for each petroleum/propane–currency pair for the models with and without the structural changes. By looking at the results of the diagnostic tests in Panel D of Tables 2 and 4, we conclude that the bivariate EGARCH model with structural breaks is superior to the same model without structural breaks for all cases with the exception of the propane market, suggesting that this model specification is the best to capture the volatility spillovers among the petroleum and foreign exchange markets.

Table 5 presents the estimation and test results for structural break dummy variables of the bivariate DCC–EGARCH model with structural breaks. We find that all dummy variables are statistically significant, underscoring the importance of including these unscheduled news related to the structural breaks in modeling the volatility transmission phenomenon. The Wald test results confirm these findings. In fact, as shown in Table 5—Panel B, the null hypothesis that all the coefficients are zeros is strongly rejected by the Wald test.

Both the mean and variance equality tests between the series for Dynamic Conditional Correlations with and without the structural break are reported in Table 6. Using the Satterthwaite–Welch and Anova tests, the results show a significant difference in the mean for the DCC series across the models with and without structural breaks. Similarly, by using the four variance equality tests including the Siegel–Tukey, Bartlett, Levene and Brown–Forsythe tests, the results exhibit a significant variance difference in the DCC series with and without structural break variables. On the whole, we conclude by highlighting the importance of including the structural break dummies in the bivariate EGARCH model in examining the transmission of volatilities, the optimal weights and the hedge ratios in the petroleum–currency holdings.

Fig. 3 depicts the differences in the estimated dynamic conditional correlations, using the bivariate EGARCH model with and without structural breaks over the daily sample period under consideration. We see significant variations and differences in the conditional correlations among the US dollar exchange rate and crude oil, kerosene and gasoline markets. The important difference is observed in July 2008 when the crude oil price reached $145 and just ahead of the summer financial meltdown in the United States. Conversely, small differences in the dynamic conditional correlation for the models with and without the sudden changes between the US dollar exchange rate and the propane markets can be observed. This distinct result may be due to the different features and uses of this product.

It is worth mentioning that the dynamic conditional correlations exhibit important variability over time, thus positing that relying on the constant conditional correlations to compute optimal portfolio weights and hedge ratios may be miss-leading. This result is consistent with Sadorsky (2014). Also, ignoring the news of structural changes may lead to spurious asset allocation and hedging strategies.

5. Discussion and economic significance of the results

As pointed out in the previous section, we discuss the economic significance of the results in terms of asset allocation and risk management.

5.1. Optimal portfolio weights and hedge ratios

To manage both the currency and petroleum risks more efficiently, we compute the optimal portfolio weights and the hedge ratios for designing the optimal hedging strategies based on the estimates of our bivariate DCC–EGARCH models without and with the structural breaks.

We consider a portfolio that minimizes risk without lowering expected returns. We assume that an investor is holding a set of petroleum products and wishes to hedge her position against unfavorable effects resulting from the exchange rate fluctuations. Following Kroner and Ng (1998), the portfolio weight is given by

$$w_t^{EX,PET} = \frac{h_t^{EX} - h_t^{EX,PET}}{h_t^{EX} - 2h_t^{EX,PET} + h_t^{PET}}, \tag{9}$$

$$w_t^{*EX,PET} = \begin{cases} 0, & \text{if } w_t^{EX,PET} < 0 \\ w_t^{EX,PET}, & \text{if } 0 \le w_t^{EX,PET} \le 1 \\ 1, & \text{if } w_t^{EX,PET} > 1 \end{cases}, \tag{10}$$

where w_t^{*} EX,PET is the weight of a petroleum in a $1 portfolio of a two asset holdings (a petroleum product and the U.S. dollar exchange rate) at time t, the terms h_t^{EX} and h_t^{PET} refer respectively to the conditional variances of the U.S. dollar exchange rate and the petroleum market, and $h_t^{EX,PET}$ represents the conditional covariance between the returns of the petroleum and exchange markets at time t. The weight of the U.S. dollar in the considered portfolio is $(1 - w_t^{*}$ $EX,PET)$.

To minimize the risk of a $1 portfolio that is long in the first asset (petroleum), the investor should short $$\beta$ of the second asset

Table 5
Estimation and test results for the dummy variables of the bivariate DCC–EGARCH model with structural breaks.

