

## On the Risk Comovements between the Crude Oil Market and the U.S. Dollar Exchange Rates

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# On the risk comovements between the crude oil market and the U.S. dollar exchange rates

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## Abstract

This article examines the volatility dependence between the crude oil price and four US dollar exchange rates using both fractional cointegration and copula techniques. The former exploits the long memory behavior of the volatility processes to investigate whether they are tied through a common long-run equilibrium. The latter is complementary as it allows to explore whether the volatility of the markets are linked in the short run. The cointegration results conclude in favor of long-run independence for the Canadian and Japan exchange rates while few evidence of long-run dependence are found for the European and British exchange rates. Concerning the copula analysis, we conclude in favor of weak dependence when we consider static copulas. Considering time-varying copulas, it appears that dependence is sensitive to market conditions as we found increasing linkages just before the 2008 market collapse and more recently, in the aftermath of the European debt crisis.

**Keywords:** Comovement, Volatility linkage, Fractional cointegration, Copula, Oil market, Exchange rate

**JEL:** E44, C22

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## 1. Introduction

Since the US Dollar (USD) is the major invoicing currency of international crude oil trading, it is well established that the oil prices and USD exchange rates display strong correlations (see [Reboredo and Rivera-Castro, 2013](#)). The tight junction between crude oil prices and USD exchange rates has important implications on both the real economy and financial markets notably through their consequences on inflation dynamics, monetary policy, trade balance, pricing and hedging strategies. Understanding how crude oil and foreign exchange markets interact is therefore of great interest for policymakers and investors.

Given that oil commodity is internationally traded in USD, a weaker USD reduces the oil prices for foreigners in terms of their home currency, leading to large sums of money flow to the oil market, thus driving up crude oil prices in

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USD. On the supply side, it tends to raise oil prices in order to stabilize the purchasing power of oil exporting countries. Empirical evidence on the effect of a weak dollar on the rise in oil prices are reported by, e.g., [Beckmann and Czudaj \(2013\)](#), [Akram \(2009\)](#), [Zhang et al. \(2008\)](#), and [Yousefi and Wirjanto \(2004\)](#). Conversely, the theoretical literature also points out the potential role of oil prices in determining exchange rate movements. Accordingly, increasing oil prices lead to exchange rate appreciation for oil-exporters and depreciation for oil-importers through positive changes in oil export revenues and energy import bills respectively (see, e.g., [Golub, 1983](#) and [Krugman, 1983](#)). Consistently with this explanation, many empirical researches provide evidence of a significant causality running from crude oil prices to USD exchange rates (see, e.g., [Bénassy-Quéré et al., 2007](#); [Chen and Chen, 2007](#); [Huang and Guo, 2007](#); [Coudert et al., 2008](#)). Finally, other studies such as [Reboredo et al. \(2014\)](#), [Reboredo and Rivera-Castro \(2013\)](#), [Salisu and Mobolaji \(2013\)](#) and [Ding and Vo \(2012\)](#) find bi-directional causality depending on the period under study.

The renewed interest in the links between oil prices and the USD has notably been stimulated by suggestive comovements on these markets, particularly since the beginning of 2000. However, most recent studies focus either on price or return relationships, thus neglecting the potential linkages between volatility processes, i.e., the possibility that volatilities could be tightened through a common informative process related to the economic news affecting these markets. Exploring whether volatilities share the same latent process is crucial for financial risk management and portfolio strategies in light of the financialization of commodity markets. In this regard, our paper aims to investigate the joint dynamics between the volatility of crude oil price and USD exchange rates over the period January 2000 to September 2013, by relying on both fractional cointegration and copula analyses.

Considering that volatility of financial returns is characterized by long-range dependence (see, e.g., [Ding et al., 1993](#); [Bollerslev and Mikkelsen, 1996](#); [Ding and Granger, 1996](#) and [Gil-Alana et al., 2013](#); [Gil-Alana and Tripathy, 2014](#); [Gil-Alana et al., 2014](#) for more recent studies), generally explained by cross-sectional aggregation of clustered information arrival processes ([Andersen and Bollerslev, 1997](#)), we adopt an econometric framework designed to capture this persistent nature. Firstly, we investigate to what extent oil price and exchange rate volatility processes are fractionally cointegrated with the aim to capture the strength of the long-run relationship linking both markets. Following the seminal work of [Bollerslev and Engle \(1993\)](#) on cointegration in variances (i.e. co-persistence), our cointegration analysis is conducted by applying both the cointegrating rank analysis of [Nielsen and Shimotsu \(2007\)](#) and the regression-based approach of [Shimotsu \(2012\)](#). Although previous researches have examined the oil-exchange rate nexus through cointegration techniques (see, e.g. [Chen and Chen, 2007](#); [Zhang et al., 2008](#)) or multivariate stochastic volatility (SV) models ([Ding and Vo, 2012](#)), they have neglected apparent co-persistence among their volatilities which is of importance regarding the possibility of a common long-run equilibrium. For instance, [Ding and Vo \(2012\)](#) analyze the volatility interactions between the oil and foreign exchange markets and find a bi-directional transmission between the two markets. [Soucek and Todorova \(2014\)](#) propose a multivariate version of the HAR model accounting for continuous jump and leverage effects. Finally, [Salisu and Mobolaji \(2013\)](#) investigate volatility transmission between oil price and US-Nigeria exchange rate by using a VAR-GARCH model

accounting for structural breaks. Their results establish a bi-directional spillovers transmission between oil and foreign exchange markets. However, these studies do not acknowledge that volatility has an observed autocorrelation function that decays very slowly. Indeed, they use standard GARCH or SV models, thereby assuming a fast exponential rate of decay.

Because many financial and regulatory activities depend upon the perceived commonality in volatility movements, modeling adequately comovement among volatilities is crucial. Consequently, the issue concerning fractional cointegration of financial market volatility has found important applications recently. For instance, [Brunetti and Gilbert \(2000\)](#) applied a ECM-FIGARCH to volatility on the NYMEX and IPE crude oil market and find a fractionally cointegrated relationship between the two volatility processes. In the same spirit, [Figuerola-Ferretti and Gilbert \(2008\)](#) study commonality in the London Metal Exchange aluminum and copper volatility processes but do not provide evidence of fractional cointegration. [da Silva and Robinson \(2008\)](#) consider a long memory SV model involving fractional cointegration under mild assumptions. Concerning the ex-post observed volatility we can also mention an emerging literature. For instance, [Christensen and Nielsen \(2006\)](#) test the implied-realized volatility relation using a stationary fractional cointegration approach. [Cassola and Morana \(2010\)](#) perform a co-persistence analysis of the euro money market realized volatility series. [Rossi and Santucci de Magistris \(2013b\)](#) test the no-arbitrage condition between spot and futures markets investigating the presence of volatility between daily range volatility series. [Rossi and Santucci de Magistris \(2013a\)](#) provide an extensive study of the mixture distribution hypothesis through cointegration and copula techniques applied to volume and volatility series. Our paper is a further contribution to this recent literature and focuses on the ex-post volatility of crude oil prices and USD exchange rates.

