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Energy prices and exchange rates of the U.S. dollar: Further evidence from linear and nonlinear causality analysis

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ABSTRACT

The causality relationships between energy prices and exchange rates have been investigated in many existing studies. Previous investigations ignore the possible nonlinear behaviors which may be caused by asymmetry, persistence or structural breaks. To fill this gap, we apply both linear and nonlinear causality tests to examine the causal relationships between energy prices and exchange rates of the U.S. dollar. Our results show that in the period before recent financial crisis, unidirectional linear causality running from petroleum prices to exchange rates and unidirectional nonlinear causality running from exchange rates to natural gas prices are revealed. In the period after the financial crisis, the bidirectional nonlinear causality relationships between petroleum prices and exchange rates can be found and there are no causality between exchange rates and natural gas prices. Moreover, we examine the source of nonlinear behaviors of causality relationships. Our evidence indicates that both volatility spillover and regime shift contribute to nonlinear causality and the explanation power of the former one is much stronger.

1. Introduction

Since the seminal work of Hamilton (1983), the linkages between energy prices and macroeconomic fundamentals have been extensively investigated in existing literatures. For example, some researchers have studied the relationships between oil prices and stock prices (Arouri, 2011; Arouri et al., 2011; Ferderer, 1996; Sadorsky, 1999, 2003), between oil prices and economic activity (Eika and Magnussen, 2000; Kilian, 2009; Prasad et al., 2007), and between oil prices and inflation rates (Chen, 2009; LeBlanc and Chinn, 2004). The goal of this paper is to examine the causality relationships between exchange rates of U.S. dollar and crude oil prices.

There are many empirical studies which contribute to the causality behavior between crude oil price and exchange rates and their results are mixed. Some of the studies support that oil price dominates exchange rates. For example, in the framework of Engle and Granger (1987) causality test, Amano and van Norden (1998a) examine the linkages between crude oil prices and U.S. effective exchange rates over the post Bretton Woods period and find that they are cointegrated with a unidirectional causality behavior running from oil prices to exchange rates. This result is also further confirmed by Chaudhuri and Daniel (1998) who investigate the contribution of real oil price behavior to the nonstationarity of exchange rates between U.S. dollar and currencies in 16 OECD countries. Amano and van Norden (1998b) also examine the relationships between domestic crude oil prices and real effective exchange rates for Germany, Japan and the U.S. Their empirical evidence indicates that oil prices Granger cause exchange rates but not vice versa. Benassy-Quere et al. (2007) find the existence of a unidirectional causality behavior which runs from oil to the dollar. Chen and Chen (2007) find that the incorporation of real oil prices can significantly improve the predictability of exchange rates, implying the existence of “out-of-sample” causality running from oil price to exchange rates. Coudert et al. (2008) find the causality running from oil prices to exchange rates and that the relationships between two variables are transmitted through the U.S. net foreign asset position. According to a monetary model, Lizardo and Mollick (2010) point out that crude oil price can significantly explain movements in the exchange rates of U.S. dollar against most of the currencies but the impact of oil price changes on the exchange rate of a country's currency differs depending on whether this country is a net oil importer or an oil exporter.

Evidence in some of the empirical studies indicate that exchange rate dominate oil prices. For instance, the empirical evidence in Sadosky (2000) indicates that energy prices and exchange rates are cointegrated. Moreover, causality analysis shows that exchange rates precede movements in heating oil and crude oil prices in the short-run. That is, exchange rates transmit exogenous shocks to energy futures prices. Using a structural vector autoregressive model (SVAR), Akram (2009) shows that a weaker dollar leads to higher oil prices.

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Some of the recent empirical studies also indicate no significant relations between oil prices and exchange rates. Based on a VAR, Sari et al. (2010) show that neither the response of dollar/euro exchange rate to oil price nor the response of oil price to exchange rate is significant, implying the absence of meaningful linkages. Soytas et al. (2009) find that oil price has no predictive power of Turkish lira–U.S. dollar exchange rate and lira exchange rate has no significant impacts on oil price in the long-term.

However, there are two major limitations in existing studies. First, the causality relationships between oil prices and exchange rates are widely detected based on conventional tests (Engle and Granger, 1987; Granger, 1969). These conventional approaches are based on vector autoregressive model (VAR) or vector error correction (VEC) specifications. Baek and Brock (1992) point out that the parametric linearity assumption is too strict and this parametric linear causality test has lower power against some nonlinear methods. In this perspective, some nonparametric tests are appealing because the causality behaviors are examined based on the predictability directly, rather than on the specific form of regressive equation. Second, as shown in many researches, the nonlinear structure of energy prices has been widely considered (Adrangi et al., 2001; Alvarez-Ramirez et al., 2008; Serletis and Andreadis, 2004; Wang and Liu, 2010). More importantly, according to Arouri and Jawadi (2010) and Akram (2004), nonlinear relationships between oil prices and exchange rates have been found based on formal econometric analysis.[1] However, to the best of our knowledge, nonlinear causality linkages between oil prices and exchange rates have not been investigated in previous studies. Which is the dominator in the framework of nonlinearity? Third, most of the studies focus on the relationships between crude oil prices and exchange rates. Very few of the researchers pay attention to prices of other energy commodities, such as gasoline and natural gas, which also play important roles in world economy.

Due to abovementioned considerations, we investigate the causality relationships between energy prices and exchange rates of the U.S. dollar. We employ daily data of crude oil, gasoline, heating oil and natural gas prices and trade-weighted exchange rates covering the period from January 2, 2003 to June 3, 2011. Our testing procedure is executed as follows. First, we divide the whole sample period into two sub-periods (January 2003–June 2007 and July 2007–June 2011) to compare the causality relationships between before and after the recent global financial crisis. Then, we examine the pairwise cointegration relationships between energy prices and exchange rates. For cointegrated pairs, we test for linear causality relationships based on vector error correction models (VECM) (Engle and Granger, 1987). Otherwise, the linear causality will be examined based on vector autoregressive (VAR) specifications. Second, we examine whether the oil price and exchange rate returns are nonlinear employing a BDS test statistic (Brock et al., 1987). If the nonlinearity is confirmed, we will test for nonlinear causality relationships between energy prices and exchange rates using a nonparametric method proposed by Diks and Panchenko (2006). Finally, for each pair of series which displays a nonlinear causality linkage, we investigate the source of nonlinear causality. In this framework, we will consider the effects of regime shift and volatility spillover (second-order co-movement) on nonlinear causality behaviors.