Time period in Table 3	WTI		Brent		Kerosene		Gasoline		Propane	
	EX	PET	EX	PET	EX	PET	EX	PET	EX	PET
Panel A: Estimation results of dummy variables										
2	−0.007**	0.135***	−0.008**	0.074***	−0.012**	0.399***	−0.010**	0.725***	−0.004	−0.046***
	(0.004)	(0.031)	(0.004)	(0.019)	(0.005)	(0.055)	(0.004)	(0.080)	(0.003)	(0.015)
3	−0.053***	−0.037**	−0.059***	−0.066***	−0.081***	−0.186***	−0.061***	−0.159***	−0.039***	−0.107***
	(0.013)	(0.016)	(0.014)	(0.014)	(0.019)	(0.032)	(0.015)	(0.033)	(0.010)	(0.010)
4	−0.021**	−0.111***	−0.022**	0.169***	−0.037***	0.583***	−0.022**	0.442***	−0.011	0.058***
	(0.008)	(0.023)	(0.009)	(0.038)	(0.012)	(0.038)	(0.009)	(0.065)	(0.007)	(0.015)
5	−0.001	0.255***	0.015**	−0.051***	0.018**	0.080**	0.014**	−0.319***	0.013**	−0.099***
	(0.008)	(0.043)	(0.007)	(0.018)	(0.008)	(0.035)	(0.007)	(0.044)	(0.005)	(0.011)
6	−0.023***	−0.109***	−0.026***	−0.150***	−0.030***	−0.342***	−0.022***	–	−0.016***	–
	(0.006)	(0.022)	(0.007)	(0.027)	(0.008)	(0.042)	(0.007)		(0.005)	
Panel B: Test for significance of dummy variables in model with structural breaks										
χ^2 statistic of Wald test	73.232***		506.540***		292.588***		105.885***		146.024***	
Likelihood ratio test	104.122***		77.491***		134.400***		106.895***		128.837***	

Notes: See the notes of Table 2. The null hypothesis of the Wald and likelihood ratio tests is that all dummy variables in each model are zero. The figures in parentheses are the standard errors. The asterisks ** and *** denote significance at the 5% and 1% levels, respectively.

Table 6
Test for equality of means and variance between DCC series from models with and without structural breaks.

	Equality mean tests		Equality variance tests			
	Satterthwaite–Welch	Anova	Siegel–Tukey	Bartlett	Levene	Brown–Forsythe
WTI–USD	−7.029***	49.403***	34.889***	1460.745***	1184.491***	1174.155***
Brent–USD	2.142**	4.587**	32.885***	1555.876***	806.327***	698.273***
Kerosene–USD	24.306***	590.775***	27.840***	9166.784***	1705.644***	715.808***
Gasoline–USD	0.998	0.995	20.327***	792.007***	348.479***	349.708***
Propane–USD	4.078***	16.627***	6.896***	103.943***	45.765***	45.635***

Notes: This table presents the statistics of the mean equality tests using Satterthwaite–Welch and Anova statistics as well as variance equality tests using Siegel–Tukey, Bartlett, Levene and Brown–Forsythe for the dynamic conditional correlations across model with and without structural breaks. The asterisks *, ** and *** denote the significance levels at 10%, 5% and 1%, respectively.

(the exchange rate). According to Kroner and Sultan (1993), the risk-minimizing hedge ratio is specified as follows:

$$\beta_t^{EX,PET} = \frac{h_t^{EX,PET}}{h_t^{EX}}. \tag{11}$$

A wide variation in the hedge ratio over time indicates that the portfolio managers have to rebalance the portfolio more often as correlations change.

5.2. Implications for portfolio management with petroleum-risk hedging strategies

The summary statistics for the optimal portfolio weights and hedge ratios computed from the estimation results of the bivariate DCC–EGARCH models without and with the structural breaks are given in Table 7. According to this table, we find a weak difference in the portfolio weights after controlling for structural breaks for all petroleum products except the WTI oil market, whose weight is three times as great without the structural breaks as with breaks.

On the other hand, we carry out robustness tests like the mean and variance equality tests, and the result are displayed in Table 8. As shown in this table, we strongly reject the null hypothesis that both the portfolio weights and the hedge ratios series have the same mean since those differences are statistically significant, except for the propane market. Given the rejection of the null hypothesis of the equality of mean among the considered series, we can conclude that the portfolio weights and hedge ratios differ and are more accurate for the model with the structural changes than for the counterpart without the structural changes. The Levene and Siegel–Tukey test as well as the other variance equality tests reported in this table strongly rejects the null of variance equality of hedge ratios except for the propane–USD pair, among the models considered.

