Conditional dependence structure between oil prices and exchange rates in Latin America: A copula-GARCH approach

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Abstract

This work studies the relationship between oil prices and exchange rates for six Latin American countries using a copula-GARCH methodology. This approach takes into account well-known particularities of both oil prices and exchange rates: excess-kurtosis, skewness and the presence of leverage effects. The results show that a co-movement relationship exists between oil prices and Latin American exchange rates, however, the strength of this relationship has evolved over time. While in the first years of the 2000s the relationship was almost non-existent, in more recent years the connection has become increasingly stronger.

JEL Classification: C58; Q43; G15; F37
Keywords: Oil prices; Exchange rates; Dependence measures; Copulas

Estructura de dependencia condicional entre los precios del petróleo y las tasas de cambio en Latinoamérica: Una aproximación desde los modelos copula-GARCH

Santiago Rico Ramírez

Abstract

Este trabajo estudia la relación entre los precios del petróleo y las tasas de cambio en Latinoamérica utilizando una metodología copula-GARCH. Esta aproximación permite modelar algunas de las particulariedades conocidas tanto para las tasas de cambio como para los precios del petróleo: exceso de kurtosis, sesgo y la presencia de efectos de apalancamiento. Los resultados muestran que existe comovimiento entre los precios del petróleo y las tasas de cambio Latinoamericanas. Sin embargo, la magnitud de esta relación ha evolucionado a través del tiempo. Mientras que durante los primeros años de la década del 2000 la relación era casi inexistente, en años más recientes, el vínculo se ha fortalecido de forma continua.

Clasificación JEL: C58; Q43; G15; F37
Palabras Clave: Precios del petróleo; Tasas de cambio; Medidas de dependencia; Copulas

1 Introduction

The study of the relationship of oil prices, the real economy, and the financial markets has received keen interest in recent years, given the volatility observed since the beginning of the new millennium. For example, the Brent Crude price has gone from under $20USD per barrel in the early 2000s to over $140USD per barrel just before the onset of the great recession in 2008. During more recent years, similar patterns were observed with peaks and lows during 2012 and 2016 respectively.

As oil is internationally traded in US dollars (USD), one of the main transmission channels between oil prices and the local economies, for countries whose currency is not the USD, is the exchange rates. Furthermore, the impact of oil price fluctuations may vary across oil-exporters and oil-importers. Even more, emerging countries characterized by financial imperfections and a primary focus in agricultural and mineral exports may experience broader impacts from oil price fluctuations because of their exacerbated external shocks ((Frankel, 2010)), and the more volatile Terms of Trade (ToT) ((Fraga, Goldfajn, & Minella, 2003)). Thus, understanding the relationship between oil prices and exchange rates is of paramount importance.

This work studies the relationship between oil prices and the U.S dollar exchange rates for six Latin American countries using daily return data from 2000 to 2018. The countries studies are Colombia, Mexico, Brazil, Peru, Chile and Uruguay. The first three are oil-exporters, while the later three are oil-importers. Thus, it is possible to establish a contrast between the exchange rate dependence on oil for these two segments of countries.

Several previous works have studied the liaison between oil prices and exchange rates. Some early works like (Dibooglu, 1996) showed that oil price shocks significantly account for deviations in PPP while (Amano & van Norden, 1998) found that oil prices Granger-cause exchange rates (and not the other way around), and that both series are cointegrated.

Studies like (Lizardo & Mollick, 2010), (Basher, Haugh, & Sadorsky, 2012), (Wu, Chung, & Chang, 2012) and (Aloui, Aïssa, & Nguyen, 2013) have found that a positive oil price shock is associated with a US dollar depreciation. However, some other works like (Bénassy-Quéré, Mignon, & Penot, 2007), (S.-S. Chen & Chen, 2007) and (Kim & Jung, 2018), show that rising oil prices can lead to US dollar appreciation. A smaller number of studies have found no or small dependence between oil and exchange rates (e.g. (Reboredo, 2012), (Zhu, Li, & Li, 2014)).

Methodology-wise, there have been three main types of studies in the literature. The first approach has focused on the cointegration and causality relations of oil and exchange rates by using the vector auto-regressive (VAR) framework. (Bénassy-Quéré et al., 2007) use a vector error correction model (VECM) to show the positive relationship that exists between oil prices and the US dollar. Furthermore, (Lizardo & Mollick, 2010) use co-integration analysis to show how this relationship varies between oil-importing and oil-exporting countries. More recently, (Gomez-Gonzalez, Hirs-Garzon, & Uribe, 2020) addressed this question using a VAR model and described how causality between oil prices and exchange rates varies between oil exporters and oil importers and how it has evolved over time.

The second group of papers has explored the use of time-varying auto-regressive models. Among them, (Wu et al., 2012) show that there is co-movement between these variables even in extreme values of their distribution (tail dependence). With data for exchange rates for multiple developed economies, (Aloui et al., 2013) uses a copula-GARCH approach to show that oil prices and the US dollar can have a negative relation, while (Aloui & Ben-Aïssa, 2016) use a vine copula-GARCH method to demonstrate that the dependence structure is not constant over time and that using these methods can substantially improve VaR calculations.

Finally, there's a set of literature that adopts wavelet-related tools to asses the comovents of these two series. (Tiwari, Mutascu, & Albulescu, 2013) used this framework to show that strong relationship between oil prices and exchange rates holds both in the short-run and the long-run. Also, (Yang, Cai, & Hamori, 2017) used wavelet coherence analysis to describe how oil shocks affect oil-importing and oil-exporting countries differently.

This study fits best in the second category of studies by employing a copula-GARCH approach to model the dependence structure between oil prices and exchange rates. This methodology poses several advantages compared to alternative methods like vector autoregression (VAR) and multivariate GARCH models. Returns are allowed to take a wide range of distributional forms that can capture the skewness and excess kurtosis typical of financial returns. Also, copula-GARCH models are suitable to describe asymmetrical and non-linear associations between assets. Finally, these models have a more considerable sensitivity to comovements in the tails of the distributions.

Our results show that there exists a significant and negative dependence between oil prices and the exchange rates studied. Nonetheless, this relationship hasn't been constant over time. Dependence was weak and even non-significant during the first half of the 2000s, yet it grew significantly during and after the 2008 financial crisis. However, the evolution of dependence doesn't seem to be associated with the development of oil-price volatility.

