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**STRUCTURAL BREAKS, DYNAMIC CORRELATIONS,
VOLATILITY TRANSMISSION, AND HEDGING
STRATEGIES FOR INTERNATIONAL PETROLEUM PRICES
AND U.S. DOLLAR EXCHANGE RATE**

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Abstract

This paper investigates asymmetric volatility spillovers, forecasts and portfolio diversification between the USD/euro exchange market and each of the major spot petroleum markets of WTI, Europe Brent, kerosene, gasoline and propane, using the bivariate exponential GARCH (EGARCH) model. The results provide evidence of significant asymmetric volatility spillovers between the U.S. dollar exchange rate and those petroleum markets. Moreover, we conclude that the persistence of volatility in all paired exchange rate-petroleum markets declines when structural breaks are controlled for in the model. Moreover, integrating the information concerning the structural breaks in this model improves the accuracy of the estimates of volatility dynamics and future volatility forecasts. Additionally, we analyze the optimal portfolio weights and hedge ratios based on the estimates of the bivariate EGARCH model with and without the structural breaks to demonstrate the relevance of our empirical results to investors in terms of developing appropriate hedging and asset allocation strategies. Thus, the findings have important implications for financial risk management, portfolio diversification, and monetary and fiscal policy operations for oil-exporting and -importing countries.

JEL Classification: G14; G15

Keywords: EGARCH; Structural breaks, Volatility spillovers; Hedge ratios.

ملخص

تبحث هذه الورقة الآثار غير المباشرة للتقلبات غير المتماثلة والتنبؤات وتنوع محفظة بين سوق الصرف للدولار الأمريكي / اليورو وكل من الأسواق الكبرى للبتروال الخام غرب تكساس الوسيط وأوروبا برنت والكبروسين والبنزين وغاز البروبان، وذلك باستخدام نموذج ثنائي المتغيرات GARCH الآسي (EGARCH). وتوفر النتائج دليل على الآثار غير المباشرة للتقلبات غير المتماثلة الكبيرة بين سعر صرف الدولار وتلك الأسواق النفطية. وعلاوة على ذلك، فإننا نستنتج أن استمرار معدل التقلب في جميع أسواق البتروال للتبادل المزدوج ينخفض عندما يتم التحكم في الفواصل الهيكلية للنموذج. وعلاوة على ذلك، ودمج المعلومات المتعلقة بفواصل الهيكلية في هذا النموذج يحسن من دقة التقديرات من ديناميات التقلب وتقلب التوقعات المستقبلية. بالإضافة إلى ذلك، نقوم بتحليل الأوزان محفظة ونسب التحوط على أساس تقديرات نموذج EGARCH ثنائي المتغيرات مع وبدون فواصل الهيكلية للتدليل على أهمية النتائج التجريبية لدينا للمستثمرين من حيث وضع استراتيجيات التحوط وتوزيع الأصول المناسبة الأمثل. وهكذا، فإن النتائج لها آثار هامة لإدارة المخاطر المالية، وتنوع محفظة، وعمليات السياسة النقدية والمالية للمصدرة للنفط والبلدان المستوردة للأيدي العاملة.

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 economy, particularly the foreign exchange markets.¹

More importantly, the petroleum prices are denominated in U.S. dollars. 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. This phenomenon is strengthened by globalization, liberalization, and deregulation in recognition of the importance of international financial and commodity markets which move together over time. A better understanding of the volatility interdependencies among those markets is one of the most important tasks for investors and policy makers.

A large body of the literature deals with the interrelationships among different markets over time, especially the interrelationships between the international petroleum and stock markets.² However, in practice, less attention has been paid to the interrelationships between the foreign exchange and commodity markets, particularly the international petroleum markets that include the crude oil, gasoline, kerosene, and propane markets under consideration in this study. Hence, examining the volatility transmission between the foreign exchange and petroleum markets is of great relevance for measuring volatility of petroleum futures prices (Kang and Yoon 2013), value at risk (Aloui and Mabrouk 2010), risk management (Hammoudeh et al. 2010), asset allocation strategy (Wu et al. 2012), and monetary and fiscal policy operations (Kim et al. 2012), among other topics.

Moreover, the interrelationships between the petroleum and foreign exchange markets 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 or bad news) than when they are positive (a price rise or good news) of the same magnitude. For this reason, the bivariate exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model is the most suitable model for accommodating the leverage effect in the volatility transmission mechanism.