The remainder of this paper is organized as follows: the next section shows the econometric methodology. Section 3 provides a data description and some preliminary analysis. Section 4 reports the empirical results. In the last section, we summarize this paper.

[1] The findings in Arouri and Jawadi (2010) suggest some low evidence of short-term and long-term linkages according to VAR modeling and cointegration analysis, respectively. However, based on a nonlinear econometric model, a strong nonlinear relationship is revealed. Akram (2004) finds negative relationships between oil prices and the value of Norwegian exchange rate, which is especially more stronger when oil prices are below 14 dollars per barrel.

2. Econometric methodology

2.1. Linear Granger causality test

For the null hypothesis variable X_t cannot Granger cause Y_t. The test equation of traditional Granger causality could be written as (Granger, 1988),

$$\Delta Y_t = \gamma + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \sum_{j=1}^{q} \beta_j \Delta X_{t-j} + \varepsilon_t, \tag{1}$$

where, γ is a constant, p and q are the lag lengths enough to make disturbance term ε_t white noise, and t is time. ΔX_t and ΔY_t denote the first difference of X_t and Y_t, respectively. The null hypothesis of no Granger causality was described as the equation, $\beta_1 = \beta_2 = \ldots = \beta_q = 0$. The standard Wald F-statistic is used to detect the Granger casual relationship as,

$$F = \frac{(RSS(p) - RSS(p,q))/q}{RSS(p,q)/(T-p-q-1)} \sim F(p,\ T-p-q-1), \tag{2}$$

where, $RSS(p,q)$ is the sum of squared residuals of Eq. (1), $RSS(p)$ is the sum of squared residuals of a univariate autoregression for ΔY_t with lag length p, and T is the number of observations.

Engle and Granger (1987) pointed out that, if two series are cointegrated, the causality testing should be based on a VECM specification rather than an unrestricted VAR. The VECM has the following form:

$$\Delta Y_t = -p(Y_{t-1} - \lambda X_{t-1}) + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \sum_{j=1}^{q} \beta_i \Delta X_{t-i} \tag{3}$$

where, $[1 - \lambda]$ is the cointegration vector and λ is the cointegration coefficient.

2.2. The Diks and Panchenko (2006)'s nonlinear Granger causality test

The nonparametric test proposed by Hiemstra and Jones (1994), which is also a modified version of the test proposed by Baek and Brock (1992), are always employed to detect the nonlinear causality relationship between two stationary time series. The Baek and Brock test assumes that each time series follows i.i.d. The Hiemstra and Jones test relaxes this strict hypothesis, allowing for the existence of short-term autocorrelations in time series. However, Diks and Panchenko (2005, 2006) point out that the relationship tested by the Hiemstra and Jones (1994)'s test is not generally compatible with the definition of Granger causality and it may lead to spurious rejections of the null hypothesis of no Granger causality. To overcome this drawback, Diks and Panchenko (2006) develop a new nonparametric method which can be used to detect possible nonlinear causality relationship between two time series. The Diks and Panchenko test can be described as follows:

Assume that $\{X_t, Y_t, t \geq 1\}$ are two strictly stationary time series. In Granger (1969)'s sense, $\{X_t\}$ is a strictly Granger cause of $\{Y_t\}$ if past and current values of X contain additional information on future value of Y that is not contained only in the past and current Y_t values.

Assume delay vectors $\mathbf{X}_t^{l_x} = (X_{t-l+1}, \ldots, X_t)$ and $\mathbf{Y}_t^{l_x} = (Y_{t-l+1}, \ldots, Y_t)$, $(l_x, l_y \geq 1)$. The null hypothesis that past observations of $\mathbf{X}_t^{l_x}$ contain no useful information of Y_{t+1} can be described using the following equation:

$$H_0 : Y_{t+1} \Big| \left(\mathbf{X}_t^{l_x}; \mathbf{Y}_t^{l_y}\right) \sim Y_{t+1} \Big| \mathbf{Y}_t^{l_y} \tag{4}$$

where, '~' denotes the equivalence in distribution. For two strict stationary time series, Eq. (4) actually considers the distribution of the (l_x+l_y+1) dimensional vector $\mathbf{W}_t=(\mathbf{X}_t, \mathbf{Y}_t, Z_t)$ where $Z_t=Y_{t+1}$. Under the null hypothesis, the distribution of $\mathbf{W}_t$ is invariant. We drop the time index and follow Bekiros and Diks (2008) and assume $l_x=l_y=1$. Thus, under the null hypothesis, the conditional distribution of Z given by $(X,Y)=(x,y)$ is equivalent to that of Z given by $Y=y$. In Eq. (2), the joint probability density distribution $f_{X,Y,Z}(x,y,z)$ and its marginal should satisfy the following equation:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)}=\frac{f_{X,Y}(x,y)}{f_Y(y)}\cdot\frac{f_{Y,Z}(y,z)}{f_Y(y)}. \tag{5}$$

The above equation implies that X and Z are independent conditionally on $Y=y$ for each fixed value of y. Diks and Panchenko (2006) show that this formulated null hypothesis implies the following equation:

$$q\equiv \mathrm{E}\left[f_{X,Y,Z}(X,Y,Z)f_Y(Y)-f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)\right]=0. \tag{6}$$