These results are in line with a large group of studies that have found a negative relationship between oil prices and exchange rates in several markets (e.g., (Aloui et al., 2013; Lizardo & Mollick, 2010; Narayan, Narayan, & Prasad, 2008)) and the ones that found that the dependence has grown after the financial crisis in 2008 (e.g., (Reboredo, 2012; Aloui & Ben-Aïssa, 2016; H. Chen, Wang, & Zhu, 2016)). Nevertheless, our study adds to the existing literature by analyzing a new set of countries during a longer time-frame. Additionally, our approach to studying dependence over time considers multiple phases of oil prices, both with copula-GARCH and DCC-GARCH methods.

This article adds to the existing literature by studying the oil prices and exchange rate co-movements with a focus on Latin American markets. Examples of related works with an emphasis on emerging markets include (He & Hamori, 2019) and (Basher et al., 2012). The former, nevertheless, focused on the BRIC countries. At the same time, the later used aggregate indexes of emerging market exchange rates and stocks to perform its estimations. (Loaiza-Maya, Gómez-González, & Melo-Velandia, 2015a, 2015b) conducted some related studies with a focus in Latin American countries. However, their focus is on dependence and contagion between the exchange rates themselves.

The rest of the article is structured as follows: Section 2 presents some additional context about the countries studied, while section 3 lays down the theoretical framework that links oil prices and exchange rates. Section 4 describes the empirical methodology, and section 5 describes the data used. Section 6 reports the main results, while section 7 discusses dependence over time. Section 8 discusses some robustness issues. Finally, Section 9 concludes.

2 The Latin American context

This section briefly develops some of the characteristics that underlie the economies of the countries considered in this study. In particular, it is interesting to discuss the export structure of each of these markets as terms of trade shocks can substantially affect exchange rates, especially in commodity-exporting economies, as is the case for most Latin American countries ((Y.-c. Chen & Rogoff, 2003)).

It is possible to spot three main segments among the countries in this study based on their export structure. The first segment is comprised of Colombia and Chile, both of which have traditionally been commodity exporters with extensive focus on a single commodity, often representing over 20% of overall exports.

Colombia went from an export-economy reliant on coffee to one with oil as a key player. At the beginning of the new millennium oil already represented more than 20% of exports with coffee falling to second place with a share of under 10%. Coal has also gained importance since the mid of the 2000s. Oil has surged in recent years, reaching a peak of 44% of total exports in 2014.

Chile's export base primarily centers around the copper, but, in contrast with Colombia, Chile is an oil importer. Other relevant commodities include molybdenum and wood pulp, yet copper's importance has continuously been increasing, and it recently has represented about 40% of the country's total exports.

The second segment of countries is made up of Mexico and Brazil. These countries share the common traits of being oil exporters with a diversified export base that often includes not just commodities but manufactured goods.

Besides oil, Mexico's most representative exports are goods such as motor vehicles and optical fiber. As mentioned before, the country has a diversified export base, and just in a few cases, the most significant export product (usually oil or motor vehicles) has taken a share over 10% of the entire export value.

Similarly, Brazil's export base has remained relatively diversified over the past twenty years. Although not being a relatively large oil exporter in a global context, oil has remained one of the country's most traded commodities yet falling behind commodities like soy, iron, and ICT equipment. The shares of the main export products have had an increase over time. However, shares higher than 10% are still rare.

Finally, the last segment contains countries where tourism is an essential source of foreign currency. Peru and Uruguay make up this group, although both countries differ considerably in their export structure.

In the case of Peru, mineral non-oil related products like copper, gold, and zinc are the most representative in its export base. As mentioned before, travel is also an essential part of Peru's sources of foreign currencies having a value close to gold exports. Even when traditionally the country had a diverse pool of exports, copper has represented over 20% of exports in recent years.

Uruguay's leading source of foreign currency is tourism, followed by non-mineral commodities like soy, leathers, meat, and rice. In the early 2000s, the income coming from tourism was thrice as large as the exports of most of the commodities exported. Even so, in recent years, the gap between commodities has shrunk, and new commodities like soy and wood pulp have gained substantial importance in the export base.

Although this study does not intend to yield causal results, the particularities of each of the countries studied fosters comparisons of the dependence dynamics between oil prices and exchange rates, given diverse market conditions.

In general, oil is a major determinant of exchange rates (see, for instance, (Habib & Kalamova, 2007), (Buetzer, Habib, & Stracca, 2012)). Also, the impact of price shocks is exacerbated in countries where the country has a large concentration of exports in the commodity receiving the shock ((Bodart, Candelon, & Carpantier, 2012)). Moreover, the degree of export base diversification can affect the sensitivity of the exchange rate to external price shocks in oil-exporting countries ((Bodart, Candelon, & Carpantier, 2015)).

The literature has also shown that developing countries are particularly sensitive to Terms of Trade (ToT) shocks, especially those focusing on agricultural and mineral exports. ((Frankel, 2010)). However, the current literature recognizes that a responsiveness difference exists between a country that exports oil and a country exporting other energy/mineral commodities. Thus, the interest of this study in comparing how do different exchange rates react to oil shocks, given the export focus of their country.

3 Theoretical framework

At a theoretical level, the literature has described two main channels of transmission between oil prices and exchange rates. The first is related to how the terms of trade (ToT) may impact the exchange rates, while the second justifies such impacts by the wealth redistribution that occurs between countries as oil prices move.

(Amano & van Norden, 1998) propose a model to study the link between oil prices and exchange rates that is well suited in the context of a small open economy. Their model considers two countries (domestic and foreign) with two sectors within the economy (tradable or non-tradable), where each of the sectors uses labor (tradable input) and oil (non-tradable input) for their production. Thus, following (S.-S. Chen & Chen, 2007) and (Nusair & Olson, 2019), we can write the log-linear approximation of the domestic and foreign price indexes as

$$p_t = \alpha p_t^T + (1-\alpha) p_t^{NT} \tag{1}$$

$$p_t^* = \alpha^* p_t^{T*} + (1-\alpha^*) p_t^{NT*} \tag{2}$$

where p^T and p^{NT} are prices of traded and non-traded goods in the home country at time t and their analogous in the foreign country are additionally marked with a $*$. The α and α^* correspond to the shares of traded goods for home and foreign economies, respectively. Furthermore, the log of the real exchange rate (q_t) is defined as the nominal exchange rate adjusted for changes in the home and foreign price levels. Hence, q_t will be given by

$$q_t = s_t + p_t - p_t^* \tag{3}$$

where s_t is the logarithm of the nominal exchange rate. Accordingly, we can write the above equation as

$$q_t = (s_t + p_t^{T*} - p_t^T) + (1-\alpha)(p_t^T - p_t^{NT}) - (1-\alpha^*)(p_t^{T*} - p_t^{NT*}) \tag{4}$$

which demonstrates how the price of oil (tradable input) is linked to the real exchange rate. From Eq. (4), if the domestic country is more dependent on imported oil, a real increase in the price of oil may increase the prices of tradable goods in the domestic country by a higher proportion than in the foreign country, which causes a real depreciation of the domestic currency. Even more, as the increase in the price of oil may worsen the terms of trade, the domestic country may opt to remain competitive by increasing the nominal exchange rate, leading to further depreciation ((S.-S. Chen & Chen, 2007)). The opposite would occur in the oil-exporting country as the real increase in oil prices, as non-tradable goods' prices increase relative to tradable goods' prices, leading to domestic currency appreciation.