There may also be structural breaks in those markets, which if ignored, can lead to sizeable upward biases in the degree of persistence in the estimated GARCH-family models.³ Kang et al. (2011) and Kang et al. (2009) show that structural breaks in the conditional variance are linked to global financial and political events. 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, weakening the degree of integration among the markets.

The present research contributes to the literature in a number of ways. First, to our knowledge, this study is the first to incorporate structural breaks into the bivariate EGARCH

¹ The exchange rate links the domestic economy with the rest of the world (Giannellis and Koukouritakis 2013).

² For studies in this literature, see Benhmad (2013), Chang and Yu (2013), Cong et al. (2008), Ewing and Thompson (2007), Jones and Kaul (1996) and Mensi et al. (2013), among others.

³ For further information, see Aggarwal et al. (1999), Hammoudeh and Li (2008), Hillebrand (2005), Mikosh and Starica (2004) and Salisu and Fasanya (2013).

approach and to 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. Second, given the fact that the United States is currently the world's second oil producer, currently producing more than 9.7 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.⁴ Moreover, the euro area imports most of its petroleum products and settles most of its important transactions in U.S. dollars. Third, 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. This consideration has implications for the persistence of volatility because marginalization of the impact of structural breaks leads to overestimation of the degree of volatility persistence, which has bearing on generating forecasts of future volatility. Finally, we use our results to calculate the optimal portfolio weights and hedge ratios with and without the structural breaks to analyze the implications of these breaks for energy investors. More specifically, we investigate whether the consideration of structural breaks alters portfolio compositions and hedge ratios. To summarize, this paper adds to the recent empirical literature by studying in depth the shock transmission and dynamic correlations between foreign exchange and petroleum markets as well as the time-varying portfolio weights and hedge ratios under structural breaks.

To do this, we use a bivariate EGARCH method. Furthermore, we examine the influence of structural breaks in volatility on the transmission of information between the dollar/euro exchange rate and the five international petroleum markets. 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.

The remainder of this paper is organized as follows. Section 2 provides a summary 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

Petroleum price behavior 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 and find that real oil prices may have been the dominant source of the movements in real exchange rates and there is also a link between real oil prices and real exchange rates. In another study that deals with emerging markets, Arouri et al. (2010) investigate the dynamic behavior of crude-oil prices for four country members of the Gulf Cooperation Council⁵ and show evidence of short-term predictability in changes in the oil price over time, except for few short sub-periods where the relationship is ambiguous. Moreover, these authors explore the possibility of structural breaks in the time-paths of the estimated predictability of the indices and detect only one breakpoint, which is for the oil markets of Qatar and the United Arab Emirates. More recently, 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

⁴ Source: [CIA World Factbook](#) 2012.

⁵ The GCC countries examined are Kuwait, Qatar, Saudi Arabia, and the UAE.

benefits than the static and other dynamic strategies. Nakajima and Hamori (2012) test the Granger-causality-in-mean and granger causality-in-variance among electricity prices, crude oil prices, and the yen-to-US-dollar exchange rate in Japan, and find that no Granger-causality-in-mean runs from the exchange market or the oil market to the power market.

Various methods are used to test the interactions among energy and exchange rate markets. 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. Additionally, using cointegration tests, Muñoz and Dickey (2009) investigate the relationships between oil prices, Spanish electricity spot prices and the USD/euro exchange rate and find that these variables 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, the 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 correlations and copulas methods, 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. Similarly, Aloui et al. (2013) apply a copula-GARCH approach and find a significantly conditional dependency between oil prices and U.S. dollar exchange rates. Benhmad (2013) uses a wavelet approach to study the linear and nonlinear Granger causality between the real oil price and the real effective U.S. dollar exchange rate and finds a strong bidirectional causal relationship between the variables for large time horizons.

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. Ding and Vo (2012) 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 financial crisis of 2007/2008. Koutmos and Booth (1995) use the multivariate EGARCH model and find strong evidence of the asymmetric volatility transmission across developed stock markets. In a similar view of our paper, Bhar and Nikilova (2009) use the bivariate EGARCH model to examine the level of integration and the dynamic relationship between the four BRIC countries (Brazil, Russia, India and China) and other regions. 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. Finally, Ewing and Malik (2013) employ both univariate and bivariate GARCH models to examine the volatility of gold and oil futures and find strong evidence of significant transmission of volatility between gold and oil returns when structural breaks in variance are accounted for in the models. Using the wavelet methodology 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. 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.