Let $\hat{f}_W(W_i)$ denote a local density estimator of a d_W-variate random vector $\mathbf{W}$ at W_i, as the following equation:

$$\hat{f}_W(W_i)=(2\varepsilon_n)^{-d_W}(n-1)^{-1}\textstyle\sum_{j,j\neq i}I_{ij}^{W}, \tag{7}$$

where, $I_{ij}^W=I(\|W_i-W_j\|<\varepsilon_n)$, $I(\cdot)$ is the indicator function and ε_n is the bandwidth, depending on the sample size n. Given this estimator, the test statistic is a scaled sample version of q in Eq. (6):

$$T_n(\varepsilon_n)=\frac{n-1}{n(n-2)}\sum_i\left(\hat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\hat{f}_Y(Y_i)-\hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)\right). \tag{8}$$

For $l_x=l_y=1$, if $\varepsilon_n=Cn^{-\beta}(C>0,\ 1/4<\beta<1/3)$, Diks and Panchenko (2006) prove under strong mixing that the statistic in Eq. (8) follows:

$$\sqrt{n}\frac{T_n(\varepsilon_n)-q}{S_n}\xrightarrow{D}N(0,1) \tag{9}$$

where, $\xrightarrow{D}$ denotes convergence in distribution and S_n is the asymptotic variance of $T_n(\cdot)$ (Diks and Panchenko, 2006). Following Diks and Panchenko's suggestion, we use a right-tailed test.[2]

3. Data

We choose daily data of prices of crude oil, gasoline, heating oil and natural gas and nominal trade-weighted U.S. exchange rates which are denoted as CO, GL, HO, NG and ER, respectively. Our sample covers the period from January 2, 2003 to June 3, 2011. We obtain the energy price data from the U.S. Energy Information Administration (EIA)[3] and exchange rate data from Federal Reserve Bank of Saint Louis.[4] Fig. 1 shows the illustrations of evolutions of exchange rates and energy prices. We can find that the dynamics of prices of different energy commodities are very similar. In the following analysis, we consider the natural logarithms of energy prices and exchange rates.

Table 1 reports the descriptive statistics of the price returns (the first difference of logarithmic prices). The mean values of five return series are close to zero and the standard deviations are much larger. The range (maximum–minimum) and standard deviation of exchange rate returns are much smaller than those of energy returns, indicating that exchange rates are less volatile than energy prices. The Jarque–Bera statistics consistently show rejections of the null hypothesis of Gaussian distributions at 1% significance level, indicating that five return series are fat-tail distributed, also evidenced by non-zero skewness and positive excess kurtosis. The Ljung–Box statistics show that the null hypothesis of no autocorrelations up to the 10th order is rejected for four of five series, confirming the series autocorrelation in exchange rates and most of the energy returns.

4. Empirical results

The linear Granger causality analysis should be performed on stationary time series to avoid the spurious regression results caused by the nonstationarity. Thus, prior to causality analysis, we should employ unit root tests to analyze the integration and stationarity properties of energy price and the U.S. dollar exchange rate series. Table 2 reports the results of unit root tests based on Augment Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP) and Kwiatkowski et al. (1992) (KPSS) methods. To save space, we do not show the detailed description of these tests. The optimal lag lengths of ADF test are chosen based on Schwarz information criterion (SIC) and the optimal bandwidths of PP and KPSS are determined based on Newey–West criterion. Based on each of these three methods, the unit root tests are performed by taking into account two different models (with constant and with constant and trend). The null hypothesis of ADF and PP tests is a unit root while that of KPSS test is stationary. In Table 2, for petroleum price series and the U.S. dollar exchange rate series, the ADF and PP statistics cannot reject the unit root null while KPSS significantly reject the null hypothesis of stationarity, implying nonstationary processes. For natural gas price series, although ADF and PP statistics show rejections of unit root null at 5% significance level with intercept only and at 10% significance level with both intercept and trend in testing equations, the KPSS statistics reject the null hypothesis of stationarity at 1% significance level. Thus, we can conclude that natural gas price series is nonstationary at 1% significance level. For the first differences of energy prices and exchange rates, the ADF, PP and KPSS statistics consistently indicate that they are stationary. Based on the above unit root tests, we can find that energy price and exchange rate series contain unit roots while the first order differences are stationary, suggesting the behaviors of I(1) processes.

To analyze the effect of recent financial crisis on the causality relationships between energy prices and exchange rates, we divide the whole sample period into two sub-periods. Period I (PI) spans January 2, 2003 to June 29, 2007, corresponding to a supply shock caused by the second Gulf War and a demand shocks of Asia economic boom. Period II (PII) spans July 2, 2007 to June 3, 2011, covering the whole period of recent financial crisis. Then, we analyze the relationships between energy prices and exchange rates in two non-overlapped sub-periods.

Table 3 reports the correlation matrix among five return series in PI and PII. We can find that the energy returns and exchange rate returns are negatively correlated while returns of each two energy commodities are positively correlated. We focus on the correlations between energy returns and exchange rate returns in detail. In both of the two periods, the correlations between exchange rate and crude oil returns are larger than those between exchange rate and returns of other energy commodities. More importantly, the correlated behaviors are stronger in PII than in PI.

Engle and Granger (1987) point out that, if two time series are cointegrated, the causality test should be based on a vector error correction model (VECM) rather than an unrestricted vector autoregressive model (VAR). Thus, in empirical analysis, it is necessary to analyze the cointegration relationships between energy prices and exchange rates before the causality analysis. Table 4 reports the results of cointegration analysis based on Johansen's maximum eigenvalues and trace test

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[2] Here, we greatly thank Dr. Diks for providing the programming code of this nonlinear causality test.
[3] Website: http://www.eia.gov.
[4] Website: http://research.stlouisfed.org/fred2/.