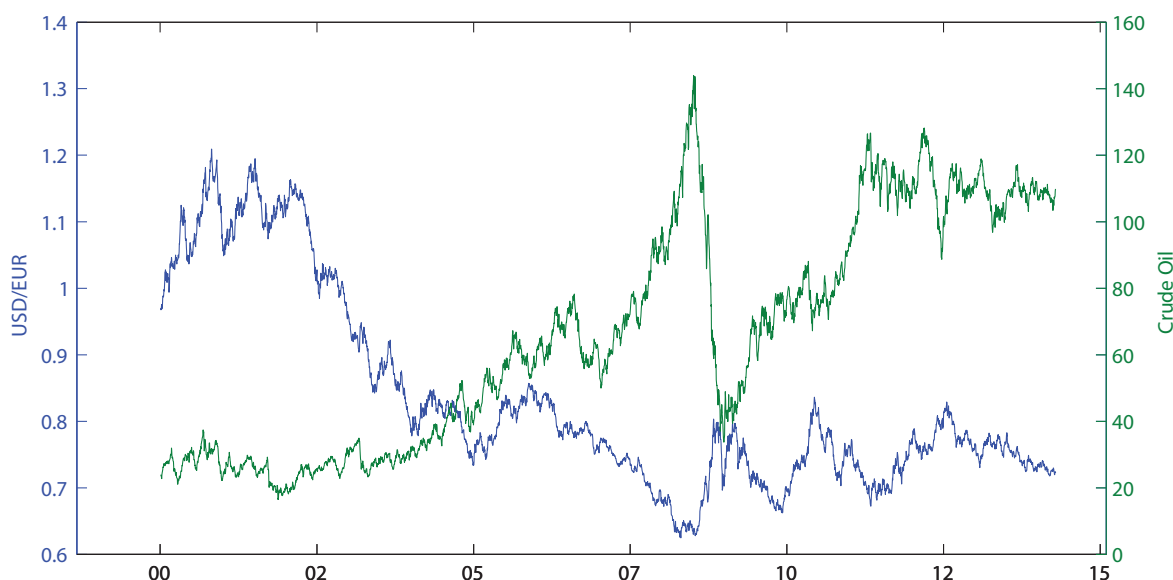
Secondly, we examine the short-run dependence structure between the USD and oil price volatilities by means of static and dynamic copulas, concentrating on extreme and time-varying dependence. Since many financial series are leptokurtic and skewed, non-Gaussian copula-based models have been largely used in the empirical literature dealing with this issue. For instance, [Reboredo \(2012\)](#) examines the comovements among oil prices and USD exchange rates and conclude in favor of a weak dependence, although the correlations substantially increase after the crisis. His findings do not conclude in favor of extreme (tail) dependence between these markets. In the same spirit, [Aloui et al. \(2013\)](#) propose an extensive analysis of this issue using a wide range of copula-GARCH models. They account for the persistent nature of the volatility but support that such a specification do not improve significantly their forecast experiment. However, they only consider static copulas and omit the possible time-varying nature of the dependence. Finally, [Wu et al. \(2012\)](#) perform a dynamic copula-GARCH analysis of the dependence between crude oil and USD exchange rate returns. The authors find that the dependence structure becomes negative and decreases continuously after 2003. To the best of our knowledge, there exists no studies examining the dependence structure, particularly in the tails, between oil and foreign exchange market volatilities. This issue is of importance because, during the 2008-09 financial turmoil, both markets have exhibit extreme conditions, suggesting potential extreme co-movements between their volatility processes. Given the long memory pattern observed in our data set, we devote a particular attention to the treatment of the autocorrelation and derive the marginal distributions from the estimation of an heterogeneous

autoregressive model. Finally, the joint distribution as well as tail and time-varying dependence are obtained from a panel of copula functions.<sup>2</sup>

To anticipate our main conclusions, we show that the dynamics underlying the volatility processes on these two markets are not tied together through a common equilibrium, suggesting that fluctuations in US dollar exchange rate and crude oil prices are segmented in the long-run. Concerning the copula analysis, we find that dependence is in general weak but time-varying, with higher correlations before and during the financial crisis and more recently, in the aftermath of the European debt crisis.

The remainder of the paper is laid out as follows. Section 2 presents the dataset. Section 3 details the strategy of estimation. Section 4 discusses the results and Section 5 concludes.

Figure 1: USD/EUR and crude oil prices



## 2. The data

Our data set runs from January 4, 2000 to April 16, 2014 so that the sample size is  $n = 3560$ . Oil log-squared returns are computed from West Texas Intermediate (WTI) oil prices (in USD per barrel), extracted from the US Energy Information Agency (EIA). For exchange rates, we consider the USD rate against other major traded currencies, that are Canadian (CAD), European (EUR), Japan (YEN) and Great Britain (GBP) currencies, downloaded from the Federal Reserve Bank of St. Louis database (foreign currency per unit of USD). As an illustration, the Figure 1 displays the respective time path of crude oil prices and USD/EUR exchange rate. As we can see, crude oil price has

<sup>2</sup>See for a analogous choice [Rossi and Santucci de Magistris , 2013a](#).

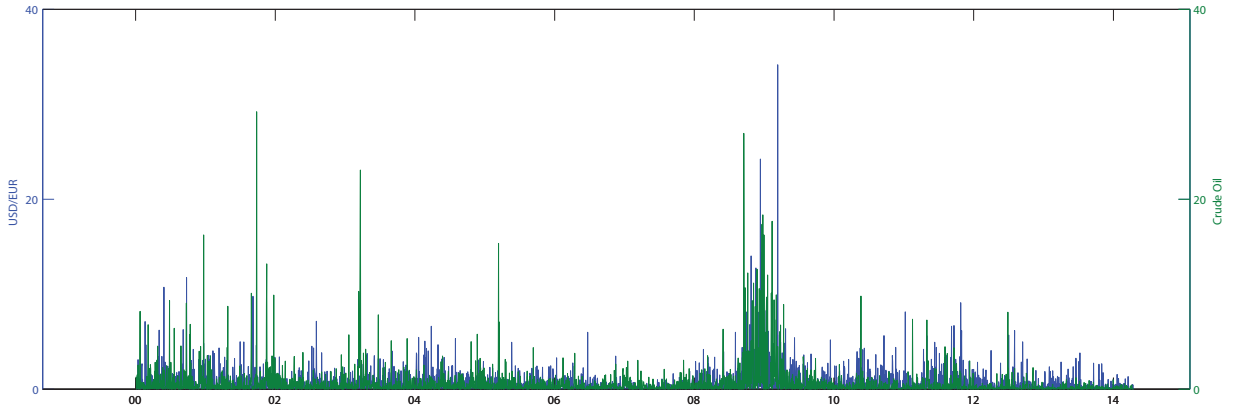
experienced increasing price, rising continuously from about 25 USD per barrel to a historical peak of 145 USD per barrel in July 2008. Over the same period the value of the USD relative to the euro has depreciated by over 50%, suggesting extreme comovements among both markets. Both have continued to evolve in the opposite direction when the financial crisis suddenly gained momentum at the end of 2008: oil prices fell sharply to 32 USD by December 2008 while the USD experienced an appreciation trend until February 2009. Since then, crude oil prices and USD have shown similar fluctuations. Moreover, these ascending and descending phases have been accompanied by episodes of substantial volatility (see Figure 2), suggesting the presence of a common informative process linking crude oil and exchange rate volatilities.

### 3. Empirical Strategy

#### 3.1. The long-run analysis

In their analysis of exchange rates volatility, [Andersen et al. \(2001\)](#) identify as a stylized fact the long memory behavior of ex-post volatility series. In line with the pioneer work of [Bollerslev and Engle \(1993\)](#), [Andersen et al. \(2003\)](#) also underline that volatilities might be cointegrated, i.e. fractionally cointegrated. In our analysis we account for this persistent nature for both, the crude oil market and the USD exchange rate markets and then investigate whether volatility series share a common long-run dynamics. Our fractional cointegration analysis operates in three steps.