Regarding the second channel, the works of (Krugman, 1983) and (Golub, 1983) describe how oil prices and exchange rates may be linked through the balance of payments. According to their models, an increase in oil prices will lead to a current account surplus for net-oil exporters and a current account deficit for net-oil importers, creating a reallocation of wealth that may impact exchange rates. The effect on exchange rates will depend on how the demand for dollars behaves in net-oil exporting and net oil-importing countries. If the increase in demand for dollars in the net-oil exporting country is smaller than the reduction in the demand for dollars in the net-oil importing country, then there will be an excess supply of dollars, and the dollar will depreciate ((Basher et al., 2012)).

4 Methodology

4.1 Marginal distribution model

Traditional modeling techniques may present shortcomings in measuring dependence between financial returns, given the particularities they present. Extreme events of appreciation/depreciation may occur with high probabilities (excess kurtosis). Volatility may show serial correlation (volatility clusters), and have asymmetric behaviors based on whether previous returns are positive or negative (leverage effect). Furthermore, the association between the exchange rates and oil prices may be asymmetrical or nonlinear.

To address these issues, we consider the asymmetric power ARCH (APARCH) model proposed by (Ding, Granger, & Engle, 1993), which is the most general form of the group of asymmetric GARCH models. Well-known nested versions of this model include the GJR-GARCH presented by (Glosten, Jagannathan, & Runkle, 1993) and the TGARCH introduced by (Zakoian, 1994).

For a series of returns r_t, the marginal model can be written as:

$$r_t = c + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

where $p, q \geq 0$, ϕ represent the autoregressive (AR) parameters and θ the moving average (MA) parameters, and ε_t is a white-noise process.

The heteroskedastic process of ε_t follows:

$$\sigma_t^\delta = \omega + \sum_{k=1}^{r} \alpha_k (|\varepsilon_{t-k}| - \gamma_k \varepsilon_{t-k})^\delta + \sum_{m=1}^{s} \beta_m \sigma_{t-m}^\delta$$

where δ is the power order of the heteroskedastic process, σ_{t-m}^δ is the forecast error of the heteroskedastic process in the previous period, and ε_{t-k} is the information about volatility in previous periods.

The parameter γ measures the asymmetric impact of previous' periods volatility on the current conditional volatility. The sign of this parameter usually varies through different types of assets with $\gamma > 0$ being common for stocks and commodities, and $\gamma < 0$ for exchange rates. The literature supports the existence of a leverage effect both for oil returns (e.g. (Kristoufek, 2014; L. Chen, Zerilli, & Baum, 2019)) and exchange rates (e.g. (McKenzie & Mitchell, 2002)).

Both the order of the ARMA process and the distribution of the white-noise process ε_t are determined empirically by optimizing the Akaike Information Criterion (AIC) [1]. The GARCH component of our model is estimated as a GARCH(1,1). Thus, the main specification used is an ARMA(p,q)-APARCH(1,1) with skewed Student-t errors. For the sake of conciseness, only the AR(1) parameters are reported in the main tables, and full results reported in the appendix.

4.2 Copula functions

A copula is a multivariate distribution function with marginal distributions defined over $[0, 1]$. Their usefulness arises from the fact that copulas present a way to express joint distribution functions as functions of their marginal distributions.

One of the most fundamental building blocks in copula theory is the fact that any joint probability distribution can be written in terms of a copula function taking the marginal distributions as arguments. At the same time, any copula function taking univariate probability distributions as arguments yields a joint distribution. Sklar's theorem formalizes these two results:

[1]For the error term we consider the normal, skewed normal, Student-t, skewed Student-t, GED and skewed GED distributions. Results for these specifications are found in the appendix.

Theorem 4.1 *Let $X_1, ..., X_d$ be random variables with marginal distribution $F_1, ..., F_d$ and joint distribution H, then there exists a copula $C : [0,1]^d \to [0,1]$ such that:*

$$H(X_1, ..., X_d) = C(F_1(X_1), ..., F_d(X_d)) \tag{5}$$

Conversely, if C is a copula and $F_1, ..., F_d$ are distribution functions, then the function H defined above is a joint distribution with margins $F_1, ..., F_d$.

Copulas are a powerful tool to understand association between random variables. Any measure of dependence that is not affected by strictly increasing transformations of the underlying variables can be expressed as a function of the copula alone ((Fan & Patton, 2014)). In particular, copulas are a key component of the coefficients of tail dependence which measure the tendency of variables to comove at extreme values of their distributions.

As explained by (Cherubini, Luciano, & Vecchiato, 2004), the coefficient of upper tail dependence is defined as:

$$\lambda_U = \lim_{v \to 1^-} \frac{1 - 2v + C(v,v)}{1 - v} \tag{6}$$

and C is said to have *upper tail dependence* iff $\lambda_U \in (0,1]$ and no upper tail dependence iff $\lambda_U = 0$. Analogously, the coefficient of lower tail dependence is defined as:

$$\lambda_L = \lim_{v \to 0^+} \frac{C(v,v)}{v} \tag{7}$$

C is said to have *lower tail dependence* iff $\lambda_L \in (0,1]$ and no lower tail dependence iff $\lambda_L = 0$.

The copulas used in this research are varied and allow the study of both symmetric and asymmetric associations between random variables. The first two copulas that make up this study are the Gaussian copula and the Student-t copula.

The bivariate Gaussian copula is defined by:

$$C(u,v) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} exp\left(-\frac{s^2 - 2\theta st + t^2}{2(1-\theta^2)}\right) dsdt$$

where ϕ is the univariate standard normal distribution and θ is the linear correlation coefficient.