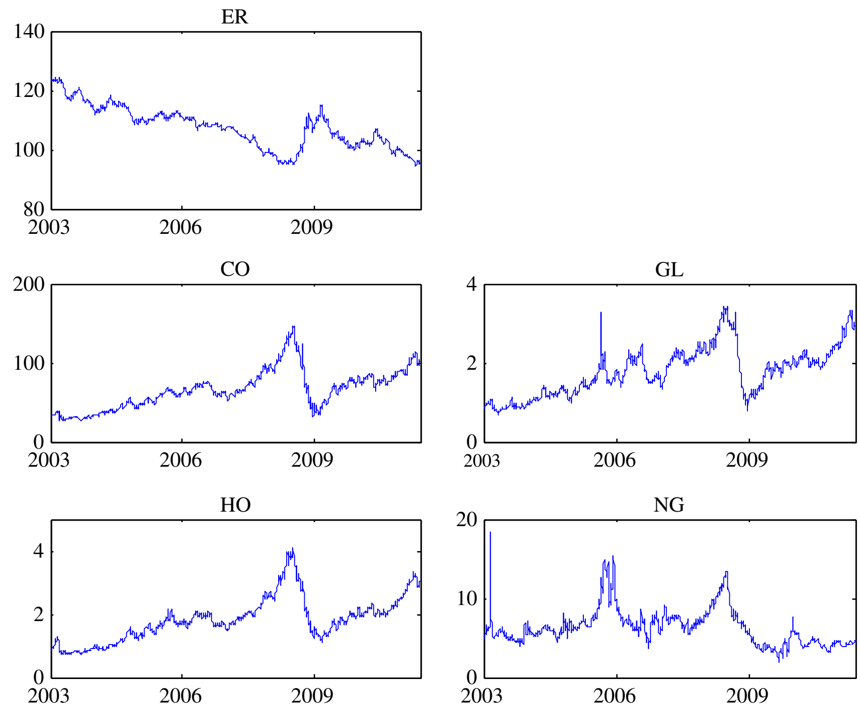

Fig. 1. Energy prices and exchange rates.

(Johansen, 1988, 1991; Johansen and Juselius, 1990).[5] In PI, none of the maximum eigenvalue statistics or trace statistics can reject the null hypothesis of no cointegration between exchange rates and oil prices. Although the trace statistic rejects the null hypothesis of no cointegration between exchange rates and natural gas prices at 10% significance level, the maximum eigenvalue statistic cannot reject. Thus, we can generally consider that exchange rates and petroleum prices are not cointegrated in PI. For the series in PI, the linear Granger causality analysis will be performed based on VAR specification. In PII, both of trace statistics and maximum eigenvalue statistics reject null hypothesis of no cointegration between exchange rates and petroleum prices at 1% significance level but cannot reject the null hypothesis of at most one cointegration equation. That is, exchange rates and petroleum prices are cointegrated. However, we still cannot find the evidence of cointegration between exchange rates and natural gas prices in PII. Thus, for the series in PII, the linear Granger causality between exchange rates and petroleum prices will be performed based on VECM specification while that between exchange rates and natural gas prices will be analyzed based on VAR specification. Our results of cointegration tests are not exactly consistent with those in Chaudhuri and Daniel (1998), Sadosky (2000), Chen and Chen (2007) and Lizardo and Mollick (2010). The major reason may be because of the inconsistency of sample period and data frequency. Although our sample period is partly overlapped with that used in Chen and Chen (2007) and Lizardo and Mollick (2010), it should be noted that the exchange rate series used in this work is the trade-weighted version, not the exchange rates of some specific currencies against the U.S. dollars employed in abovementioned two studies.

In order to examine the long-run causality, we test for weak exogeneity on the cointegrating relationship, which is equivalent to test for the hypothesis that the coefficients of the error-correction term (ECM) are zero. Our results show that the ECM coefficients of natural gas prices in PI and petroleum prices in PII are significant at 1% level but those of exchange rates are not significant,[6] indicating that the exchange rates are weakly exogenous to energy prices in the long-run. That is, exchange rates Granger cause energy prices in the long-run, but not vice versa.

Table 5 reports the results of short-run linear Granger causality analysis based on VAR specification (non-cointegrated pairs) or VECM specification (cointegrated pairs) as discussed above. The optimal lag length is determined based on Schwarz Information Criteria (SIC). For convenience, in the following analysis, we use a symbol "$X \rightarrow Y$" to denote the null hypothesis that the X does not Granger cause Y. Following Bekiros and Diks (2008), we briefly show the statistical significance of the testing results because it is enough for us to analyze the causality relationships. The evidence in Table 5 indicates that linear Granger causality relationships do not exist between natural gas returns and exchange rates returns. In contrast to natural gas and exchange rates, we can find unidirectional causality relationships running from petroleum prices to exchange rates in both of the two periods. This result confirms the evidence in Amano and van Norden (1998a), Lizardo and Mollick (2010) but is not exactly consistent to that in Sadosky (2000). The reason may be the inconsistency of sample period and frequency discussed above. Only one exception of causality relationships is that exchange rates can also linearly Granger cause the change of crude oil prices in PII, reinforcing the recent findings in Akram (2009) that a weaker dollar leads to higher commodity prices. Table 5 also reports the results of linear Granger causality tests on VAR filtered residuals for un-cointegrated pairs or VECM residuals for cointegrated pairs. We can find that the linear causality behaviors between petroleum prices and exchange rates disappear after the procedure of VAR or VECM filtering.

In previous studies, the nonlinear structure of energy prices has been confirmed (Adrangi et al., 2001; Alvarez-Ramirez et al., 2008; Serletis and Andreadis, 2004; Wang and Liu, 2010). Moreover, nonlinear linkages between energy prices and exchange rates have

[5] To save space, we do not show the methodology of Johansen's cointegration test. The detailed description can be seen in these three corresponding reference, or in Sadosky (2000) which also studies the relationships between energy prices and exchange rates.

[6] To save space, we do not show the estimates in detail. They can be obtained upon request.

Table 1
Descriptive statistics of energy price and exchange rate returns.

	ΔER	ΔCO	ΔGL	ΔHO	ΔNG
Mean	−1.29e−4	5.39e−4	5.73e−4	5.85e−4	−2.05e−05
Maximum	0.016	0.164	0.235	0.110	0.577
Minimum	−0.023	−0.152	−0.179	−0.110	−0.568
Std. dev	0.003	0.026	0.030	0.024	0.049
Skewness	−0.118	−0.116	0.107	−0.092	0.632
Excess kurtosis	3.886	4.632	5.168	1.264	24.741
Jarque–Bera	1338.415***	1899.003***	2362.315***	144.121***	54184.13***
Q(10)	20.538**	54.467***	23.863***	7.184	95.863***

Note: The Jarque–Bera statistic tests for the null hypothesis of Gaussian distribution. Q(10) is the Ljung–Box statistic of the return series for up to the 10th order serial correlation.
* Denotes rejections at 10% significance level.
** Denotes rejections at 5% significance level.
*** Denotes rejections at 1% significance level.