Toyoshima et al. (2013) extend the study of Chang et al. (2011) which does not apply the Asymmetric Dynamic Conditional Correlation (A-DCC) to the subject matter. Specifically, Toyoshima et al. (2013) examine the performance of three multivariate GARCH models (i.e., the DCC model, A-DCC model and Diagonal Baba-Engle-Kraft-Kroner (Diagonal BEKK) model) by applying them to the spot and futures West Texas Intermediate (WTI) oil returns. Moreover, to build a hedging strategy for the oil market based on these multivariate conditional volatility models, those authors also compute the time-varying optimal hedge ratio (OHR). Assessing the results in terms of the variance of portfolios and the hedging effectiveness index, the performance of the models in terms of reducing the variance is good in this order A-DCC, DCC and Diagonal-BEKK. Similar to Toyoshima et al. (2013), we examine the performance of an asymmetric GARCH model and calculate the portfolio weights and hedges. However, we differ from those authors by assessing the performance of the bivariate EGARCH model by focusing on its relevance when the structural breaks are included in comparison when they are not included.

3. Empirical Methods

3.1 Bivariate EGARCH model

In this paper, we use the bivariate EGARCH model developed by Nelson (1991) 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.⁶ 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:

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

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, $\sigma_{EX,t}^2$, $\sigma_{PET,t}^2$, and $\sigma_{EX,PET,t}$ represent the variance of the U.S.

⁶ 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.

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:

$$\begin{cases} \ln(\sigma_{EX,t}^2) = \alpha_{EX,0} + \alpha_{EX,1}f_1(z_{EX,t-1}) + \alpha_{EX,2}f_2(z_{PET,t-1}) + \gamma_{EX} \ln(\sigma_{EX,t-1}^2) \\ \ln(\sigma_{PET,t}^2) = \alpha_{PET,0} + \alpha_{PET,1}f_1(z_{EX,t-1}) + \alpha_{PET,2}f_2(z_{PET,t-1}) + \gamma_{PET} \ln(\sigma_{PET,t-1}^2) \end{cases} \quad (2)$$

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:

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

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

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):

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

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 $\xi_{EX,PET,t}$.⁷ 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,

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

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

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

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

To our knowledge, no work has considered structural breaks in the EGARCH model before, but we will do so in this study. If we use a bivariate EGARCH model with sudden change dummies, we can consider information transmission between the markets, asymmetry, and structural breaks in volatility, allowing us to estimate volatility more accurately.

To capture the structural breaks in both the petroleum returns and the U.S. dollar exchange rate data series, we use Inclán and Tiao's (1994) ICSS algorithm. ICSS has been extensively used by several studies, including by Aggarwal et al. (1999), Arouri et al. (2012), Hammoudeh and Li (2008), Kang et al. (2011), Kumar and Maheswaran (2013), and Vivian and Wohar (2012), among others, to identify the points of shocks/sudden changes in the volatility of return series.

For each time interval, the unconditional variance is given by σ_j for $j = 1, 2, \dots, N_T$, where N_T is the total number of changes or jumps in the variance in T observations. We use the cumulative sum of squares procedure to assess the number of changes or jumps in the variance and the time point of each variance shift. We incorporate sudden-change dummies obtained from the ICSS algorithm in the above EGARCH model to estimate volatility with structural breaks more accurately.

3.3 Data and stochastic properties

3.3.1 Data

We use daily closing spot price data for the U.S. dollar/euro exchange rate, WTI and Brent crude oil prices expressed in U.S. dollars per barrel, and kerosene, gasoline and propane priced in U.S. dollars per gallon, for the daily period ranging from December 15, 1998 to May 1, 2012. The closing prices for the petroleum products are obtained from the U.S. Energy Information Administration (EIA) database, and the exchange rate is extracted from the Oanda website.⁸ We use the U.S. dollar 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 most international commercial transactions are made in this currency. The continuously compounded daily returns are computed by taking the difference in the logarithm of two consecutive prices.

⁷ $\xi_{EX,PET,t} \in (-\infty, +\infty)$.

⁸ The EIA website for the petroleum prices is <http://www.eia.gov>, and the Oanda website is <http://www.oanda.com>.

Figure 1 displays the evolution of the petroleum prices for the WTI, Europe Brent, kerosene, gasoline and propane prices 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 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.

On the other hand, the time paths of the return series over the study period are plotted in Figure 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 means of these return series vary between -0.065 and 0.074, with Brent oil having the highest mean.