On the other hand, the bivariate Student-t copula can be expressed as:

$$C(u,v) = \int_{-\infty}^{t_v^{-1}(u)} \int_{-\infty}^{t_v^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \left(1 + \frac{s^2 - 2\theta st + t^2}{v(1-\theta^2)}\right)^{-\frac{\nu+2}{2}} dsdt$$

where $t_v^{-1}(u)$ represents the inverse of the CDF of the standard univariate Student-t distribution with ν degrees of freedom.

The Gaussian copula and the Student-t belong to the Elliptical copula family. They share the common characteristic of being symmetrical. However, the Gaussian copula possesses zero tail dependence, whereas the Student-t models symmetrical tail dependence and tends to converge to the Gaussian copula as the degrees of freedom grow. For both copulas, $\theta > 0$ means the variables have positive dependence, $\theta = 0$ when they're independent, and $\theta < 0$ in the case of negative dependence.

Another relevant group of copulas is the Archimedian family. These copulas can present asymmetric tail dependence with different copulas reflecting dependence structures with higher dependence on the upper or lower tails of the distribution, or both.

The Gumbel copula, for example, is suited for dependence structures concentrated in the upper tail and is given by:

$$C(u,v) = exp\Bigg(- \Big[(-ln(u))^{\theta} + (-ln(v))^{\theta}\Big]^{\frac{1}{\theta}}\Bigg),\ \theta \in (1, +\infty)$$

where $\theta \to 1$ indicates independence and $\theta > 1$ indicates positive dependence.

Analogously, the Clayton copula exhibits negative tail dependence and can be written as:

$$C(u,v) = \Bigg(u^{-\theta} + v^{-\theta} - 1\Bigg)^{-\frac{1}{\theta}},\ \theta \in (0, +\infty)$$

where $\theta \to 0$ means the variables are independent, while $\theta \to \infty$ indicates positive dependence.

The last Archimedian copula considered in this study is the Frank copula. This copula is the only one in the family suited to model both upper and lower tail dependence. In contrast to the rest of copulas in the Archimedian family, the Frank copula is symmetric. This copula can be expressed as:

$$C(u,v) = -\frac{1}{\theta} ln\Bigg(1 + \frac{exp(-\theta u) - 1(\exp(-\theta v) - 1)}{exp(-\theta) - 1}\Bigg),\ \theta \in (-\infty, +\infty)$$

In this case, there will be positive dependence as $\theta \to +\infty$, independence when $\theta \to 0$, and negative dependence when $\theta \to -\infty$.

In a similar fashion, the Plackett copula is also symmetrical and can model dependence in both tails of the distribution. This copula is formally wrriten as:

$$C(u,v) = \frac{[1 + (\theta - 1)(u+v) - [(1 + (\theta - 1)(u+v))^2 - 4uv\theta(\theta - 1)]^{\frac{1}{2}}]}{2(\theta - 1)},\ \theta \in (0, +\infty) - 1$$

where there will be independence when $\theta = 1$, positive dependence where $\theta > 1$, and negative dependence when $\theta < 1$.

5 Data

We use a long data set of nominal exchange rates and oil prices spanning from January 4, 2000 to December 31, 2018 obtained from the Bloomberg platform. The exchange rates correspond to six Latin American markets rates: Colombia (COP), Brazil (BRL), Mexico (MXN), Chile (CLP), Peru (PEN) and Uruguay (UYU). Moreover, observations for oil prices correspond to two major oil indexes: the West Texas Intermediate (WTI) and the Brent Crude.

Our currency observations correspond to nominal exchange rates which measure the amount of local currency by one unit of USD. This means that when the exchange rate rises, the local currency depreciates while USD appreciates. At the same time, oil prices are expressed in US dollars per oil barrel. Returns are computed using the difference of the logarithm of two consecutive prices.

The exchange rates selected account for a wide variety of underlying economic structures. These include, for example, countries with a large focus on oil exports (e.g. Colombia), countries where non-oil related minerals account for a sizable portion of the exports (e.g. Chile), and countries where non-commodity exports are an important source of foreign currency (e.g. Uruguay).

Table 1 contains descriptive statistics for all the series. There are notable differences in the variance of returns across all assets. It is specially clear that oil is more volatile that exchange rates. Excess kurtosis and skewness are observed in all cases.

Table 1: Descriptive Statistics

Statistic	Min	Max	Mean	St. Dev.	Kurt.	Skew.
COP	−0.077	0.052	0.0001	0.007	8.050	−0.061
MXN	−0.047	0.071	0.0001	0.007	10.11	0.67
BRL	−0.119	0.086	0.0002	0.010	9.07	0.041
PEN	−0.045	0.068	−0.00001	0.003	69.02	1.11
CLP	−0.033	0.047	0.00006	0.009	3.765	0.339
UYU	−0.083	0.146	0.0002	0.009	46.87	2.691
BRENT	−0.144	0.127	0.0002	0.022	2.922	−0.150
WTI	−0.165	0.164	0.0001	0.024	4.008	−0.130

Similarly, Table 2 shows stochastic properties of the returns. Both exchange rates and oil prices are serially correlated and exhibit ARCH effects. In addition, the Jarque-Bera test provides additional, and highly statistically-significant, evidence of the non-normality of the assets examined.

Table 2: Stochastic properties

Statistic	$Q(36)$	$Q^2(36)$	ARCH(12)	Jarque-Bera
COP	83.95***	2918***	768***	13235***
MXN	96.67***	3811***	1070***	21400***
BRL	72.99***	4632***	1283***	16539***
PEN	207.42***	1670***	1550***	930830***
CLP	92.86***	2404***	609***	2993***
UYU	244.49***	1990***	341***	343686***
BRENT	79.52***	3834.9***	610***	1748***
WTI	60.14***	4137***	608***	3201***

Notes: $Q(36)$ ($Q^2(36)$) is the Ljung-Box statistic for serial correlation with 36 lags in the returns (squared returns). ARCH(12) is the statistic for the ARCH-LM test for heteroskedasticity with 12 lags. Jarque-Bera is the χ^2 statistic for the normality test.

6 Results

6.1 Dependence overview

The first results to analyze are the high-level correlation estimates for each of the exchange rates and the BRENT oil prices. The results shown in Table 3 indicate that, for all exchange rates, there is a negative correlation. Hence, an increase in oil prices is linked with an appreciation of the local currency. Furthermore, the magnitude of the correlation is more considerable for all oil-exporting countries. Even more, the case of Uruguay stands out due to the minimal value of its correlation, probably due to the relevance of its non-export related currency sources. Kendall's τ and Spearman's ρ provide additional support to these results.