Specifically, the WTI market weight decreases from 14.8% under no structural breaks to 4.1% with breaks in the portfolio with the U.S. dollar. Under the structural breaks, the optimal petroleum portfolio weights range from 3.0% for gasoline to 6.2% for propane, highlighting the importance of holding propane in the portfolios relative to the other petroleum products. This result suggests that for the gasoline market, the optimal weight in a $1 petroleum–exchange rate portfolio should be 3% for gasoline, with the remaining 97% invested in the U.S. dollars. Overall, our findings imply that investors holding petroleum assets should have more U.S. dollars than petroleum products in their portfolios in order to minimize risk, while keeping unchanged the expected returns under structural breaks.

As for the hedge ratios, we find a significant decrease for all petroleum markets, with the exception of the WTI market, after incorporating the structural breaks, rendering the hedge ratios negative for all markets except the WTI market when the structural breaks are considered. This indicates that a short position in petroleum and a long position in the U.S. dollars should be taken; hence, a long hedge (purchasing) is superior to a short hedge (selling). The low values of the hedge ratios highlight the importance of the foreign exchange\markets in designing optimal hedging strategies. These ratios range between −0.225 in the Brent–USD portfolio to 0.069 in the WTI–USD portfolio. These results are important in establishing that a $1 short (long) position in Brent (WTI) can be hedged for 22.5 (6.9) cents with a long (short) position in the U.S. dollar exchange rate. This result becomes slightly stronger under the structural breaks, when investors should long more dollars to hedge a $1 short position in petroleum products, including Brent, gasoline, kerosene, and propane. Note that, as the minimum and maximum values indicate, each of the hedge ratios shows considerable variability, implying that hedging positions must be adjusted frequently.

Fig. 4 shows the optimal hedge ratios dynamics with and without the structural breaks and the differences in the estimated time-varying hedge ratios between the bivariate DCC–EGARCH models with

Table 7
Summary statistics for the portfolio weights and the hedge ratios.

	Portfolio weight				Hedge ratio			
	Mean	St. dev.	Min	Max	Mean	St.dev.	Min	Max
Panel A: Values are calculated using estimates of the bivariate DCC–EGARCH model without structural breaks								
WTI–USD	0.148	0.256	0.000	1.000	0.041	0.152	−0.662	0.382
Brent–USD	0.056	0.024	0.015	0.127	−0.217	0.111	−0.530	−0.046
Kerosene–USD	0.040	0.019	0.001	0.115	−0.013	0.036	−0.151	0.546
Gasoline–USD	0.029	0.016	0.000	0.096	0.008	0.447	−1.803	17.278
Propane–USD	0.061	0.031	0.000	0.165	−0.038	0.276	−8.606	0.928
Panel B: Values are calculated using estimates of the bivariate DCC–EGARCH model with structural breaks								
WTI–USD	0.041	0.018	0.003	0.096	0.069	0.097	−2.190	0.782
Brent–USD	0.057	0.025	0.010	0.126	−0.225	0.161	−0.812	0.224
Kerosene–USD	0.045	0.024	0.001	0.119	−0.090	0.163	−0.926	0.095
Gasoline–USD	0.030	0.015	0.000	0.127	−0.024	0.417	−11.68	5.321
Propane–USD	0.062	0.030	0.000	0.174	−0.040	0.279	−9.713	1.236

Note: The portfolio weights and hedge ratios are for the petroleum products versus the U.S. dollar.

Table 8
Tests for equality of means and variance for portfolio weight and hedge ratios series from models with and without structural breaks.

	Equality mean tests		Equality variance tests			
	Satterthwaite–Welch	Anova	Siegel–Tukey	Bartlett	Levene	Brown–Forsythe
Panel A: *Portfolio weight*						
WTI–USD	24.235***	587.344***	62.564***	13,353.20***	2457.747***	1026.661***
Brent–USD	−2.440**	5.955**	4.185***	2.569	8.345***	11.022***
Kerosene–USD	−9.293***	86.363***	1.814*	227.090***	94.882***	75.572***
Gasoline–USD	−2.338**	5.465**	3.551***	2.185	10.628***	9.006***
Propane–USD	−1.372	1.882	0.137	1.059	0.746	0.282
Panel B: *Hedge ratio*						
WTI–USD	−8.877***	78.794***	30.080***	640.962***	619.313***	602.319***
Brent–USD	2.342**	5.483**	10.905***	458.401***	253.153***	226.679***
Kerosene–USD	26.639***	709.649***	29.776***	5841.055***	1533.510***	815.075***
Gasoline–USD	2.964***	8.783***	18.456***	15.659***	22.777***	25.717***
Propane–USD	0.376	0.141	5.830***	0.289	0.317	0.570