Figure 2: USD/EUR and crude oil volatilities



In a first step, we estimate the integration orders of each individual volatility series, denoted  $\delta$ , using the two-step exact local Whittle estimator of [Shimotsu \(2010\)](#) which accommodates both, stationary ( $\delta < 0.5$ ) and non-stationary ( $\delta \geq 0.5$ ) variables (recall that the process is mean reverting as long as  $\delta < 1$ ). It is defined as  $\hat{\delta} = \arg \min_{\delta} R(\delta)$  where

$$R(\delta) = \log \hat{G}(\delta) - 2\delta \frac{1}{m} \sum_{j=1}^m \log \lambda_j, \quad \hat{G}(\delta) = \frac{1}{m} \sum_{j=1}^m I_{x(\delta)}(\lambda_j) \quad (1)$$

with  $I_{x(\delta)}(\lambda_j)$  the periodogram of  $(1-L)^\delta x_t$  evaluated at frequency  $\lambda_j = (2\pi j)n^{-1}$ . Concretely, this estimator consists in a semi-parametric treatment of a frequency domain representation of the autocovariance function so that the short-run dynamics are not modeled and our results are robust to misspecification. Indeed, the parameter  $\delta$  is simply estimated by exploiting a degenerating band around the origin of the spectral density of the volatility. However the procedure is sensible to the choice of  $m$ , a bandwidth filter used to focus on near zero frequencies.<sup>3</sup> Hence, we report the results (see Table 1) for several bandwidths running from  $m = \lfloor n^{0.4} \rfloor$  to  $m = \lfloor n^{0.5} \rfloor$  and thereby taking into account an appropriate bandwidth requirement (see e.g. Frederiksen et al. , 2012). Interestingly, the results reveal that the volatility of the raw series have long memory, confirming the findings of many studies (see e.g. Andersen et al. , 2001, 2003). Because the results are sensible to the bandwidth choice, in the following we still consider the two bandwidths  $m = \lfloor n^{0.4} \rfloor$  and  $m = \lfloor n^{0.5} \rfloor$ . We also perform the test of Qu (2011) for the presence of true long memory, as it is established in the literature that nonlinearities or slowly varying trends can lead to spurious long memory. The results are reported in table 2 and confirm the presence of true long-range dependence.

Table 1: Long memory estimates for  $m = \lfloor n^k \rfloor$

$k$	USD/CAD	USD/EUR	USD/GBP	USD/JPY	Crude oil
0,40	0.3558	0.5552	0,6079	0,3398	0,4665
0,45	0,4251	0,7593	0,8084	0,3462	0,6320
0,50	0,5690	0,5762	0,6842	0,3917	0,6245

Table 2: Test of Qu (2011) for the presence spurious long memory

$k$	USD/CAD	USD/EUR	USD/GBP	USD/JPY	Crude oil
0.4	0,3561	0,6341	0,5552	0,6862	0,4990
0.45	0,7187	0,7689	0,8392	0,3220	0,8486
0.5	0,8930	0,5664	0,5769	0,5899	0,9923

*Notes:* Under the null hypothesis, the process has true long memory; under the alternative hypothesis the process is affected by nonlinearities. We use here a trimming parameter equal to 0.05 implying a critical value at 10% significance level equal to 1.022.

In a second step, we test whether the long memory parameters of all series are homogeneous because this is a necessary condition for two time series to be non-trivially cointegrated. We adopt the procedure of Nielsen and Shimotsu (2007). Denoting  $y_t$  and  $x_t$ , the exchange rate and the crude oil volatility series and  $\delta_{(y,x)} = (\delta_y, \delta_x)'$  their respective long memory parameters, under the null hypothesis of  $H_0 : \delta_y = \delta_x$ , the test statistic of Nielsen and Shimotsu (2007) is given by

$$\hat{T}_0 = mS \begin{pmatrix} \hat{\delta}_y \\ \hat{\delta}_x \end{pmatrix} \left( S \frac{1}{4} \hat{D}^{-1} (\hat{G} \odot \hat{G}) \hat{D}^{-1} S' + h(n)^2 \right)^{-1} S \begin{pmatrix} \hat{\delta}_y \\ \hat{\delta}_x \end{pmatrix}, \quad h(n) = (\log n)^{-2} \quad (2)$$

<sup>3</sup>This bandwidth is theoretically bounded by  $n^{4/5}$  but in practice a too small bandwidth increases the variance of the estimator while a too large  $m$  generally increases the bias. The volatility series are particularly exposed to such a bias because of the presence of microstructure noise (short-run dynamics) that is likely to contaminate the low frequencies.

where  $\hat{\delta}_y$  and  $\hat{\delta}_x$  are consistent estimates of  $\delta_y$  and  $\delta_x$  obtained with the estimator of Shimotsu (2010),  $\odot$  denotes the Hadamard product,  $S = [1; -1]$  and  $D = \text{diag}(\hat{G}_{11}, \hat{G}_{22})$ . Nonetheless, under  $H_0$ ,  $\hat{T}_0 \xrightarrow{p} 0$  if their is cointegration and  $\hat{T}_0 \xrightarrow{d} \chi^2_{p-1}$  otherwise so that the procedure requires to estimate the cointegration rank,  $\hat{r}$ . To obtain  $\hat{r}$ , Nielsen and Shimotsu (2007) propose to solve the following optimization problem,

$$\hat{r}_k = \arg \min_{u=0,1} L(u), \quad L(u) = v_k(n)(2-u) - \sum_{j=1}^{2-u} \tau_j, \quad (3)$$

with  $\tau_j$  the  $j$ -th eigenvalue of the correlation matrix  $\hat{P}(\delta_*) = \hat{D}(\delta_*)^{-1/2} \hat{G}(\delta_*) \hat{D}(\delta_*)^{-1/2}$ ,  $\delta_*$  the common value for the integration orders and  $v_k(n)$  a tuning parameter defined as  $v_k(n) = m_G^{-k} \in \{m_G^{-0.35}, m_G^{-0.25}, m_G^{-0.15}\}$  where  $m_G$  is a specific bandwidth used to obtain  $\hat{G}(\delta_*)$  and set to  $m_G = \lfloor n^{k-0.05} \rfloor$ . Notice that the test is more conservative when  $v_k(n)$  is large. The results are reported in Table 4 and discussed in Section 4.

In the third step, we perform a regression-based cointegration analysis. It is based on a semi-parametric treatment of the so-called triangular representation of Phillips (1991) and Nielsen (2004),

$$y_t - \beta x_t = \varepsilon_{1t}(-\gamma), \quad (4)$$

$$x_t = \varepsilon_{2t}(-\delta), \quad (5)$$

in which the cointegration occurs when the strength of the long run relationship is positive (i.e.  $\delta - \gamma > 0$ ) and  $\beta \neq 0$ . Our semi-parametric approach relies on the two-step exact local Whittle estimator of Shimotsu (2012). It estimates jointly all parameters of interest of the model, that are  $\beta$ ,  $\gamma$  and  $\delta$  and operates in two steps. The first step consists in estimating a tapered version of the local Whittle estimator of Robinson (2008). The second step consists in minimizing the following concentrated objective function

$$R_m(\theta) = \log \det \hat{G}(\theta) - 2(\gamma + \delta) \frac{1}{m} \sum_{j=1}^m \log \lambda_j, \quad \hat{G}(\theta) = \frac{1}{m} \sum_{j=1}^m \text{Re} \left( I_{X(\delta, \gamma)}(\lambda_j) \right), \quad (6)$$