Table 3: Correlation estimates for oil prices and exchange rates

Statistic	Pearson	Kendall	Spearman
COP	-0.2625	-0.1493	-0.2196
MXN	-0.2365	-0.1352	-0.1996
BRL	-0.2050	-0.1259	-0.1855
PEN	-0.1102	-0.0969	-0.1432
CLP	-0.1916	-0.1237	-0.1816
UYU	-0.0332	-0.0440	-0.0660

6.2 Marginal distributions

As mentioned in the methodology section, the main specification of the study is ARMA(p,q)-APARCH(1,1) with skewed Student-t distributed errors.

The high values of the β parameter, as well as its high significance, show that volatility is highly persistent. For all series but Peru, this parameter is very close to 0.9. Also, oil prices display evidence of the existence of a leverage effect as the γ parameter is highly significant and positive. For exchange rates, however, the γ parameter is negative and highly significant for all series but Chile and Uruguay. A negative γ parameter suggests the presence of an inverse leverage effect. This behavior is explained by the fact that an increase in the exchange rate (a depreciation of the local currency) is generally perceived as negative for the economy, thus driving volatility higher.

Following the APGARCH estimation, standardized residuals are computed for each of the return series. Next, the standardized residuals are transformed into pseudo-observations that are the final input for the copula parameter estimation. The pseudo-observations are uniformly distributed and contained in the $[0, 1]$ interval, which is an essential requirement for the copula estimations to be valid.

Table 4: APGARCH Marginal Distribution Estimates

	Dependent variable:							
	BRENT	WTI	COP/USD	MXN/USD	BRL/USD	PEN/USD	CLP/USD	UYU/USD
c	-0.00001	-0.00001	0.0001	0.0001	0.00003	0.00000	0.00000	0.00001
	(0.00003)	(0.00002)	(0.0001)	(0.0001)	(0.00003)	(0.00000)	(0.00003)	(0.00001)
ϕ	0.813^{***}	0.942^{***}		-0.219	-0.090^{***}	-0.822^{***}	0.614^{***}	0.807^{***}
	(0.055)	(0.029)		(0.374)	(0.034)	(0.023)	(0.141)	(0.021)
ω	0.0001^{***}	0.0003^{***}	0.00001^{***}	0.00001^{***}	0.0001^{***}	0.0001^{***}	0.00002^{***}	0.0001^{***}
	(0.00004)	(0.0001)	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00003)
α	0.046^{***}	0.047^{***}	0.155^{***}	0.086^{***}	0.115^{***}	0.285^{***}	0.094^{***}	0.221^{***}
	(0.005)	(0.005)	(0.014)	(0.011)	(0.011)	(0.027)	(0.010)	(0.026)
γ	0.515^{***}	0.632^{***}	-0.127^{***}	-0.329^{***}	-0.345^{***}	-0.094^{**}	-0.087^{*}	0.034
	(0.101)	(0.111)	(0.038)	(0.071)	(0.060)	(0.037)	(0.047)	(0.047)
β	0.961^{***}	0.959^{***}	0.875^{***}	0.911^{***}	0.894^{***}	0.794^{***}	0.913^{***}	0.830^{***}
	(0.004)	(0.004)	(0.011)	(0.011)	(0.011)	(0.017)	(0.010)	(0.020)
δ	0.916^{***}	0.856^{***}	1.358^{***}	1.467^{***}	1.162^{***}	1.017^{***}	1.265^{***}	1.016^{***}
	(0.172)	(0.161)	(0.154)	(0.184)	(0.146)	(0.119)	(0.177)	(0.122)
skew	0.924^{***}	0.895^{***}	1.041^{***}	1.111^{***}	1.056^{***}	1.037^{***}	1.023^{***}	1.053^{***}
	(0.019)	(0.019)	(0.020)	(0.023)	(0.022)	(0.020)	(0.021)	(0.024)
shape	7.965^{***}	9.343^{***}	5.235^{***}	8.051^{***}	9.135^{***}	3.283^{***}	7.954^{***}	3.771^{***}
	(0.870)	(1.126)	(0.408)	(0.852)	(1.054)	(0.177)	(0.816)	(0.249)
Observations	4,856	4,755	4,895	4,936	4,817	4,680	4,900	3,701
$Q(36)$	43.79	64.827^{***}	43.80	39.93	27.93	56.98^{**}	46.07	15.85
$Q^2(36)$	22.14	858.9^{***}	37.49	29.37	33.98	31.42	7.53	40.15
ARCH(36)	37.97	206.64^{***}	44.636	28.666	36.743	20.35	7.8462	0.6374

Note: *p<0.1; **p<0.05; ***p<0.01

6.3 Copula parameter estimates

Table 5: Copula dependence parameter estimates

	Dependent variable:					
	COP/USD	MXN/USD	BRL/USD	PEN/USD	CLP/USD	UYU/USD
Gaussian Copula						
θ	-0.20^{***}	-0.19^{***}	-0.18^{***}	-0.12^{***}	-0.18^{***}	-0.07^{***}
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.016)
Student-t						
θ	-0.2^{***}	-0.19^{***}	-0.18^{***}	-0.13^{***}	-0.18^{*}	-0.07^{***}
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.017)
ν	17.14	19.41	29.0	22.92	14.75	29.11
Clayton						
θ	-0.19^{***}	-0.19^{***}	-0.18^{***}	-0.12^{***}	-0.18^{***}	-0.06^{***}
	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)	(0.019)
Gumbel						
θ	-1.14^{***}	-1.13^{***}	-1.10^{***}	-1.07^{***}	-1.11^{***}	-1.04^{***}
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Frank						
θ	-1.21^{***}	-1.17^{***}	-1.07^{***}	-0.77^{***}	-1.12^{***}	-0.38^{***}
	(0.087)	(0.087)	(0.088)	(0.089)	(0.087)	(0.10)
Plackett						
θ	0.54^{***}	0.55^{***}	0.59^{***}	0.68^{***}	0.57^{***}	0.83^{***}
	(0.023)	(0.023)	(0.025)	(0.029)	(0.024)	(0.040)
Observations	4,895	4,936	4,817	4,680	4,900	3,701
Note:						*p<0.1; **p<0.05; ***p<0.01

Copula parameter estimates in Table 5 show to be highly significant across all exchange rates/copula pairs. Moreover, all of them suggest the existence of a negative relationship between oil prices and exchange rates, as was hypothesized earlier in this document. The strength of the relationship varied across countries, being stronger for oil exporters than oil importers, and being particularly low for the UYU/USD exchange rate. Additionally, the estimates of the ν parameter for the Student-t copula remained between 12.7 and 29.11. Hence, moderate extreme co-movement cannot be discarded for any of the currencies.