Table 2
Results of unit root test.

	ER	CO	GL	HO	NG	ΔER	ΔCO	ΔGL	ΔHO	ΔNG
Intercept only										
ADF	−1.586	−1.715	−1.967	−1.465	−2.875**	−45.178***	−21.767***	−45.399***	−47.702***	−38.545***
PP	−1.645	−1.640	−1.966	−1.453	−2.951**	−45.270***	−47.667***	−45.400***	−47.675***	−46.102***
KPSS	4.243***	3.615***	3.423***	3.600***	1.467***	0.079	0.057	0.039	0.060	0.049
Trend and intercept										
ADF	−2.330	−2.390	−2.784	−2.145	−3.217*	−45.169***	−21.765***	−45.388***	−47.691***	−38.539***
PP	−2.486	−2.286	−2.817	−2.141	−3.322*	−45.261***	−47.656***	−45.389***	−47.664***	−46.149***
KPSS	0.411***	0.579***	0.566***	0.658***	0.725***	0.066	0.047	0.036	0.057	0.027

Note: This table reports the results of testing for unit root in logarithms of energy prices and exchange rates and their first order differences. The null hypothesis of ADF and PP tests is unit root and that of KPSS test is stationarity. The optimal lag lengths of ADF test are chosen based on Schwarz information criterion (SIC) and the optimal bandwidths of PP and KPSS are determined based on Newey–West criterion.
* Denotes rejections of the null hypothesis at 10% significance level.
** Denotes rejections of the null hypothesis at 5% significance level.
*** Denotes rejections of the null hypothesis at 1% significance level.

been found in recent studies (see, e.g., Akram, 2004; Arouri and Jawadi, 2010). Thus, it is necessary to examine nonlinear Granger causality. For this consideration, we detect the nonlinear structure of our sample data in two sub-periods and then test the nonlinear causality between energy and exchange rate returns using a nonparametric method proposed by Diks and Panchenko (2006).

We employ a BDS test to detect the nonlinear structure of five return series and show the results in Table 6. We choose the length in σ^2 to be 0.7 and let the embedding dimension (m) vary from 2 to 6. In both of the two periods, the BDS statistics of five return series at most of embedding dimensions show rejections of the null hypothesis of independent identity distributions at 1% significance level, in favor of nonlinear structures. The only exception is that the BDS statistics of exchange rate returns at m = 2 reject the null hypothesis at 10% significance level. Thus, we consider that the energy and exchange rate returns in both of the two periods display significant nonlinear properties, confirming the results in existing literatures.

Table 7 reports the results of Diks and Panchenko's nonparametric Granger causality test applied on the log-returns. Following Bekiros and Diks (2008), we discuss the results for lags $l_x = l_y = 1$. To perform this causality test, the constant C for the bandwidth ε_n is set at 7.5, which is close to the value of 8.0 for ARCH process suggested by Diks and Panchenko (2006). With the optimal value of $\beta = 2/7$ given by Diks and Panchenko (2006) and about 1000 observations in each period, this implies that the selected bandwidth of ε_n is about one standard deviation of time series for both of the two periods. We also report the results of this nonlinear causality test for VAR/VECM residuals in order to investigate whether any remaining causality relationships are strictly nonlinear. In PI, only unidirectional nonlinear causality running from exchange rate returns to natural gas returns can be found at 10% significance level. The results also show that nonlinear causality relationships do not exist between exchange rate returns and four petroleum returns. For the pairs of VAR/VECM residuals, we find no nonlinear causality relationships. That is, in PI, only linear causality relationships can be found. In PII, the results are more consistent among different pairs of series. We cannot find any evidence of nonlinear causality behaviors between exchange rates and natural gas prices. However, significant bidirectional causality relationships exist between the exchange rates and four petroleum prices. Even for the VAR/VECM residuals, this kind of nonlinear causality relationship is still significant at 1% level, further confirming the nonlinearity in nature. Our empirical evidence on bidirectional causality behaviors seems to be in contrast to results in Sadosky (2000) who shows a unidirectional causality running from exchange rates to energy prices, also different from those in Amano and van Norden (1998a) who show a unidirectional causality running from crude oil prices to exchange rates. Our results of bidirectional causality behaviors do not support the statement

Table 3
Correlation matrix among energy price and exchange rate returns.

	ΔER	ΔCO	ΔGL	ΔHO	ΔNG
PI					
ΔER	1				
ΔCO	−0.148	1			
ΔGL	−0.063	0.512	1		
ΔHO	−0.098	0.615	0.661	1	
ΔNG	−0.057	0.049	0.087	0.095	1
PII					
ΔER	1				
ΔCO	−0.428	1			
ΔGL	−0.302	0.661	1		
ΔHO	−0.403	0.758	0.763	1	
ΔNG	−0.121	0.079	0.099	0.111	1

Note: PI: January 2, 2003–June 29, 2007 and PII: July 2, 2007–June 3, 2011.

Table 4
Results of cointegration test between energy prices and exchange rates.