On the other hand, the WTI returns yield the lowest mean during the sample period, implying that this benchmark no longer exhibits scarcity in the five petroleum markets because it is trapped in the storage tanks at Gushing, Oklahoma. Furthermore, gasoline has the highest risk, as evident by its standard deviation, which amounts to 3.29%, followed by kerosene (2.76%) and propane (2.58%). The skew value is mixed between positive and negative numbers. Furthermore, the kurtosis values of all return series are more than three times the value of a normal distribution. The Jarque–Bera normality test also indicates that the returns for the petroleum prices and the exchange rate are not normally distributed. The Ljung–Box test shows a significant correlation at the 1% level for all return series.

To initially establish that we are dealing with nonstationary time series, we implement two types of the unit root tests and one type of stationary test. The two unit root tests are the augmented Dickey and Fuller (1979) and the Phillips and Perron (1988) tests, and the stationary test is the Kwiatkowski, Phillips, Schmidt, and Shin (1992) test. The results of the unit root and stationarity tests strongly suggest that all return series are stationary processes. On the other hand, 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.⁹

4. Results

In this section, we present the estimation results obtained from the bivariate EGARCH model for the exchange rate and petroleum returns, 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 EGARCH models, where each model contains the daily U.S. dollar exchange rate returns and the daily return for one of each of the five petroleum/propane prices. The estimation results of the bivariate EGARCH (1,1) models are

⁹ Estimation results for the unit root and ARCH-LM tests and unconditional correlations for the returns of the exchange rate and the petroleum prices are not presented here, but available under request addressed to corresponding author.

reported in Table 2. Examining the returns-generating process, the estimation results show that the one-period lagged values of the U.S. dollar exchange rate and each of the petroleum markets 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, indicating the presence of diversification opportunities for portfolio investors. 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 information about any of the petroleum market returns, implying that the U.S. dollar can be a hedge in normal times or a safe haven during crises for these petroleum products. On the whole, we reject the hypothesis of significant cross-market mean spillovers among the considered markets (with the exception of the propane returns, which respond to 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, 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). 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 indicates that the bivariate 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. This finding is consistent with that of Nakajima and Hamori (2012) with respect to electricity prices, crude oil prices, and the Japanese yen–U.S. dollar exchange rate.

The half-life (HL) is used to evaluate the persistence of volatility shocks. Accordingly, these findings show that the Brent market takes 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., 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 impact 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 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 negative asymmetry 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 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 six variables, with the exception of kerosene. The leverage effect is thus present in five series.

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 market volatility for WTI, Brent, kerosene, gasoline, and propane, with the estimated coefficients being (0.013), (0.011), (0.017), (0.015), and (0.019), respectively. Meanwhile, the volatility of the U.S. dollar exchange rate is influenced by the past innovations in WTI, Brent, kerosene, and propane, with the values of the estimated parameters being (0.051), (0.025), (0.053), and (0.096), respectively. Our results indicate that a 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, lower petroleum demand reduces the demand for the U.S. dollar, resulting in its depreciation (Wang and Wu 2012).

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

4.2 Dynamic conditional correlation

To further analyze the time-varying characteristics of correlations between the U.S. dollar exchange rate and each of the petroleum and propane price returns, we estimate the dynamic conditional correlation coefficients. The results are displayed in Table 2. The values of the dynamic conditional correlation parameter, C_2 in Eq. (8), are significant and close to one (with the exception of 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.

4.3 Structural breaks in variance

Figure 2 illustrates the return behavior for the exchange rate and the 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 are correlated with global economic and political events.

The first structural break is associated with the 9/11 New York attack in 2001. 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 in 2008, with the subsequent volatility change being consistent with the euro-zone debt crisis. These results are consistent with those of 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 as a result of the recent discovery of shale natural gas. The second volatility increases for propane during the period 2008–2009 are correlated with the recent financial crisis. For the U.S. exchange rate markets, two volatility increases are identified: the first is during the period December 2007–September 2008 which marks the Great Recession period, and the second is in September 2008–April 2009. Thus, we conclude that the observed regime changes in variance could be attributed largely to major extreme events, as documented by Hammoudeh and Yuan (2008).

4.4 Return and volatility spillovers with structural breaks

Modeling volatility without incorporating structural breaks may generate spurious regressions due to resulting overestimated volatilities (Lastrapes 1989). We reiterate that the main purpose of the present research is to investigate volatility transmission among petroleum and foreign exchange markets. To get an accurate measure of volatility, we include the dummy variables corresponding to structural breaks in the bivariate EGARCH (1,1) model.