It is also noteworthy that results do not suggest a vast dependence difference among oil exporters, even when they have fundamentally different export structures. Although oil plays a significant role in Colombia's exports, its dependence is not substantially larger than that of Mexico and Brazil, which have a much more diversified export base.

Comparing Colombia and Chile, as economies with a significant focus on a single commodity, their dependence similarity is striking. Chile's broad focus on copper exports could partially explain this fact if there is a tendency between copper prices and oil to move together. Some literature has found that copper does exhibit excess comovement with oil prices; however, this is still an open research topic ((Fernandez, 2015; Lescaroux, 2009)).

For Peru and Uruguay, both countries with a lesser dependence on exports to source foreign currency, dependence values are notoriously different than for the rest of countries. In particular, Peru's exchange rate has a smaller dependence on oil than Chile, both being copper exporters.

Table 6: Copula goodness of fit tests

	Dependent variable:					
	COP/USD	MXN/USD	BRL/USD	PEN/USD	CLP/USD	UYU/USD
Gaussian	1.11^{**}	0.78^{**}	0.50^{*}	0.06	0.42^{*}	0.00
Student-t	0.53	2.14	2.12	1.11	0.62	2.99
Clayton	0.07	0.62^{*}	6.08^{***}	0.01	0.65	0.05
Gumbel	0.08^{**}	1.62^{***}	6.59^{***}	0.40^{*}	1.30^{**}	0.068
Frank	0.35^{*}	0.44^{***}	0.07	0.07^{*}	0.46^{**}	0.00
Plackett	0.05^{***}	0.03^{*}	0.03^{**}	0.03^{**}	0.02	0.02

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The performance of each of the copulas is assessed using the goodness-of-fit test proposed by (Huang & Prokhorov, 2014). Results reported in Table 6 show that the copula that suits the oil-price / exchange rate pairs the best is the Student-t copula. This result is consistent with the findings of other studies (e.g. (Aloui et al., 2013; Reboredo, 2012)). Furthermore, the preference of the Student-t copula over copulas like the Clayton and the Gumbel provides evidence that the dependence structure is symmetric, meaning that dependence behaves similarly during events of surge as it does during events of decline.

Moving forward, the coefficients of tail dependence are computed for the Student-t copula, given that it provides the best estimation among the copula models. The coefficients of tail dependence are reported in Table 7. Based on the results, there is evidence of very low tail dependence, with the upper bound of dependence being 0.0003 in the case of Colombia. This may partially be attributed to the country's very large share of oil exports.

Table 7: Copula dependence parameter estimates

	Dependent variable:					
	COP/USD	MXN/USD	BRL/USD	PEN/USD	CLP/USD	UYU/USD
λ_U	0.0000544	0.0000204	0.0000003	0.0000103	0.000213	0.00000136
λ_L	0.0000544	0.0000204	0.0000003	0.0000103	0.000213	0.00000136

As robustness checks, the same estimations were performed using several error distributions (normal, skewed normal, Student-t, GED, and skewed GED), and using the WTI index as price reference. The results were all qualitatively consistent with the ones presented in the main specification.

7 Dependence over time

Another interesting question is whether the dependence structure between oil prices and exchange rates has varied over the years. This is particularly relevant given that oil prices have had several distinctive stages during the period here studied and the advent of the global financial crisis in 2008.

We use two different methodologies to assess the evolution of dependence over time. In the first approach, the full sample is divided into subperiods based on tests of structural change of oil prices. Then, we estimate the main specification of this work for each of them. In the second approach, the methodology is shifted from copula-GARCH to a DCC-GARCH model. A dynamic correlation matrix characterizes this model, thus it is possible to see the evolution of the conditional correlation over time.

7.1 Dependence during different periods of oil prices

To identify the different periods of oil prices, the test developed by (Bai & Perron, 1998) is used. The test enables the identification of structural breakpoints in the data endogenously. The estimation indicates the presence of breakpoints on four dates: August 8th, 2004, June 19th, 2007, January 12th, 2011, and November 13th, 2014.

Figure 2 shows the evolution of oil prices in the years of this study as well as the estimated breakpoints. During the first period, oil prices are relatively low and moving sideways until the beginning of the second period, where they start a surge. During the third period, prices continue to rise and peak at $142 in July 2008. After that, prices fell to $36 in December 2008. After the 2011 breakpoint, prices remain high and have a new phase of sideways movement to then fall into the final period in 2014.