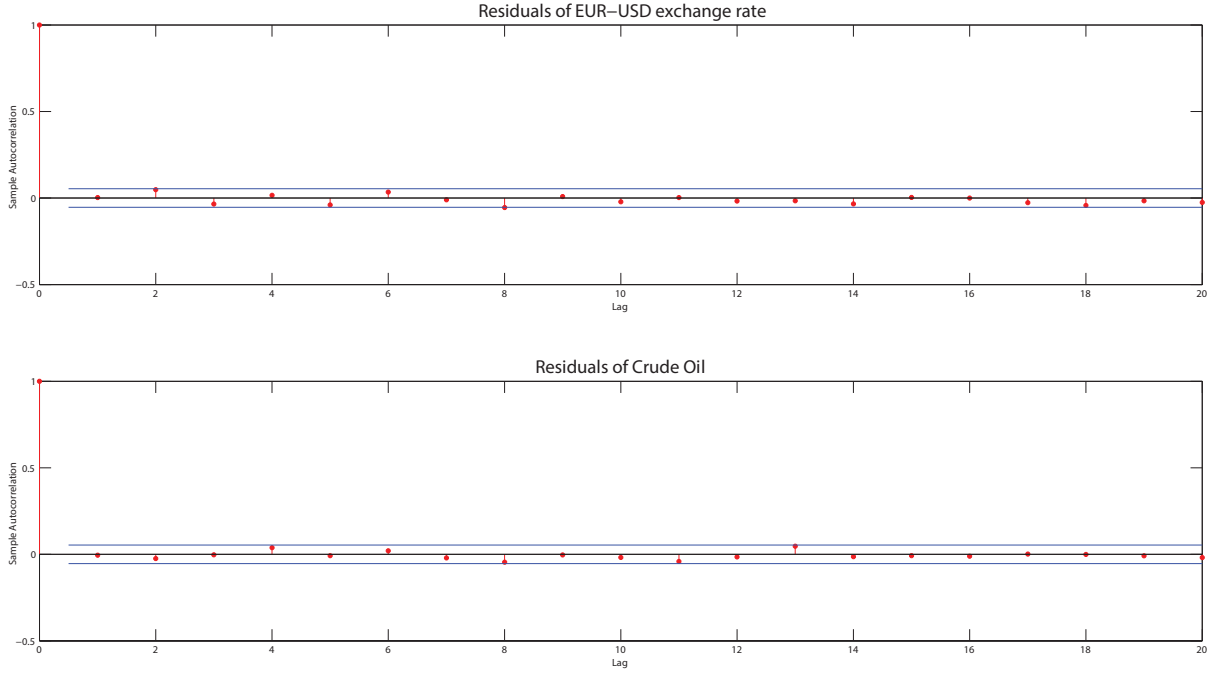
where  $\theta = (\delta, \gamma, \beta)'$  and  $X_t(\delta, \gamma) = (x_t, y_t - \beta x_t)'$ . Exploiting  $\hat{G}(\theta)$ , this procedure is also able to estimate the off-diagonal parameter,  $\rho$ , of the residuals covariance matrix. The results are reported in Table 5 and discussed in Section 4.

### 3.2. The copula-based HAR model

To complete our analysis and in line with some recent studies (see e.g. Aloui et al. , 2013; Reboredo , 2011, 2012; Wu et al. , 2012) we aim to measure the crude oil and exchange rate dependence through their marginal distributions. Conversely to the aforementioned studies, we focus on volatility process rather than returns. Accordingly, we have to account for the persistent nature of the volatility and thus appropriately filter the autocorrelation. We have investigated two concurrent models; the fractionally integrated VAR (FIVAR) and the heterogeneous autoregressive model



Figure 3: Autocorrelation functions



(HAR).<sup>4</sup> In both cases, the results are similar although the remaining autocorrelation is smaller with the copula-based HAR model (see e.g. the USD/EUR and crude oil volatilities autocorrelation functions on Figure 3). Therefore, in the following, we only report the results for this model.

Now, we turn to the copula-based framework. Copula theory started with [Sklar \(1959\)](#) and the so-called Sklar's theorem which states that any multivariate distribution can be factored into the marginal cumulative distributions and a copula function describing the dependence between the components. Regarding our two-dimensional framework, we say that for  $x_1$  and  $x_2$  two random variables with joint distribution function  $F(x_1, x_2)$  and univariate marginal distributions  $F_1(x_1)$  and  $F_2(x_2)$  there exists a copula  $C(u_1, u_2)$  such that  $F(x_1, x_2) = \Pr(X_1 < x_1, X_2 < x_2) = C(F_1(x_1), F_2(x_2))$ . For  $F_1(x_1)$  and  $F_2(x_2)$  continuous, the copula is unique (see [Cherubini et al. , 2012](#); [Heinen and Valdesogo , 2012](#), for a more detailed account of copulas).

We consider both symmetric and asymmetric copula functions to capture the dependence and the tail dependence between the variables. In the former case, the lower tail dependence  $\lambda_L$  is equal to the upper tail dependence  $\lambda_U$  respectively defined as

$$\lambda_L = \lim_{u \rightarrow 0^+} \Pr(U_1 < u | U_2 < u) = \lim_{u \rightarrow 0^+} \frac{C(u, u)}{u},$$

$$\lambda_U = \lim_{u \rightarrow 1^-} \Pr(U_1 > u | U_2 > u) = \lim_{u \rightarrow 1^-} \frac{C^*(u, u)}{1 - u},$$

<sup>4</sup>A volatility copula-based FIVAR model is also used in [Rossi and Santucci de Magistris \(2013a\)](#).

where  $C^*(u_1, u_2) = 1 - u_1 - u_2 + C(1 - u_1, 1 - u_2)$  is the survival copula associated with  $C$ . In the asymmetric case,  $\lambda_L$  can be different  $\lambda_U$ .

We use two elliptical copulas that are the popular normal and Student- $t$ . For  $\{u_1, u_2\} \in [0, 1]$  they are defined as

$$C_n(u_1, u_2) = \int_{-\infty}^{\phi^{-1}(u_1)} \int_{-\infty}^{\phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(-\frac{s^2 - 2\rho st + t^2}{2(1-\rho^2)}\right) ds dt \quad (7)$$

and

$$C_S(u_1, u_2) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(1 + \frac{s^2 - 2\rho st + t^2}{v(1-\rho^2)}\right)^{-\frac{v+2}{2}} ds dt \quad (8)$$

where  $\phi^{-1}(\cdot)$  and  $t_v^{-1}(\cdot)$  denote the inverse normal and Student- $t$  distribution's CDF respectively,  $\rho \in (-1, 1)$  denotes the correlation coefficient and  $v$  is the degrees of freedom. While the normal copula has no tail dependence, the Student- $t$  is able to capture symmetric tail dependence. Accordingly, the sign of  $\rho$  reveals the positive or negative nature of the relation between the variables. We also employ four Archimedean copulas that are the Gumbel, the Clayton, the Frank and the symmetrized Joe-Clayton (SCJ) copulas:

$$\begin{aligned} C_G(u_1, u_2) &= \exp\left(-\left((-\ln u_1)^\alpha + (-\ln u_2)^\alpha\right)^{1/\alpha}\right), \quad \alpha \in (1, +\infty) \\ C_C(u_1, u_2) &= \left(u_1^{-\alpha} + u_2^{-\alpha} - 1\right)^{-1/\alpha}, \quad \alpha \in (0, +\infty) \\ C_F(u_1, u_2) &= -\frac{1}{\alpha} \ln\left(1 + \frac{(\exp(-\alpha u_1) - 1)(\exp(-\alpha u_2) - 1)}{\exp(-\alpha) - 1}\right), \quad \alpha \in (-\infty, +\infty) \\ C_{SJC}(u_1, u_2) &= \frac{1}{2}\left(C_{JC}(u_1, u_2) + C_{JC}(1 - u_1, 1 - u_2) + u_1 + u_2 - 1\right) \end{aligned}$$

with,

$$\begin{aligned} C_{JC}(u_1, u_2) &= 1 - \left(1 - \left((1 - (1 - u_1)^{\mu_U})^{-\mu_L} + (1 - (1 - u_2)^{\mu_U})^{-\mu_L} - 1\right)^{-\frac{1}{\mu_L}}\right)^{\frac{1}{\mu_U}}, \\ \mu_U &= \frac{1}{\log_2(2 - \lambda_U)}, \quad \mu_L = \frac{-1}{\log_2(\lambda_L)}, \quad \{\lambda_L, \lambda_U\} \in (0, 1), \end{aligned}$$

where  $C_{JC}(u_1, u_2|\lambda_L, \lambda_U)$  is the Joe-Clayton copula. Conversely to elliptical copulas, the Clayton and Gumbel functions can capture extreme asymmetric dependence (in lower tail for the Clayton and upper tail for the Gumbel). Because the tail dependence  $\lambda_L$  and  $\lambda_U$  are likely to diverge for these copulas, we also consider their survival versions, namely the Gumbel rotated and the Clayton rotated. Notice that the Frank copula has zero tail dependence. When the parameter  $\alpha$  tends to its lower bound, there is independence of the two variables and dependence otherwise. Concerning the SJC,  $\lambda_L$  and  $\lambda_U$  are simultaneously estimated so that both, the lower and upper tail dependence are directly captured. Importantly, the SJC allows for asymmetric dependence admitting the symmetric case as a special case.

All the aforementioned copulas are assumed to be constant over time. Nonetheless, the dependence between the crude oil and the exchange rate volatilities is likely to vary over time. Following [Patton \(2006\)](#) we consider a time-varying version of the normal, the Student- $t$ , the Gumbel and the SJC copulas by specifying an ARMA(1, $q$ )-type for the correlation parameter,

$$\rho_t = \Lambda\left(\psi_0 + \psi_1\rho_{t-1} + \psi_2\frac{1}{q}\sum_{j=1}^q\Phi^{-1}(u_{1,t-j})\Phi^{-1}(u_{2,t-j})\right), \quad \rho_t \in (-1, 1) \quad (9)$$

where  $\Lambda(x) = (1 - \exp(-x))(1 + \exp(-x))^{-1}$ ,  $\Phi^{-1}(x) = \phi^{-1}(x)$  for the normal and  $\Phi^{-1}(x) = t_v^{-1}(x)$  for the Student- $t$  (see [Manner and Reznikova, 2012](#), for a survey on time-varying copulas). For the Gumbel and the SJC copulas, the dynamic of the dependence parameter is slightly different and detailed in [Patton \(2006\)](#).

The estimation of the copula-based HAR models is performed following the inference for the margins approach of [Joe and Xu \(1996\)](#) that is a two-step maximum likelihood procedure. In a first step, we estimate the marginal densities by using their empirical cumulative distribution functions, namely  $\hat{F}_1(x_1)$  and  $\hat{F}_2(x_2)$  and we transform the obtained observations into uniform variates. Given that volatilities are clearly non-Gaussian, we assume here that the marginal distributions are Skew- $t$  rather than normal distributions (see [Rossi and Santucci de Magistris, 2013a](#), for a similar assumption). In a second step, we estimate the copula as  $\hat{\theta} = \arg \max_{\theta} \sum_{i=1}^n \ln C(\hat{F}_1(x_1), \hat{F}_2(x_2))$ .

We propose some descriptive statistics displayed in Table 3, with the aim of motivating the choice of the Skew- $t$  distribution. Indeed, these statistics exhibit high values for the kurtosis, suggesting the leptokurtic feature of volatility distributions. Furthermore, these volatilities show fat tails at their upper extremities. These observations clearly provide evidences against the normality assumption for all marginal distributions.

Table 3: Descriptive statistics of squared log-returns

	USD/GBP	USD/EUR	USD/YEN	USD/CAD	Crude oil
Mean	0.0068	0.0078	0.0086	0.0066	0.1147
Median	0.0021	0.0024	0.0025	0.0017	0.0319
SD	0.0184	0.0159	0.0199	0.0018	0.3018
Skewness	12.424	8.5136	10.594	12.429	8.041
Kurtosis	239.87	148.40	191.12	242.56	94.977

## 4. Dependence analysis

### 4.1. Long-run dependence

Table 4 reports the test statistics  $\hat{T}_0$  and the rank estimates. The integration orders displayed in Table 1 are statistically equals when the null hypothesis is accepted at conventional significance levels. Accordingly, when  $k = 0.4$  the test concludes in favor of equality of integration orders for the oil-exchange rate volatility relationships involving all currencies, at a threshold of 10% (i.e. a critical value of 2.71). These results are robust to the choice of a different

Table 4: Rank estimates and homogeneity of integration orders

$k = 0.4$		USD/CAD		USD/EUR		USD/GBP		USD/JPY				
$\kappa$	$\hat{\rho}$	$L(0)$	$L(1)$	$\hat{\rho}$	$L(0)$	$L(1)$	$\hat{\rho}$	$L(0)$	$L(1)$	$\hat{\rho}$	$L(0)$	$L(1)$
0,15	1	-0.692	-1.110	1	-0.692	-1,152	1	-0.692	-1,187	1	-0.692	-0,945
0,25	1	-1.015	-1.272	1	-1.015	-1,313	1	-1.015	-1,348	1	-1.015	-1,106
0,35	1	-1.258	-1.393	1	-1.258	-1,435	1	-1.258	-1,470	0	-1.258	-1,228
$\hat{T}_0$		0.965			0,687			1,935			0.942	
$k = 0.5$		USD/CAD		USD/EUR		USD/GBP		USD/JPY				
$\kappa$	$\hat{\rho}$	$L(0)$	$L(1)$	$\hat{\rho}$	$L(0)$	$L(1)$	$\hat{\rho}$	$L(0)$	$L(1)$	$\hat{\rho}$	$L(0)$	$L(1)$
0,15	0	-0.845	-0,835	1	-0,845	-0,979	1	-0,845	-0,979	0	-0,845	-0,698
0,25	0	-1,199	-1,012	0	-1,199	-1,156	0	-1,199	-1,156	0	-1,199	-0,875
0,35	0	-1,445	-1,135	0	-1,445	-1,279	0	-1,445	-1,279	0	-1,445	-0,998
$\hat{T}_0$		0,338			0,294			0,450			5,470	

bandwidth because when  $k = 0.5$ , we easily accept the null of equality of the integration order (except for the yen). Following [Nielsen and Shimotsu \(2007\)](#), we conduct the rank estimates by using the correlation matrix  $\hat{P}(\bar{\delta}_*)$ . When the matrix has a reduced rank,  $\hat{\rho}$  takes the value 1 and we can conclude in favor of a cointegration mechanism. For many relationships, the results depend on  $k$ , implying some limitations when interpreting the results. For instance, all currencies seem to be cointegrated with the crude oil when  $k = 0.4$ , but these cointegrating relationships disappear when  $k = 0.5$ . Since the results lead to contradictory evidence depending on the parameter  $k$ , we need to be careful when interpreting these results.