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

However, upon a careful inspection of the variance equation under structural breaks, one can discern from the significance of $\alpha_{PET,1}$ that all five petroleum markets absorb shocks produced in the foreign exchange markets, whereas news in both the 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 priced for Europe, which is dominated by the euro and is a good measure of scarcity, 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. 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 the Brent and propane markets. This finding is consistent with those of Lastrapes (1989), Hammoudeh and Li (2008), Kang et al. (2011), Kang et al. (2009) and Ewing and Malik (2013).

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 (from 7.65 to 2.37) days for the WTI market and by 6.28 (9.70 to 3.42) days for the Brent market. Relative efficiency 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 and each of the petroleum market 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 and can be integrated into portfolio models. Energy investors should be aware that the correlations are dynamic and evolve over time. Thus, the amount of portfolio diversification within a given asset allocation should be changed over time.

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 optimal hedging strategies based on the estimates of our bivariate EGARCH models without and with 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 their position against unfavorable effects resulting from the exchange rate fluctuations. Following Kroner and Ng (1998), the portfolio weight is given by

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

$$w_t^{*EX,PET} = \begin{cases} 0, & \text{if } w_t^{EX,PET} < 0 \\ w_t^{EX,PET}, & \text{if } 0 \leq w_t^{EX,PET} \leq 1, \\ 1, & \text{if } w_t^{EX,PET} > 1 \end{cases}, \quad (10)$$

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 first asset (petroleum), the investor should short β of the second asset (the exchange rate). According to Kroner and Sultan (1993), the risk-minimizing hedge ratio is specified as follows:

$$\beta_t^{EX,PET} = \frac{h_t^{EX,PET}}{h_t^{EX}}. \quad (11)$$

A wide variation in the hedge ratio over time indicates that the portfolio managers would need 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 portfolio weights and hedge ratios computed from the estimation results of the bivariate EGARCH model without and with structural breaks are given in Table 5. 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 structural breaks as with breaks. 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.

Specifically, 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 exchange rate markets in making optimal hedging strategies. These ratios range from -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 the 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.

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 a long WTI and short U.S. dollar exchange hedge represents the most expensive hedge for both cases. We have shown through this example how financial/energy market participants could use our empirical results 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 relationship between the petroleum prices and the U.S. exchange rate attracts the attention of both investors and policy makers. The U.S. dollar is the invoicing 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, portfolio weights, and hedge ratios between the U.S. dollar/euro exchange rate and five petroleum prices, including the prices of Brent, WTI,

gasoline, kerosene, and propane. We use the bivariate EGARCH model with structural breaks, identified by Inclán and Tiao's (1994) ICSS algorithm, to avoid the possibility of volatility overestimation.

We identify at least five structural breaks for both the gasoline and propane prices and six breaks for the rest of markets. The incorporation of these structural breaks in our models leads to a significant decrease in volatility persistence and news asymmetry for all markets. On the whole, 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. 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 hedge ratios and report evidence attesting to the importance of cross-market hedging. It is noteworthy that it is cheaper to hedge long petroleum positions while shorting the U.S. dollar with Brent than with WTI.

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 preventative 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. In particular, they are relevant to the monetary policies of the fast growing BRICS countries (Brazil, Russia, India, China and South Africa) because they are large importers of commodities like crude oil. Except for Russia, which is the largest global oil producer, the BRICS countries are very important oil consumers of fuels for two simple reasons. This group accounts for more than a quarter of the world's land area, and it embraces 40% of world population, which enjoy rapidly rising per capita income. According to the BP Statistical Review of World Energy (June 2013), China has the second-largest economy in the world (after the United States) is the second largest global consumer of oil in both 2011 and 2012, with 9.750 million and 10.221 million barrels daily for those two years, respectively. India is the fourth global consumer, with 3.488 (3.652) million barrels daily in 2011 (2012). Al-Fayoumi (2009) argues that emerging oil-importing countries tend to be increasingly more energy intensive than more advanced economies, and therefore are more exposed to higher oil prices. 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. Oil shocks are indeed considered to be inflationary by many economists (e.g., Hooker, 2002) and they force central banks to adopt a tighter monetary policy, and 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. Oil price shocks however pose a difficult challenge to balancing the trade-off between higher inflation and higher unemployment (Herrera and Pesavento 2007). Bernanke et al. (2004) suggest that monetary policy makers tend to keep inflation low at the cost of a slowdown in economic activity. The central banks implement the monetary policy via interventions in the foreign exchange market, which in turn affects the macroeconomy including petroleum prices.