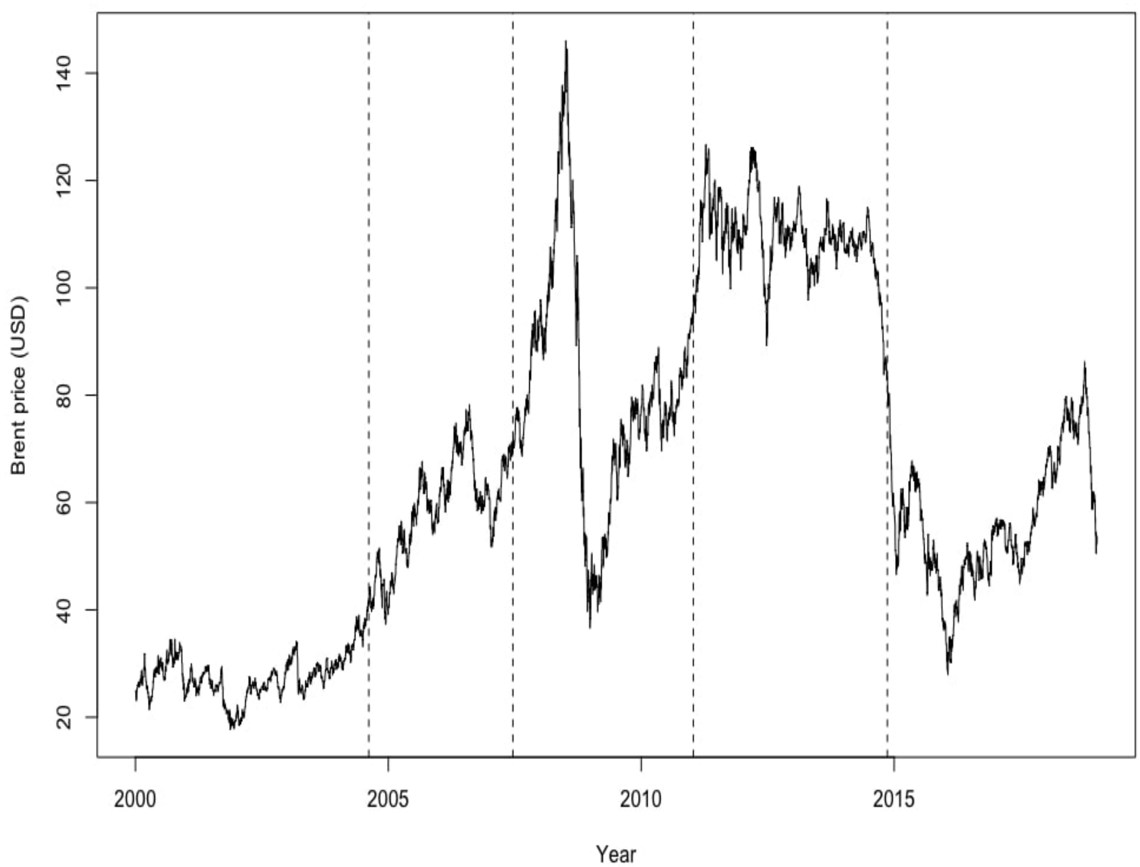

Figure 1: Oil price evolution and breakpoints

After the sample split, the marginal distribution results show contrasting differences. The β parameters remain high and highly significant through all five periods which indicates that, volatility persistence has been a common denominator through time for these group of assets. On the other hand, the asymmetry parameters vary substantially from one period to another both in magnitude and significance. However, they remain highly significant for Mexico and Brazil in all time frames. For the sake of brevity, the full results of the marginals estimations are reported in the appendix.

Table 8: Copula dependence parameter estimates

	Dependent variable:					
	COP/USD	MXN/USD	BRL/USD	PEN/USD	CLP/USD	UYU/USD
2000 to 2004						
θ	-0.03	0.00	-0.03	0.00	-0.02	0.00
	(0.020)	(0.030)	(0.030)	(0.030)	(0.031)	(0.036)
ν	30	21.47	30	30	18.86	30
λ_U	0.00000281	0.00000978	0.00000243	0.00000414	0.00064888	0.00000405
λ_L	0.00000281	0.00000978	0.00000243	0.00000414	0.00064888	0.00000405
2004 to 2007						
θ	-0.01	-0.07	-0.01	0.00	-0.03	0.02
	(0.038)	(0.038)	(0.039)	(0.040)	(0.038)	(0.052)
ν	30	30	30	30	30	30
λ_U	0.00000370	0.00000142	0.00000208	0.00000340	0.00000241	0.00000615
λ_L	0.00000370	0.00000142	0.00000208	0.00000340	0.00000241	0.00000615
2007 to 2011						
θ	-0.31^{***}	-0.36^{***}	-0.42^{***}	-0.26^{***}	-0.29^{***}	-0.08^{**}
	(0.031)	(0.028)	(0.026)	(0.032)	(0.032)	(0.039)
ν	9.71	18.79	30	11.89	8.4	30
λ_U	0.00095512	0.00000269	0.00000000	0.00004478	0.00225611	0.00000115
λ_L	0.00095512	0.00000269	0.00000000	0.00004478	0.00225611	0.00000115
2011 to 2014						
θ	-0.24^{***}	-0.28^{***}	-0.21^{***}	-0.19^{***}	-0.32^{***}	-0.11^{***}
	(0.032)	(0.031)	(0.032)	(0.032)	(0.029)	(0.037)
ν	9.38	9.06	15.14	12.71	19.09	15.69
λ_U	0.00195006	0.00177482	0.00013681	0.00052472	0.00000445	0.00000061
λ_L	0.00195006	0.00177482	0.00013681	0.00052472	0.00000445	0.00000061
2014 to 2018						
θ	-0.42^{***}	-0.27^{***}	-0.2^{***}	-0.2^{***}	-0.28^{***}	-0.14^{***}
	(0.025)	(0.028)	(0.030)	(0.030)	(0.028)	(0.031)
ν	15.89	30	17.47	30	30	30
λ_U	0.00000674	0.00000002	0.00004651	0.00000013	0.00000002	0.00000037
λ_L	0.00000674	0.00000002	0.00004651	0.00000013	0.00000002	0.00000037
Observations	4,955	4,955	4,955	4,955	4,955	4,955
Note:						*p<0.1; **p<0.05; ***p<0.01

The copula estimations in Table 8 show that dependence has changed drastically over time. During the years previous to 2007, dependence was non-significant, although negative, for all exchange rates. Similarly, tail dependence coefficients were extremely close to zero.

On the contrary, after 2007, dependence between oil prices and exchange rates has increased tremendously. After this year all currencies show very significant negative dependence with oil prices. The period with largest dependence was the one between

2007 and 2011. After that, dependence decreased slightly between 2011 and 2014, but has risen again starting in 2014. Tail dependence is the highest during 2011 to 2014 with an upper bound of 0.0109, but they are still very weak for the remaining periods.

7.2 DCC-GARCH

The DCC-GARCH model was proposed by (Engle, 2002) and (Tse & Tsui, 2002). The mode is a type of multivariate GARCH characterized by dynamic correlation matrix. This methodology enables us to map the evolution of correlation over time for multiple assets. In addition, we use the asymmetric version of this model to account for leverage effects, as it's been done in previous sections. The model can be written as follows:

$$H_t = D_t R_t D_t$$

where D_t is a diagonal matrix containing the time-varying standardized deviations from univariate GARCH models, and $R_t = (diag(Q_t))^{-\frac{1}{2}} Q_t (diag(Q_t))^{-\frac{1}{2}}$. Q_t represents the evolution of the correlation in the model and is expressed as:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}$$

where Q_t is the time-varying covariance matrix of u_t, and $\bar{Q} = E[u_t u'_t]$ is the unconditional variance matrix of u_t ((Chiang, Jeon, & Li, 2007)).

Using this model we're able to assess the evolution of conditional correlations between oil prices and the six studied exchange rates over time in a multivariate setting. This allows to additionally account for the relationships that may exist between exchange rates themselves.

The conditional correlation plots shown in Figure 3 are consistent with the results obtained from our estimations in subperiods. The conditional correlation is weaker during the first years of the sample, but it grows as time advances towards 2010. Afterward, conditional correlation tends to dim, but it grows again following 2015. In the most recent years, however, the strength of the relationship was debilitated again.