Notes: This table presents the results of the mean equality tests using Satterthwaite–Welch and Anova statistics as well as variance equality tests using Siegel–Tukey, Bartlett, Levene and Brown–Forsythe for the optimal portfolio weight and dynamic hedge ratios across model with and without structural breaks. The asterisks *, ** and *** denote the significance levels at 10%, 5% and 1%, respectively.

and without the sudden changes and confirms the results in Table 5. However, the inclusion of the news set of sudden changes leads to a higher variability of the estimated hedge ratio. Omitting this factor could lead to a worse hedge strategy. For the propane asset, the difference is small especially during the 2007–2011 period that embraces the global financial crisis and the Eurozone debt crisis.

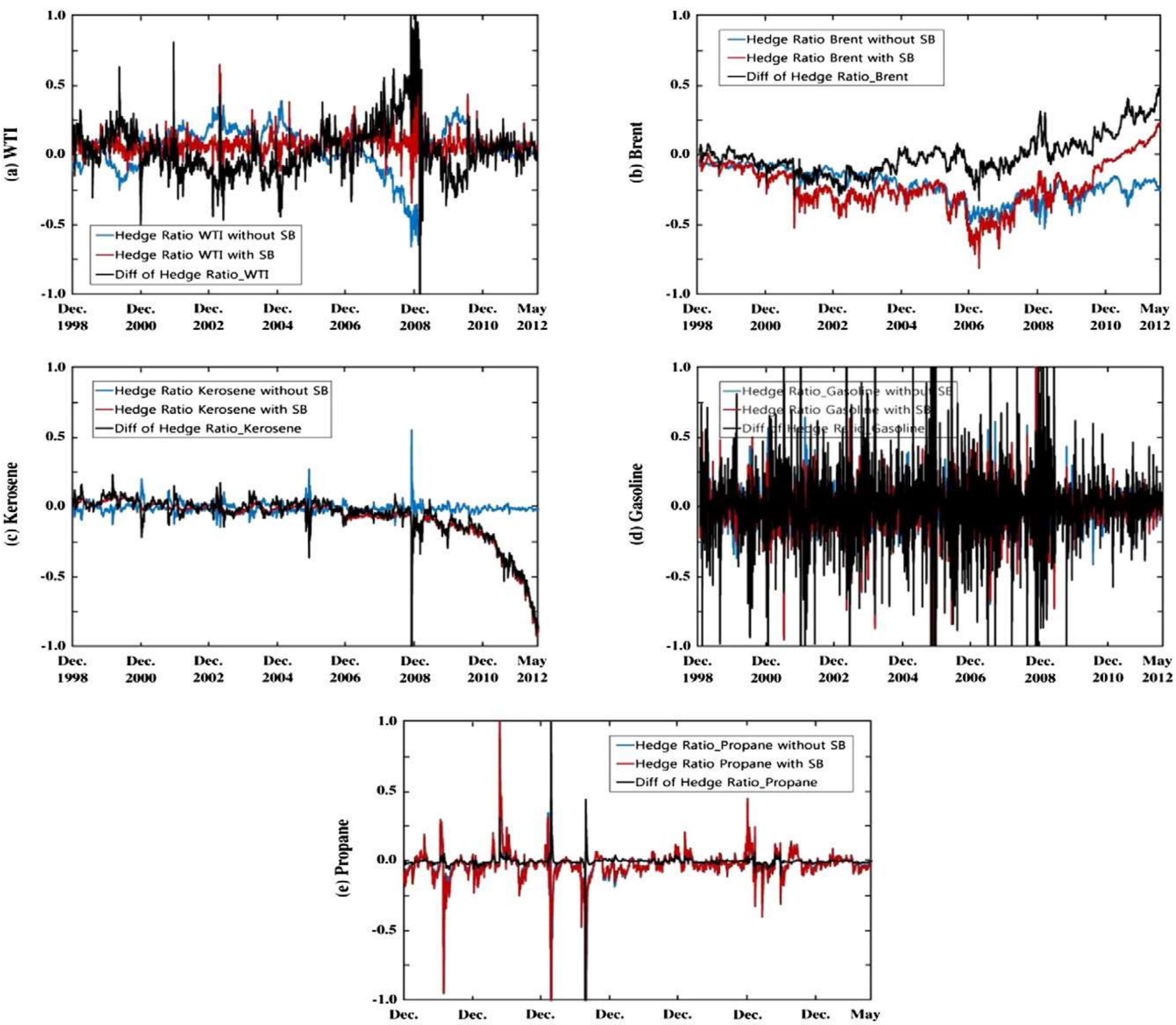

Fig. 4. Time-paths of the dynamic hedge ratios with and without structural breaks and the differences between them.