No. of cointegration equations	PI								PII							
	Trace statistic				Max-eigen statistic				Trace statistic				Max-eigen statistic			
	ER–CO	ER–GL	ER–HO	ER–NG	ER–CO	ER–GL	ER–HO	ER–NG	ER–CO	ER–GL	ER–HO	ER–NG	ER–CO	ER–GL	ER–HO	ER–NG
None	8.617	10.974	8.578	13.693*	6.506	8.678	6.776	11.029	24.282***	22.583***	22.350***	8.780	22.507***	21.177***	20.892***	5.759
At most 1	2.111	2.296	1.802	2.664	2.112	2.296	1.802	2.664	1.776	1.406	2.458	2.021	1.776	1.406	2.458	2.021

Note: This table shows the results of Johansen cointegration test. PI: January 2, 2003–June 29, 2007; PII: July 2, 2007–June 3, 2011.
* Denotes rejections of the null hypothesis at 10% significance level.
** Denotes rejections of the null hypothesis at 5% significance level.
*** Denotes rejections of the null hypothesis at 1% significance level.

in Hamilton (1983), who uses Granger causality tests with a wide range of U.S. economic variables and finds that oil price shocks are exogenous to the macroeconomics of the United States. Besides the inconsistency of sample period and data frequency, the major reason of different causality results is that previous researches only take the linear relationships into account.

Our evidence indicates that in both of the two periods, oil price can linearly and nonlinearly Granger cause exchange rates. The reason is that increase in oil price deteriorates current account of the U.S. (Kilian et al., 2009). The decrease in terms of trade can result in depreciation of U.S. dollar. Since oil price is denominated by dollar, higher oil price may depress oil demand. Lower oil demand can reduce the demand for U.S. dollar, resulting in its depreciation. As shown in Krugman (1980, 1983) and Golub (1983), higher oil prices can lead to wealth transfer from U.S. and Europe to OPEC. If we assume that the imports of U.S. account for a small fraction in the export of OPEC, the wealth transfer from Europe to OPEC should contribute to the improvement of the U.S. trade balance, certainly having influence on exchange rates of U.S. dollar (Coudert et al., 2008). The nonlinear causality behavior from oil price can be partly explained by the asymmetric response of economic activity to oil price shocks (Hamilton, 1996, 2003, 2011) and the negative effects of oil price uncertainty (second-order movement) on economic activity (Elder and Serletis, 2010).

Our evidence shows that in the period before financial crisis (PI) exchange rate cannot Granger cause oil prices. This can be explained by supply and demand fundamentals of oil. First, it is widely accepted that oil supply is exogenous to economic variables (see, e.g., Kilian, 2009; Kilian and Park, 2009). The reasons are: a) some of the political events that lead to the reduction of oil output in oil-exporting countries are occasional and unpredictable; b) the long-lead time and capital intensive nature of petroleum production projects lead to a very low price elasticity of crude oil supply in the short-term; and c) due to the high degree of uncertainty in the crude oil market, oil producers may adjust oil production when oil price persistently increases or decreases over a long period. Oil production will not change when occasional shocks occur. Thus, the effects of exchange rates on oil supply are very weak. Second, as shown in Hamilton (2009) and Kilian (2009), increases in oil prices in the period 2003–2007 (PI) are mainly driven by demand in emerging countries such as China and India. For instance, during the period 2003–2007, China's oil consumption increased from 5.77 million barrels per day to 7.82 million barrels per day, accounting for more than 30% of increases in the world total consumption (from 79.82 to 86.43).[7] However, Chinese Yuan is a currency pegged to the dollar. The depreciation of U.S. dollar has no influence on China's oil demand (Coudert et al., 2008), thus having relatively weak impacts on world oil demand. Therefore, we can say that the increases in oil demand in these countries are mainly caused by economic growth, rather than the depreciation of the exchange rate of U.S. dollar.

Table 5
Results of linear causality analysis.

Variable		PI				PII			
		Raw data		ECM/VAR filtered series		Raw data		ECM/VAR filtered series	
X	Y	$X\to Y$	$Y\to X$	$X\to Y$	$Y\to X$	$X\to Y$	$Y\to X$	$X\to Y$	$Y\to X$
ER	CO		**			**	*		
ER	GL		***				**		
ER	HO		***				***		
ER	NG								

Note: This table reports the results of linear causality test between energy prices and exchange rates. The causality analysis for the cointegrated pairs is performed based on VEC specifications and that for noncointegrated pairs is performed based on VAR specifications. The optimal lag lengths are determined based on Schwarz Information Criterion (SIC). '$X\to Y$' denotes the null hypothesis that X does not Granger cause Y. PI: January 2, 2003–June 29, 2007 and PII: July 2, 2007–June 3, 2011.
* Denotes the rejections of the null hypothesis at 10% significance level.
** Denotes the rejections of the null hypothesis at 5% significance level.
*** Denotes the rejections of the null hypothesis at 1% significance level.

After the financial crisis linear or nonlinear causality behaviors running from exchange rates to oil prices can be found. The plausible explanations are as follows. First, with the recovery of world economy from financial crisis, depreciation in U.S. dollars can stimulate oil demand in a country with floating exchange rate. In some of large economies with floating exchange rates, the percent changes of oil consumption in 2010 over 2009 are positive.[8] Second, depreciation of U.S. dollar after financial crisis may cause the expectation of future's higher oil price and stimulate the speculations in the oil market.

However, from the above analysis, our results show that the exchange rates and natural gas prices are not cointegrated in each period. The causality analysis indicates that there are no linear causality between exchange rates and gas prices. Only nonlinear causality running from exchange rates to natural gas prices exists in the first period can be found at 10% significance level. The nonlinear relationships may be caused by nonlinear transaction cost functions, the role of noise traders, and to market microstructure effects (Bekiros and Diks, 2008). In PII, natural gas prices and exchange rates have no cointegration or causality relationships. In contrast to natural gas prices, the relationships between petroleum prices and exchange rates are much stronger.

The plausible explanations can be obtained from the demand and supply fundamentals of natural gas and crude oil. Figs. 2 and 3 show the yearly net imports and consumption of natural gas and crude oil in the U.S. The net imports of natural gas account for about 10% of the total consumption while the net imports of crude oil account for a much greater share of total consumption (about 50%). The demand of natural gas, most of which can be met by domestic supply, has very weak effects on the current account. On the contrary, the change of oil demand has much greater effects on the current account. Thus, the relationships between oil prices and exchange rates are stronger than those between natural gas prices and exchange rates.