Table 5: Cointegration system for USD/CAD and oil volatilities

$k$	USD/CAD		USD/EUR		USD/GBP		USD/YEN	
	0,4	0,5	0,4	0,5	0,4	0,5	0,4	0,5
$\beta$	0.009 (0.306)	0.320 (0.216)	0.841 (0.405)	0.633 (0.152)	0.804 (0.610)	1.192 (0.255)	0.206 (0.148)	0.216 (0.134)
$\gamma$	0.292 (0.084)	0.350 (0.064)	0.359 (0.096)	0.388 (0.065)	0.384 (0.097)	0.422 (0.060)	0.187 (0.094)	0.297 (0.065)
$\delta$	0.517 (0.084)	0.628 (0.064)	0.461 (0.096)	0.614 (0.065)	0.472 (0.097)	0.615 (0.060)	0.506 (0.094)	0.627 (0.065)
$\rho$	0.7025	0.1881	-0.2587	-0.1464	0.2490	-0.5196	0.3611	0.0719

The rank analysis is useful to detect the presence of cointegration but is not informative concerning the strength of the relationship. In order to obtain more information about the strength of these long-term relationships and investigate whether the rank analysis is confirmed, we apply the estimator of [Shimotsu \(2012\)](#). The results are reported in Table 5 for  $m = \{0.4, 0.5\}$ . Notice that the coefficient  $\beta$  represents the long-run coefficient while the gap  $\hat{\delta} - \hat{\gamma}$  provides informations about the persistence of deviations from the long-run equilibrium and thus the strength of the cointegration (i.e. the larger  $\hat{\delta} - \hat{\gamma}$ , the more the strength of the cointegration relationship is). Overall, we find only moderate evidence suggesting that volatilities are tied together over the long run since, in most cases, the estimates of  $\beta$  are small and not significant. Concerning the GBP and to a lesser extent the EUR, the estimates of  $\beta$  are statistically

significant only with  $m = 0.5$ , indicating that the results are sensitive to the bandwidth. Moreover, the gap between the memory parameter estimates (i.e.  $\delta - \gamma$ ) are generally small, indicating that the strength of these relationships is weak. Consequently, it is hard to conclude in favor of robust cointegration relationships for these variables.

To summarize the results, we find only little evidence that oil and exchange rate volatilities have a common origin and share the same latent process, suggesting that volatilities observed on both markets are not tied together on the long-run. Consequently, we turn our attention to the copula analysis because correlation between exchange rate and oil volatilities may exist in the short-run and particularly during extreme events.

#### 4.2. Marginal distributions dependence

In Tables 6-9, we report the estimates of the dependence parameters for height copula functions (the Normal, Student- $t$ , Gumbel, Gumbel-rotated, Franck, Clayton, Clayton-rotated and symmetrized Joe-Clayton copulas) as well as five time-varying copula functions (the Normal, Student- $t$ , Gumbel, Gumbel-rotated and symmetrized Joe-Clayton copulas).

Table 6: CAD - Copula-HAR

	$\rho$	$\nu$	$\alpha$	$\psi_0$	$\psi_2$	$\psi_1$	$\lambda_L$	$\lambda_U$	$\tau_K$	$AIC$	$BIC$	$LL$
$C_N$	0,123								0,079	-78,83	-78,83	-39,41
$C_S$	0,113	6,232					0,046	0,046	0,072	-325,26	-325,26	-162,63
$C_G$			1,072					0,091	0,068	-124,27	-124,27	-62,13
$C_{G-R}$			1,082				0,102		0,076	-204,87	-204,87	-102,43
$C_F$			0,737						0,081	-51,71	-51,71	-25,85
$C_C$			0,150				0,010		0,070	-139,01	-139,01	-69,50
$C_{C-R}$			0,114					0,002	0,054	-78,35	-78,34	-39,17
$C_{SJC}$							0,045	0,011		-209,82	-209,82	-104,91
TV- $C_N$				0,355	0,088	-1,524				-89,74	-89,74	-44,87
TV- $C_S$		6,341		0,283	0,045	-0,900				-332,74	-332,73	-166,37
TV- $C_G$				-0,489	0,836	-0,434				-144,89	-144,88	-72,44
TV- $C_{G-R}$				-0,237	0,672	-0,563				-238,54	-238,53	-119,27
TV- $C_{SJC}$				0,97	-19,97	-4,03				-238,54	-238,53	-125,45
				0,790	-11,649	-1,440						

The estimates from the Gaussian copula indicate a positive but weak relationship between oil and USD exchange rate volatilities, suggesting a joint and contemporaneous dynamic between the two processes. The results appear to be homogeneous across currencies, with  $\rho$  and Kendall's  $\tau$  estimates ranging respectively from 0.086 (YEN) to 0.123 (CAD), and 0.055 (YEN) to 0.079 (CAD). These results are consistent with estimates from the Franck copula as the Kendall's  $\tau$  ranges from 0.069 to 0.081. When considering the student- $t$  copula, the results also conclude in favor of weak extreme dependence as  $\tau_k$  values are not higher than 0.072 (CAD). Nonetheless, we have to interpret the results carefully because elliptical distribution hypothesis might be unappropriated for volatility processes which are expected

to be skewed. In other words, the results from Normal and Student-t copulas might be very crude approximation of the dependence structure and therefore not really informative (see e.g. [Heinen and Valdesogo , 2012](#)).

Table 7: EUR - Copula-HAR

	$\rho$	$\nu$	$\alpha$	$\psi_0$	$\psi_2$	$\psi_1$	$\lambda_L$	$\lambda_U$	$\tau_K$	$AIC$	$BIC$	$LL$
$C_N$	0,117								0,075	-66,25	-66,25	-33,12
$C_S$	0,105	4,457					0,085	0,085	0,067	-418,86	-418,86	-209,43
$C_G$			1,072					0,091	0,067	-115,46	-115,46	-57,73
$C_{G-R}$			1,096				0,118		0,088	-238,14	-238,14	-119,07
$C_F$			0,671						0,074	-41,56	-41,56	-20,78
$C_C$			0,176				0,019		0,081	-162,96	-162,96	-81,48
$C_{C-R}$			0,103					0,001	0,049	-62,73	-62,73	-31,36
$C_{SJC}$							0,070	0,004		-226,15	-226,14	-113,07
TV- $C_N$				0,104	0,054	0,767				-82,59	-82,59	-41,29
TV- $C_S$		4,581		0,088	0,023	0,900				-431,72	-431,72	-215,86
TV- $C_G$				0,100	0,503	-1,272				-143,85	-143,85	-71,92
TV- $C_{G-R}$				-0,184	0,632	-0,533				-284,29	-284,28	-142,14
TV- $C_{SJC}$				-0,32	-16,85	3,13				-284,29	-284,28	-182,07
				-1,705	-3,266	4,588						