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. 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 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 market 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.

Finally, in order to reduce market risk and maintain the values of commodity portfolios, the oil-exporting countries (e.g., Russia and those in the Gulf Cooperation Council, the Middle East and the North Africa countries) should diversify their investments in the precious metals at the times when their oil dollar revenues accumulate. Joy (2011) finds that : (i) During the past 23 years, gold acted as a hedge against the US dollar ; (ii) Gold has been a poor safe haven ; (iii) In recent years gold has behaved, increasingly, as an effective hedge against currency risk associated with the fluctuations in the value of the US dollar. On the other hand, Ciner et al. (2013) argue that gold can be considered as a safe haven against exchange rates in both the United States and the United Kingdom, highlighting its monetary asset role. Reboredo (2013a) shows that gold can act as a safe haven against extreme oil price movements. Reboredo (2013b) finds that gold can act as a hedge against USD exchange rates on average, and as a safe haven asset against extreme USD rate movements.

On the whole, our findings on volatility transmissions have several financial and policy implications for policy makers and traders in terms of pursuing effective fiscal policy management, controlling oil inflationary pressures or fluctuations in exchange rates, and conducting market risk management for oil-importing and -exporting countries.

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Figure 1: Price Behavior for The Exchange Rate and The Petroleum Markets

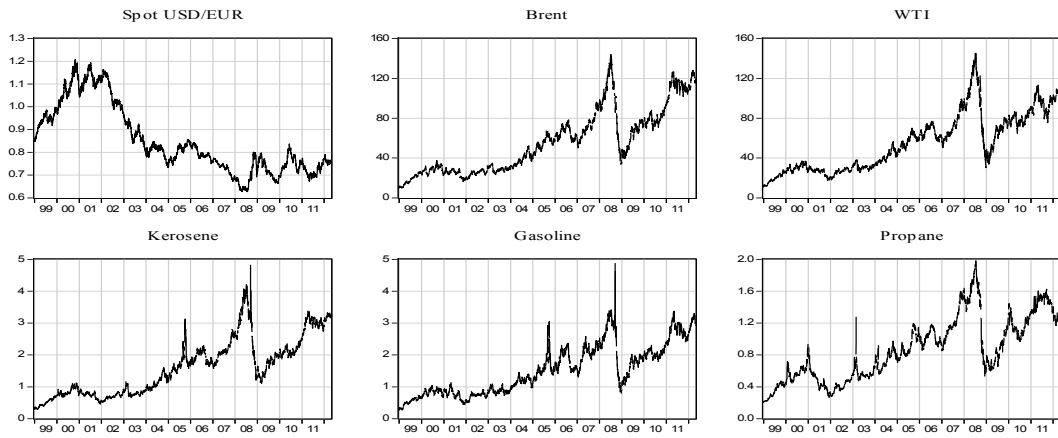
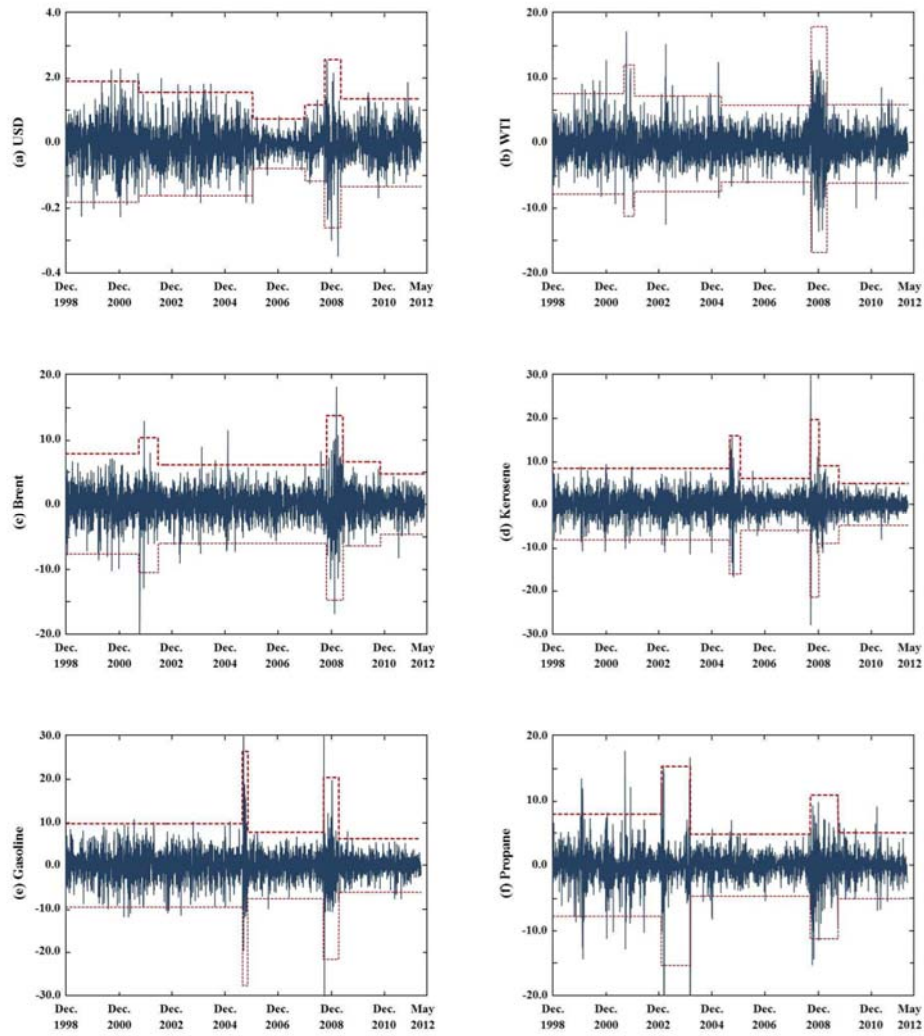