Our evidence shows that in PII oil prices and exchange rates display bidirectional nonlinear causality relationships. The causality behaviors between exchange rates and energy prices have been detected in

[7] The data of world oil consumption is obtained from BP Statistical Review of World Energy 2011.
[8] Some of countries with positive percent change of oil consumptions are: Japan (1.5%), India (2.9%), South Korea (2.5%) and Brazil (9.3%).

Table 6
Results of BDS test.

Length in S.D. (σ^2)	Embedding dimension (m)	W statistic									
		Before the financial crisis					After the financial crisis				
		ΔER	ΔCO	ΔGL	ΔHO	ΔNG	ΔER	ΔCO	ΔGL	ΔHO	ΔNG
0.7	2	1.818*	3.122***	3.182***	2.972***	9.363***	4.632***	8.884***	7.946***	4.295***	5.890***
0.7	3	2.399**	3.054***	2.722***	4.089***	11.620***	6.391***	12.075***	9.812***	5.498***	7.459***
0.7	4	2.876***	3.370***	2.820***	4.699***	13.479***	7.278***	13.798***	10.839***	6.420***	7.790***
0.7	5	3.260***	3.601***	2.849***	4.962***	15.228***	8.143***	14.727***	11.425***	7.228***	8.149***
0.7	6	3.886***	3.769***	3.427***	5.530***	17.047***	9.074***	15.760***	12.109***	8.513***	9.021***

Note: This table reports the results of BDS test.
* Denotes the rejections of the null hypothesis at 10% significance level.
** Denotes the rejections of the null hypothesis at 5% significance level.
*** Denotes the rejections of the null hypothesis at 1% significance level.

many existing literatures. However, the source of Granger causality, especially that of nonlinear form has not been investigated. Bekiros and Diks (2008) show that the volatility spillover can partly contribute to nonlinear causality by analyzing the causality behaviors of GARCH–BEKK filtered VECM residuals of oil spot and futures. Following Bekiros and Diks (2008), we employ a GARCH–BEKK (Engle and Kroner, 1995) model to study the effects of volatility spillover (second-order co-movement) on nonlinear causality in our case. The BEKK–GARCH(1,1) specification is defined as:

$$H_t = C'C + \sum_{j=1}^{q} A'_{jk}\varepsilon_{t-j}\varepsilon'_{t-j}A_{jk} + \sum_{j=1}^{p} G'_{jk}H_{t-j}G_{jk}, \;\; \varepsilon_t = H_t^{1/2}v_t \tag{10}$$

where, C, A_{jk} and G_{jk} are $(N \times N)$ matrices and C is an upper triangular. H_t is the conditional covariance matrix of ε_t with $\varepsilon_t|\Phi_{t-1} \sim (0, H_t)$ and Φ_{t-1} is the available information set at time $t-1$. Thus, the residuals are obtained by whitening the residuals $H^{-1/2}\varepsilon_t$.

Arouri and Jawadi (2010) find that the relationships between exchange rates and oil prices display significant regime change using a Smooth Transition Regression (STR) model allowing for the reproduction of asymmetry, persistence, structural breaks and discontinuity in the adjustment. We can expect that another possible source of nonlinear causality may be the regime switching of long-run relationships caused by some external shocks. Thus, recent financial crisis which broke out in PII may result in the existence of nonlinear causality relationships. In the case of one threshold (two regimes), Balke and Fomby (1997) propose a TVECM of order $l+1$ as,

$$\begin{aligned} \Delta x_t &= A'_1 X_{t-1}(\beta) + u_t, \text{if} w_{t-1}(\beta) \le \gamma \\ \Delta x_t &= A'_2 X_{t-1}(\beta) + u_t, \text{if} w_{t-1}(\beta) > \gamma \end{aligned} \tag{11}$$

Table 7
Results of nonlinear causality analysis.

Variable		PI				PII			
		Raw data		ECM/VAR filtered series		Raw data		ECM/VAR filtered series	
X	Y	$X \to Y$	$Y \to X$	$X \to Y$	$Y \to X$	$X \to Y$	$Y \to X$	$X \to Y$	$Y \to X$
ER	CO					***	***	***	***
ER	GL					***	***	***	***
ER	HO					***	***	***	***
ER	NG	*							

Note: This table reports the results of nonlinear causality test between energy prices and exchange rates. '$X \to Y$' denotes the null hypothesis that X does not Granger cause Y. We set the lag length $l_x = l_y = 1$. PI: January 2, 2003–June 29, 2007 and PII: July 2, 2007–June 3, 2011.
* Denotes the rejections of the null hypothesis at 10% significance level.
** Denotes the rejections of the null hypothesis at 5% significance level.
*** Denotes the rejections of the null hypothesis at 1% significance level.

with,

$$X_{t-1}(\beta) = \begin{Bmatrix} 1 \\ w_{t-1}(\beta) \\ \Delta x_{t-1} \\ \Delta x_{t-2} \\ \cdots \\ \Delta x_{t-l} \end{Bmatrix}, \tag{12}$$

where x_t is a p-dimensional time series I(1) co-integrated with one $p \times 1$ co-integrating vector β. $w_t(\beta)$ is the error correction term, and u_t is the error term assumed to be an *iid* sequence with Gaussian distribution and finite covariance matrix. The values of error correction term $w_{t-1}(\beta)$ above or below the threshold value γ allow the coefficients to change between two regimes. Specially, the estimates of $w_{t-1}(\beta)$ in each regime denote different adjustment speeds of the series towards equilibrium. A_1 and A_2 are the coefficient matrix and γ is the threshold value. The TVECM model in Eq. (11) can be alternatively written as,

$$\Delta x_t = A'_1 X_{t-1}(\beta) d_{1t}(\beta, \gamma) + A'_2 X_{t-1}(\beta) d_{2t}(\beta, \gamma) + u_t, \tag{13}$$

where

$$d_{1t}(\beta, \gamma) = 1(w_{t-1}(\beta) \le \gamma) \text{ and } d_{2t}(\beta, \gamma) = 1(w_{t-1}(\beta) > \gamma), \tag{14}$$

and $1(\cdot)$ denotes the indicator function. As this TVECM can capture the regime change of cointegration, we perform a nonlinear causality analysis on the TVECM filtered residuals of series in PII.[9]