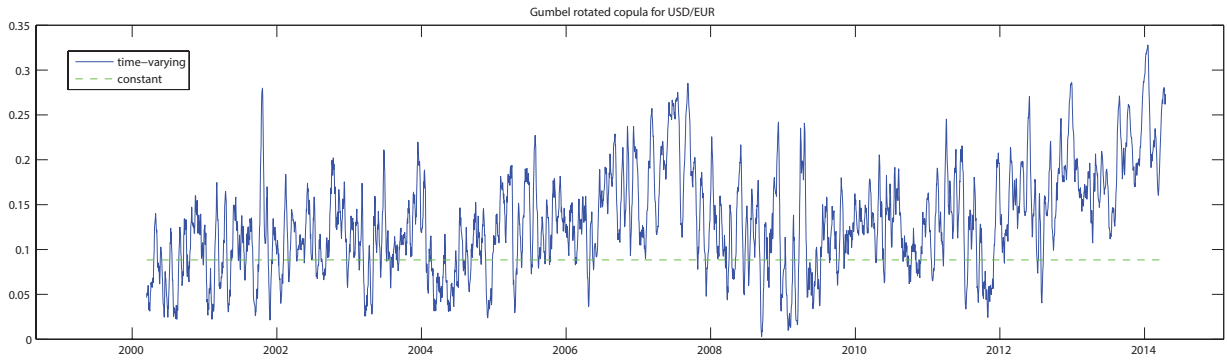
Accordingly, to characterize the extreme and asymmetric dependence, we examine the parameters derived from the Clayton and Gumbel copula functions and their rotated versions. The results indicate that lower tails are more correlated than upper tails although the correlations are generally weak as the differences between copulas. For instance, the Kendall's  $\tau$  obtained from the Gumbel-rotated copula, which capture lower tail dependence, are always higher than those obtained from the Gumbel copula (around 0.07 for upper tails and 0.08 for lower tails, excepted for the YEN for which correlations are slightly smaller). This interesting finding is corroborated by the results derived from the SJC, Clayton and Clayton-rotated copulas.

As a whole, the static dependence between both volatilities is generally weak. However, we can suppose that dependence might follow a time-varying dynamic process leading to substantial higher correlations depending on the market conditions. This hypothesis is confirmed by the log-likelihood as well as the model selection criteria (AIC and BIC). More precisely, these criteria designate the Student-t copula as the best model although the Gumbel-rotated and SJC copula generally display concurrent results. The time-varying relationship between oil and foreign exchange markets can be illustrated by considering the case of the EUR currency.

Figures 4-5 display the time-path and average of the dependence in the Normal, Student-t, Gumbel-rotated and SJC copulas, over the sample period. Interestingly, the dynamic of the dependence reveals that correlation parameters are relatively stable before 2007. However, over the period 2007-2008, we find important fluctuations of correlations as the parameters vary strongly with a range that depends on the copula. Regarding time-varying dependence deduced from asymmetric copulas capturing lower tail dependence (Figures 4 and 5), we find that correlations have significantly increased just before the crisis. Indeed, although oil prices have sharply increased and reached an historical

Table 8: GBP - Copula-HAR

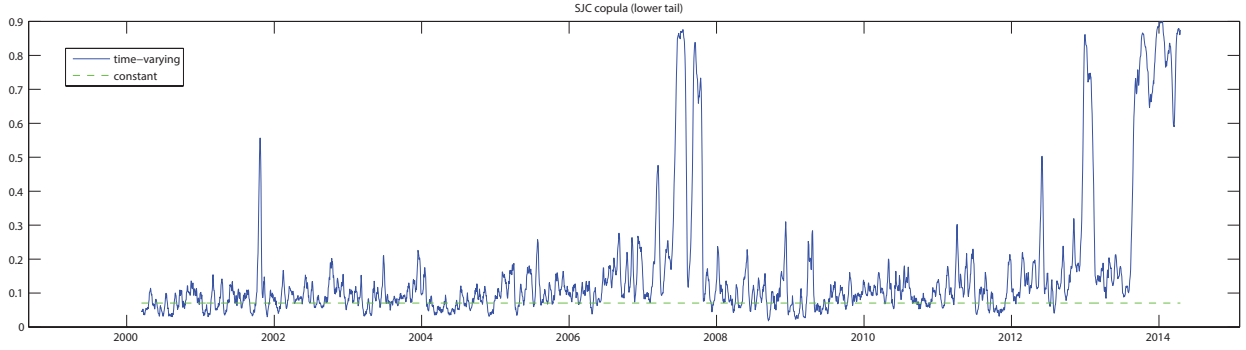
	$\rho$	$\nu$	$\alpha$	$\psi_0$	$\psi_2$	$\psi_1$	$\lambda_L$	$\lambda_U$	$\tau_K$	$AIC$	$BIC$	$LL$
$C_N$	0,117								0,074	-69,63	-69,62	-34,81
$C_S$	0,096	4,980					0,068	0,068	0,061	-372,21	-372,21	-186,10
$C_G$			1,070					0,089	0,066	-117,34	-117,34	-58,67
$C_{G-R}$			1,088				0,109		0,081	-220,06	-220,06	-110,03
$C_F$			0,626						0,069	-36,05	-36,05	-18,02
$C_C$			0,163				0,014		0,075	-154,65	-154,65	-77,32
$C_{G-R}$			0,106					0,001	0,050	-67,47	-67,47	-33,73
$C_{SJC}$							0,057	0,006		-219,24	-219,24	-109,62
TV- $C_N$				0,321	0,129	-1,765				-90,52	-90,52	-45,26
TV- $C_S$		5,102		0,203	0,053	-0,900				-389,56	-389,55	-194,78
TV- $C_G$				0,477	-0,065	-0,423				-122,32	-122,31	-61,16
TV- $C_{G-R}$				2,345	-1,551	-0,992				-249,71	-249,71	-124,85
TV- $C_{SJC}$				-0,458	-15,52	-2,19				-249,71	-249,70	-118,83
				-1,304	-5,008	2,968						

Figure 4: Dynamic Kendall's  $\tau$  for the Gumbel-rotated copula

peak during this period, volatility on both markets was particularly low which explains the fact that we find higher correlations before 2008 in the lower tail.

However, during the subprime crisis, volatility on both markets has switched from lull to turmoil periods in response to financial events and economic news. Conversely to asymmetric copulas, the correlation parameters of the Normal and Student- $t$  copulas have increased from 0.08 to 0.27 and 0.08 to 0.45 respectively over the year 2008-09. In other words, these growing and positive tail dependence suggest that oil and foreign exchange market volatilities are linked through a common informative process that increased simultaneously the probability of observing extreme volatility conditions on both markets. However, we have to be cautious when interpreting these results because symmetric copulas could be unappropriated here when considering the shape of the marginal distributions. Finally, we observe that correlations have raised more recently probably due to the recovery from the debt crisis in Europe,

Figure 5: Time varying lower tail dependence for the SJC copula



and the associated euro appreciation that encouraged oil importations in USD.

Table 9: YEN - Copula-HAR

	$\rho$	$\nu$	$\alpha$	$\psi_0$	$\psi_2$	$\psi_1$	$\lambda_L$	$\lambda_U$	$\tau_K$	$AIC$	$BIC$	$LL$
$C_N$	0,086								0,055	-44,02	-44,02	-22,01
$C_S$	0,097	9,496					0,014	0,014	0,062	-154,62	-154,62	-77,31
$C_G$			1,052					0,067	0,049	-64,10	-64,10	-32,05
$C_{G-R}$			1,055				0,071		0,052	-87,72	-87,72	-43,86
$C_F$			0,694						0,077	-48,37	-48,37	-24,18
$C_C$			0,101				0,001		0,048	-63,26	-63,26	-31,63
$C_{C-R}$			0,083					0,000	0,040	-42,70	-42,69	-21,35
$C_{SJC}$							0,013	0,003		-92,98	-92,97	-46,49
TV- $C_N$				0,267	0,210	-2,007				-71,82	-71,82	-35,91
TV- $C_S$		9,625		0,239	0,081	-0,900				-162,95	-162,94	-81,47
TV- $C_G$				-1,221	1,419	-0,141				-67,68	-67,67	-33,84
TV- $C_{G-R}$				-0,707	1,000	-0,296				-102,85	-102,85	-51,43
TV- $C_{SJC}$				-0,911	-19,85	1,312				-102,85	-102,84	-50,66
				-1,746	-7,434	5,900						