Figure 2: Return Behavior for the Exchange Rate and Petroleum Markets



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	0.070	0.066	0.044
Median	0.000	-0.139	0.118	0.125	0.084	0.000
Maximum	2.524	17.091	18.129	32.642	37.173	17.673
Minimum	-3.460	-16.413	-19.890	-27.749	-38.675	-49.913
Std. Dev.	0.509	2.573	2.405	2.763	3.292	2.580
Skew	-0.051	0.288	-0.244	-0.097	0.133	-3.113
Kurtosis	5.881	7.294	7.932	14.76	17.85	65.180
JB	1692***	2624***	3473***	19332***	30840***	556170***
Q(14)	64.05***	31.94***	38.78***	35.65***	34.00***	47.81***

Notes: 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 Bivariate EGARCH Model for the US 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
<i>Mean equation</i>											
$C_{EX,0}$	$C_{PET,0}$	-0.001 (0.007)	-0.093** (0.040)	0.002 (0.007)	0.089** (0.037)	-0.001 (0.007)	0.150*** (0.041)	-0.003 (0.007)	0.164*** (0.048)	0.001 (0.007)	0.105*** (0.033)
$\beta_{EX,1}$	$\beta_{EX,2}$	0.111*** (0.018)	-0.033 (0.078)	0.109*** (0.017)	-0.103 (0.072)	0.109*** (0.018)	0.049 (0.084)	0.108*** (0.018)	0.024 (0.091)	0.102*** (0.017)	-0.046 (0.061)
$\beta_{PET,1}$	$\beta_{PET,2}$	-0.025 (0.017)	0.024*** (0.003)	0.022 (0.018)	-0.027*** (0.003)	-0.015 (0.019)	-0.016*** (0.002)	0.002 (0.018)	-0.010*** (0.002)	0.068*** (0.016)	-0.019*** (0.003)
<i>Variance equation</i>											
$\alpha_{EX,0}$	$\alpha_{PET,0}$	-0.007*** (0.002)	0.159*** (0.016)	-0.005** (0.002)	0.119*** (0.010)	-0.006*** (0.002)	0.165*** (0.013)	-0.004** (0.002)	0.341*** (0.022)	-0.007*** (0.002)	0.241*** (0.011)
$\alpha_{EX,1}$	$\alpha_{EX,2}$	0.077*** (0.007)	0.051*** (0.010)	0.076*** (0.007)	0.025** (0.010)	0.077*** (0.007)	0.053*** (0.009)	0.074*** (0.006)	0.006 (0.014)	0.074*** (0.007)	0.096*** (0.009)
$\alpha_{PET,1}$	$\alpha_{PET,2}$	0.013*** (0.003)	0.129*** (0.013)	0.011*** (0.003)	0.112*** (0.011)	0.017*** (0.003)	0.157*** (0.011)	0.015*** (0.003)	0.254*** (0.014)	0.019*** (0.003)	0.257*** (0.011)
γ_{EX}	γ_{PET}	0.992*** (0.001)	0.913*** (0.009)	0.993*** (0.001)	0.931*** (0.006)	0.991*** (0.001)	0.919*** (0.007)	0.993*** (0.001)	0.854*** (0.010)	0.989*** (0.001)	0.872*** (0.006)
δ_{EX}	δ_{PET}	0.195*** (0.061)	0.384*** (0.077)	0.260*** (0.066)	-0.503*** (0.087)	0.309*** (0.062)	-0.001 (0.051)	0.243*** (0.065)	0.149*** (0.044)	0.290*** (0.061)	0.171*** (0.028)
<i>Correlation parameters</i>											
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