Table 8 reports the results of nonlinear causality analysis before and after GARCH-BEKK filtering[10] and TVECM filtering. After the TVECM filtering, bidirectional nonlinear causality relationships can be found at 1% significance level for ER–CO and ER–GL pairs. Although the statistical significance of nonlinear causality running from heating oil prices to exchange rates becomes weaker after TVECM filtering, it is still significant at 5% level. Thus, the effects of regime change of cointegration on nonlinear causality behaviors are very weak. However, after BEKK–GARCH(1,1) filtering, the nonlinear causality behaviors almost disappear. The only exception is that crude oil prices can nonlinearly Granger cause exchange rates at 10% significance level. The possible reason is that "*third or higher-order causality may be a significant factor of the remaining interdependence*", as stated in

[9] We examine the significance of threshold effect (regime change) of cointegration relationship using a Wald test proposed by Hansen and Seo (2002). The results indicate a significant regime change. To save space and be consistent with the main purpose of causality analysis, we do not show the test results and the detailed description of Hansen and Seo (2002)'s threshold test.

[10] The fitting results of BEKK–GARCH indicate the existence of significant volatility spillovers. To save space, we do not show the results of BEKK-GARCH(1,1) specification which can be obtained upon request.

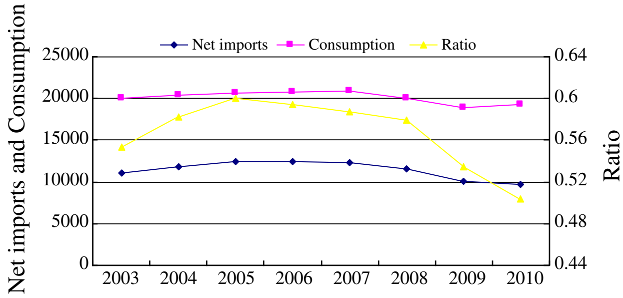

Fig. 2. Net imports (the left vertical label), consumption (the left vertical label) and the ratio (net imports/consumption) (the right vertical label) of crude oil.
Data source: http://www.eia.org.

Table 8
Results of nonlinear causality test for GARCH–BEKK filtered and TVECM filtered series.

		Raw data		GARCH–BEKK filtered data		TVECM filtered data	
X	Y	$X \rightarrow Y$	$Y \rightarrow X$	$X \rightarrow Y$	$Y \rightarrow X$	$X \rightarrow Y$	$Y \rightarrow X$
ER	CO	***	***		*	***	***
ER	GL	***	***			***	***
ER	HO	***	***			***	**

Note: This table reports the results of nonlinear causality test for pairs of GARCH-BEKK and TVECM filtered residuals in the period after the recent financial crisis. '$X \rightarrow Y$' denotes the null hypothesis that X does not Granger cause Y. We set the lag length $l_x = l_y = 1$.
* Denotes the rejections of the null hypothesis at 10% significance level.
** Denotes the rejections of the null hypothesis at 5% significance level.
*** Denotes the rejections of the null hypothesis at 1% significance level.

Bekiros and Diks (2008). Thus, the explanation power of volatility spillover is much larger.

5. Conclusion

Causality relationships between exchange rates and energy prices have been extensively investigated in the existing studies (Amano and van Norden, 1998a, 1998b; Sadosky, 2000). However, the previous studies only take the linear causality relationships into account, not considering the nonlinear form. For this motivation, besides linear causality relationships, we also investigate nonlinear causality behaviors between trade-weighted exchange rates of U.S. dollar and energy prices using a nonparametric test proposed by Diks and Panchenko (2006). Our results show that exchange rates and natural gas prices are not cointegrated and weak nonlinear causality relationship running from exchange rates to natural gas prices is found only in the period before financial crisis. For exchange rates and oil prices, only linear causality relationships running from oil prices to exchange rates are found in the period before the recent financial crisis. In the period after the recent crisis, both bidirectional linear and nonlinear causality relationships can be found between exchange rates and crude oil prices. Gasoline and heating oil prices can linearly Granger cause exchange rates but not vice versa while the nonlinear causality relationships are bidirectional. Overall, in the period after recent financial crisis, bidirectional causality relationships exist between exchange rates and petroleum prices.

Our results are not consistent with oil price exogeneity in Hamilton (1983) or exchange rate exogeneity in Sadosky (2000). Maybe the discrepancy is caused by the different data or different sample period. However, the major reason is that we take the possible nonlinear causality into account.

Additionally, we also investigate the effects of volatility spillover and regime change on nonlinear causality behaviors. Based on the analysis of the pairwise causality relationships of GARCH-BEKK(1,1) filtered residuals and threshold VECM filtered residuals, we find that both volatility spillover and regime change can only partly contribute to this kind of nonlinear causality. The explanation could be that exchange rate and oil price returns exhibit higher-order co-movements, just like the study of relationships between oil spot and futures prices in Bekiros and Diks (2008), or the cointegration relationships display more than two different regimes considered in this paper. Moreover, the major source of nonlinear form of Granger causality is volatility spillover, rather than regime change.

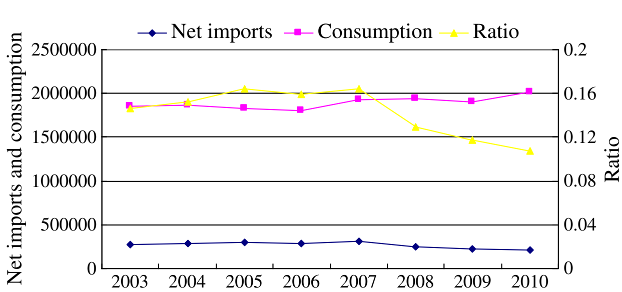

Fig. 3. Net imports (the left vertical label), consumption (the left vertical label) and the ratio (net imports/consumption) (the right vertical label) of natural gas.
Data source: http://www.eia.org.

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