The optimal portfolio weights and the time-varying hedge ratios is explained in part by the petroleum risks including for instance unexpected jumps in global petroleum demand, petroleum reserve policy, OPEC news announcements, major regional and global economic crisis (sovereign debt risk) and geopolitical risks. These events can bring about structural breaks in the petroleum markets. Thus, if we consider these structural breaks using dummy variables, the accuracy of calculating the optimal portfolio weights and the time-varying hedge ratios will be improved.

Overall, we can conclude that the least expensive hedge is the long Brent-and-short U.S. dollar exchange hedge with and without the structural breaks, whereas the long WTI and short U.S. dollar exchange hedge represents the most expensive hedge for both cases. We have shown through this example how our empirical results could be used by the financial/energy market participants to make optimal portfolio allocation decisions. The results also show that the choice of the model matters in choosing optimal portfolios.

6. Conclusions and policy implications

The cross-market relationship between the petroleum prices and the U.S. exchange rate has attracted the attention of both investors and policy makers. The U.S. dollar is the invoicing and settlement currency for international petroleum transactions and is also considered a resource currency. This currency is the primary channel through which a petroleum price shock is transmitted to the real economy and to financial markets. It is also well-known that oscillations in the U.S. dollar exchange rate are believed to underlie the volatility of petroleum prices.

In this paper, we examine the (asymmetric) volatility spillovers, volatility persistence, dynamic conditional correlations, time-varying hedging strategies between the U.S. dollar/euro exchange rate and five petroleum prices, including the prices of Europe Brent, WTI, gasoline, kerosene, and propane. We use the bivariate DCC–EGARCH model with structural breaks, identified by Inclán and Tiao's (1994) ICSS algorithm, to avoid the possibility of volatility overestimation. The results show strong evidence in favor of the presence of structural breaks in the variance of the series under investigation. The incorporation of these structural breaks in our models leads to a significant decrease in volatility persistence and news asymmetry for all markets. Additionally, we highlight the implications of our results for investors as they aim to implement appropriate hedge and asset allocation strategies so as to reduce their risk more efficiently. Thus, we have computed the optimal portfolio weights and the time-varying hedge ratios and reported evidence attesting to the importance of cross-market hedging. It is worth noting that it is cheaper to hedge long petroleum positions while shorting the U.S. dollar with Brent than with WTI. In sum, omitting the structural breaks might distort the direction of information inflows and the volatility spillover mechanism. They also lead to a worse hedging strategies. To conclude, the consideration of the asymmetric effects as well as the structural breaks in volatility models improves our understanding of the origins and directions of the shock transmission and persistence behavior over time and among markets.

Our empirical evidence has several policy implications. First, the portfolio risk managers and policy makers should take caution in investing simultaneously in currency and energy markets. These decision makers should possess the necessary information on the directions of spillovers among these markets in order to take preventive measures to be able to deal with major events, especially those that cause contagion during future crises. Moreover, the volatility spillovers from the petroleum prices to the dollar/euro exchange rate have implications for import inflation and the general price level. They also have bearing on the value of imports and the balance of payments of the countries that have non-dollar denominated currencies. An oil price increase is usually considered bad news for oil-importing countries where the shock induces recessionary or inflationary pressures, and may be both which is known as stagflation. The oil shocks force central banks to adopt a tighter monetary policy, thereby contributing to a decline in economic activity. Whereas for oil-exporting countries, higher oil prices are considered good news as they tend to have a positive impact on economic activity.

Second, portfolio strategies are sensitive to the petroleum–currency nexus. However, the petroleum and non-petroleum economies have a different view of the changes in the petroleum prices and the appreciation/depreciation of their currencies, particularly during extreme price movements. The level of dependence of a country on such assets explains why a rise in the petroleum prices is linked to the appreciation or depreciation of the U.S. exchange rate versus their currencies. For example, an increase in the petroleum prices is linked to a significant depreciation (appreciation) in the value of the U.S. dollar against the currencies of the petroleum-exporting (importing) nations. The propane price will lead to a significant increase in the U.S. dollar rate against the currencies of the propane-importing nations such as those in the euro zone. On the other hand, the significant volatility spillovers from the petroleum markets to the US/euro foreign exchange market imply that the risk of investors in the petroleum market is transmitted to the risk of investment in the foreign exchange market.

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