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). The figures in parentheses are standard errors. The asterisks *, **, *** denote significance at the 10%, 5% and 1% level, respectively.

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 periods are detected by the ICSS algorithm.

Table 4: Estimation Results Of Bivariate 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
<i>Mean equation</i>											
$C_{EX,0}$	$C_{PET,0}$	-0.003 (0.007)	-0.113*** (0.039)	-0.001 (0.007)	0.103*** (0.036)	-0.003 (0.007)	0.113*** (0.039)	-0.004 (0.007)	0.130*** (0.047)	-0.001 (0.007)	0.105*** (0.032)
$\beta_{EX,1}$	$\beta_{EX,2}$	0.112*** (0.018)	-0.059 (0.081)	0.109*** (0.018)	-0.040 (0.071)	0.114*** (0.018)	-0.051 (0.088)	0.111*** (0.018)	-0.034 (0.099)	0.107*** (0.018)	-0.009 (0.064)
$\beta_{PET,1}$	$\beta_{PET,2}$	-0.031* (0.018)	0.025*** (0.003)	0.018 (0.016)	-0.028*** (0.003)	-0.010 (0.019)	-0.017*** (0.003)	-0.003 (0.018)	-0.010*** (0.002)	0.069*** (0.017)	-0.020*** (0.003)
<i>Variance equation</i>											
$\alpha_{EX,0}$	$\alpha_{PET,0}$	-0.027*** (0.007)	0.483*** (0.061)	-0.030*** (0.008)	0.336*** (0.048)	-0.045*** (0.011)	0.801*** (0.077)	-0.031*** (0.008)	1.001*** (0.109)	-0.023*** (0.006)	0.371*** (0.022)
$\alpha_{EX,1}$	$\alpha_{EX,2}$	0.058*** (0.010)	0.037** (0.017)	0.062*** (0.010)	0.014 (0.016)	0.056*** (0.010)	0.071*** (0.023)	0.061*** (0.010)	0.018 (0.025)	0.060*** (0.009)	0.052*** (0.011)
$\alpha_{PET,1}$	$\alpha_{PET,2}$	0.020*** (0.006)	0.159*** (0.021)	0.009** (0.004)	0.084*** (0.019)	0.025*** (0.006)	0.218*** (0.029)	0.018*** (0.006)	0.215*** (0.027)	0.017*** (0.004)	0.279*** (0.015)
γ_{EX}	γ_{PET}	0.969*** (0.007)	0.747*** (0.031)	0.966*** (0.008)	0.817*** (0.026)	0.951*** (0.011)	0.601*** (0.037)	0.964*** (0.008)	0.573*** (0.046)	0.973*** (0.006)	0.816*** (0.011)
δ_{EX}	δ_{PET}	0.305*** (0.110)	0.486*** (0.098)	0.354*** (0.116)	-1.202*** (0.294)	0.525*** (0.138)	-0.189*** (0.080)	0.304*** (0.112)	0.063 (0.088)	0.395*** (0.103)	0.186*** (0.036)
<i>Correlation parameters</i>											
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

Notes: see the notes of Table 2. Most of the coefficients of the dummies for structural breaks are statistically significant. But we do not report the estimation results for the dummies to save space.

Table 5: Summary Statistics for the Portfolio Weights and the Hedge Ratios

	<i>Portfolio weight</i>				<i>Hedge ratio</i>			
	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max
<i>Panel A: Values are calculated using estimates of the bivariate EGARCH model without structural breaks</i>								
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
<i>Panel B: Values are calculated using estimates of the bivariate EGARCH model with structural breaks.</i>								
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.