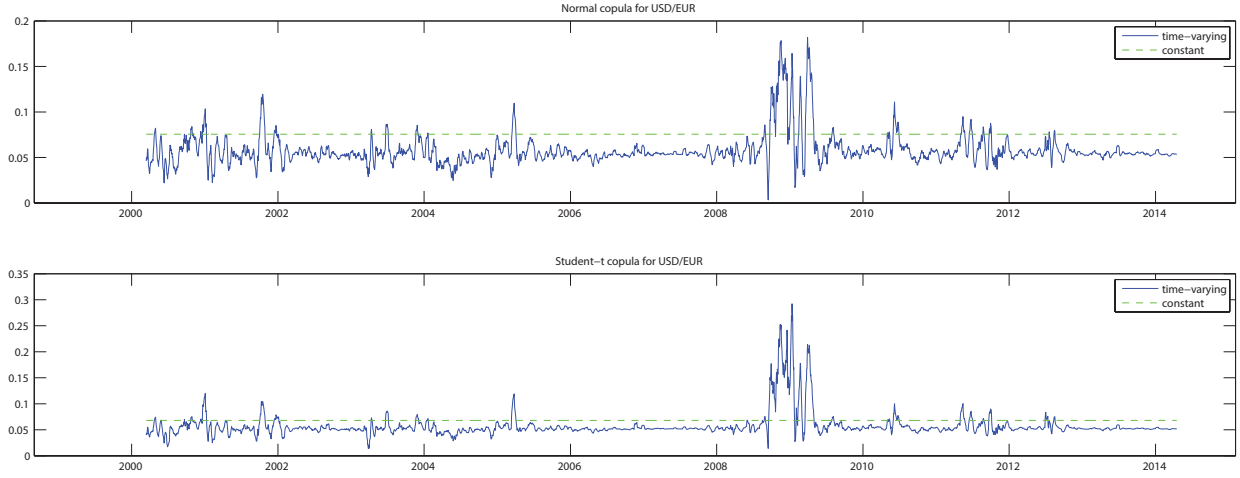
Notice also that unreported graphics concerning the USD/CAD, the USD/GBP and the USD/YEN exchange rates conclude in the same direction and are available upon request.

#### 4.3. Discussion

Our empirical results have important financial and economic implications for both policymakers and investors. Overall, the findings derived from the cointegration analysis are consistent with the view that the long-term risk in foreign exchange and oil markets are dominated by idiosyncratic components. Fluctuations in oil price over the last decade might result from a combination of several structural factors that are independent from the value of the USD. We can mention the geopolitical tensions which have consequences for oil prices and confidence, the large volume



Figure 6: Dynamic Kendall's  $\tau$  for the Normal and Student-t copulas



of institutional investments in oil market over the last decade, the oil demand related to economic growth of Asian countries and the declining reserves in oil-producing regions. From the foreign exchange markets point of view, it is recognized that the downward trend of the USD against most major currencies and its associated volatility are closely linked to the US current account and Federal budget deficits and the low saving rates weighing heavily on the USD.

Looking at the results country-by-country, the absence of cointegration for the USD/CAD case logically reveals that the more the importance in global oil production, the lower the dependence between foreign exchange and oil market volatilities. Similar evidence are provided by [Aloui et al. \(2013\)](#). Indeed, Canada is one of the largest producers of crude oil, while the United Kingdom and the Euro-zone are net-oil importers with a relatively low domestic production compared to the top world oil producers. Accordingly, foreign exchange and crude oil markets are more likely to be interlinked for European countries. Concerning the results for USD/JPY, the lack of dependence between both markets is more surprising as Japan highly dependent on energy imports and more particularly on crude oil (Japan is the third largest oil importer). This finding could be explained by different factors such as the significant decrease in oil consumption since 2005 given the rapid growth of oil price, but also the strong commitment of Japanese authorities to reduce the oil's share in key industrial sectors in favor of alternative energy sources.

In terms of risk management, our results are also informative. The lack of cointegration suggests that portfolio diversification based on USD denominated assets and oil contracts, with long-run investment horizon, should not be efficient. Conversely, according to our dynamic copula analysis, portfolio diversification remains possible for short-term investment horizon, albeit depending on the market conditions as regards of time-varying correlations. Indeed, commodity and stock markets behave differently, especially during episodes of financial stress such as 2008-09, encouraging traders to buy oil contracts to offset the decline in the value of USD denominated assets when they expect a weaker USD. Accordingly, the associated volatilities are more likely to interact, thus leading to higher upper

tail dependence as shown by our findings. In the same way, the continuing rise of oil price between 2006 and the financial crash of 2008, has been boosted by the depreciation of the USD. As a consequence, the increase in oil price has contributed to intensify the US current account deficit over this period, exacerbating the USD depreciation. Moreover, the increase in the lower tail dependence observed between 2006-2007 also reveals the greater interaction between the two markets during the first stage of the oil price bubble.<sup>5</sup> This explanation is consistent with the low volatility period preceding the collapse of the oil market and the USD/EUR appreciation in mid-2008, if we consider that the volatility is generally low in the early phase of a bubble episode and rises rapidly before and during the burst (see e.g. [Rotermann and Wilfling , 2014](#)).

Finally, as mentioned by [Reboredo and Rivera-Castro \(2013\)](#), currency depreciation could act as an adjustment instrument in face of inflationary pressures resulting from higher oil price. In this regard, the exchange rate should be more efficient if dependence with oil is high, which is not the case here. Consequently, active monetary policy should be regarded as the best way for controlling inflation associated to an increase of oil price, notably before 2006 and for countries in our sample that are net-importers, such as the United Kingdom, Euro-zone and Japan.

## 5. Conclusion

In this paper, we examined the comovements between crude oil and several USD exchange rate series through a comprehensive assessment of the dependence structure of their volatility processes over the period 2000-2014. We pursued two distinct but complementary empirical strategies. The first consisted in exploiting the persistent nature (long memory behavior) of the volatility processes to perform a stationary fractional cointegration analysis, i.e. a long-term comovement analysis, of the risk on the two markets. We found only few evidence of cointegration between oil and foreign exchange market volatilities thereby suggesting the absence of long-run dependence. Accordingly, volatilities seem to not share the same latent process and are guided by independent structural factors over the long run, supposing that investors can benefit from a diversification mechanism as volatility arbitrage remains possible for long-term horizon investments.

The previous results are informative in long-run but do not necessarily imply that both processes are independent in short-run. Accordingly, we also led a copulas-HAR analysis of volatilities with the aim to assess extreme, asymmetric and dynamic dependence. To this end, we used a broad set of copulas able to capture lower and upper tail correlations as well as time-varying correlations. Our results shown that dependences are generally weak, even if lower tail correlations appear to be slightly higher than upper tail correlations. Moreover, the time-varying analysis provide evidences that dependences are sensitive to market conditions as we found increasing linkages just before the 2008 market collapse and more recently, in the aftermath of the European debt crisis.

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<sup>5</sup>Several empirical studies investigate the presence of a bubble on the crude oil market before the subprime crisis. Recently, [Lammerding et al. \(2013\)](#) revealed the presence of a oil price bubble starting in early 2005 and bursting in mid-2008.

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