The results of this section are aligned with other studies that have appraised the evolution of dependence between oil prices and exchange rates over time. However, most studies have focused on understanding the changes in the dependence before and after the financial crisis. In general, the literature has found that the dependence between oil prices and exchange rates has intensified following the 2008 financial crisis, regardless of the exchange rates under consideration (see, for example, (H. Chen et al., 2016; Aloui & Ben-Aïssa, 2016; de Truchis & Keddad, 2016; Sebai, Naoui, et al., 2015; Turhan, Sensoy, & Hacihasanoglu, 2014)). Moreover, this work presents evidence that, although the higher dependence has remained, it has shown substantial fluctuations over time.

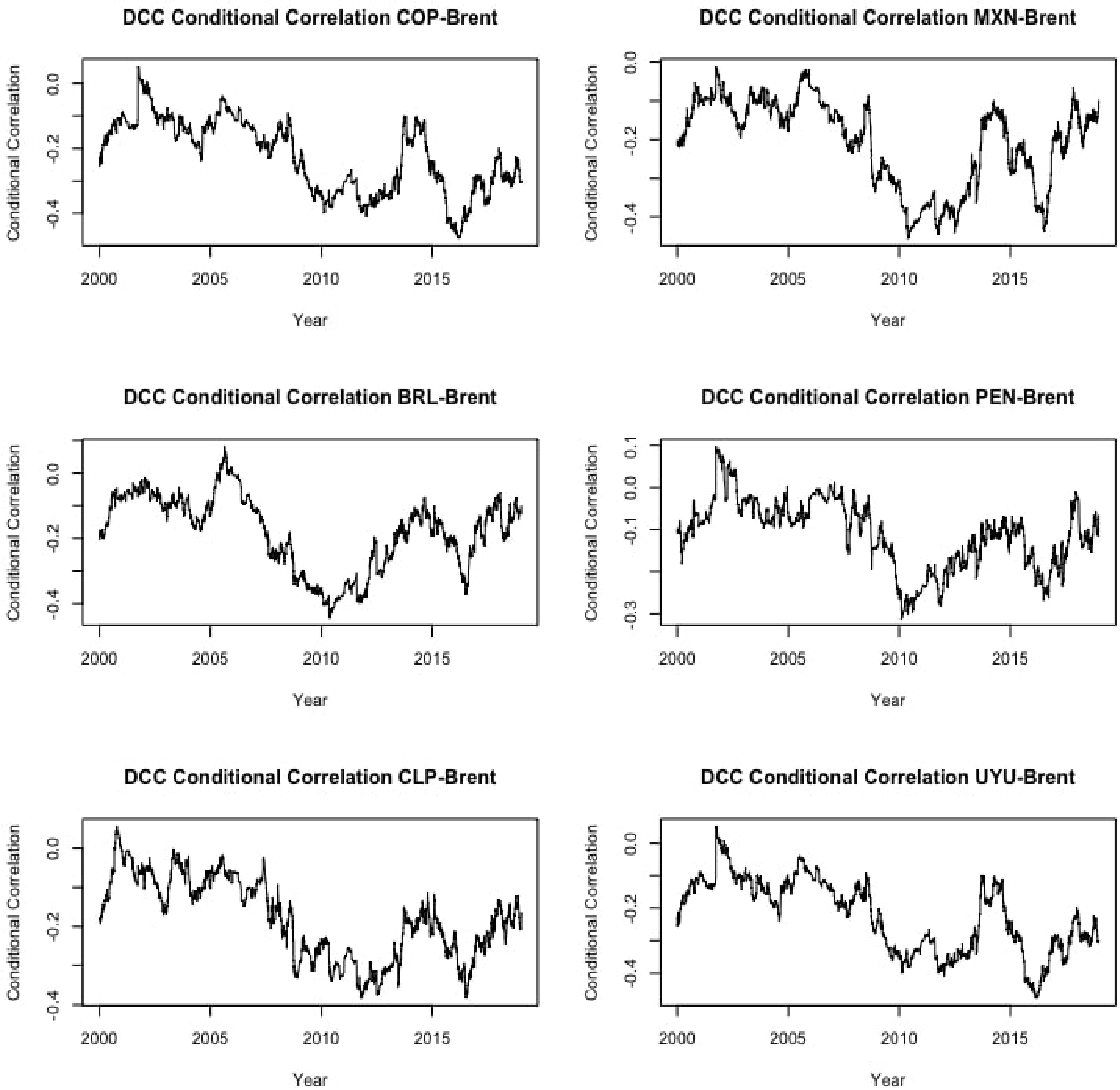

Figure 2: Dynamic conditional correlation amongst oil prices and exchange rates

8 Robustness check: Confounding global shock

Besides oil price shocks, there may be some other global shocks that may simultaneously affect all exchange rates. Such a shock could explain the lack of heterogeneity in dependence structure across countries with fundamentally different export bases. Such a concern has previously addressed in the literature by including the lagged returns of the S&P500 (see (Chiang et al., 2007; González-Hermosillo, Martin, Fry, & Dungey, 2003)). Thus, the original mean model is extended to include a one-day lag of the S&P500 returns as a control for a global common factor. Hence, the new estimated model is an ARMAX(p,q)-APARCH(1,1). The results, shown in Table 9, are consistent with the results of the original model.

Table 9: APGARCH Marginal Distribution Estimates with Global Shock

	Dependent variable:						
	data						
	BRENT	COP/USD	MXN/USD	BRL/USD	PEN/USD	CLP/USD	UYU/USD
c	−0.0002	0.0001	0.0001	0.0002	−0.00005	−0.0000	0.0002
	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.00002)	(0.0001)	(0.00001)
ϕ	0.936***		−0.80***	0.84***	−0.760***	−0.044	0.864***
	(0.052)		(0.294)	(0.010)	(0.005)	(1.17)	(0.131)
ω	0.0001***	0.00001***	0.0000	0.0001***	0.0000***	0.0000	0.0001
	(0.00001)	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.0000)	(0.00003)
α	0.047***	0.159***	0.067***	0.116***	0.275***	0.073***	0.178***
	(0.002)	(0.014)	(0.006)	(0.011)	(0.027)	(0.010)	(0.020)
γ	0.487***	−0.138***	−0.189***	−0.336***	−0.0601***	−0.016***	0.039
	(0.068)	(0.037)	(0.018)	(0.045)	(0.008)	(0.002)	(0.047)
β	0.960***	0.870***	0.900***	0.894***	0.783***	0.906***	0.883***
	(0.003)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.012)
δ	1.089***	1.378***	2.533***	1.156***	2.252***	2.98***	1.008***
	(0.054)	(0.042)	(0.009)	(0.126)	(0.013)	(0.144)	(0.100)
GlobalShock	0.0000	0.0001***	0.0000***	0.0009	0.0000***	0.0000***	0.0000
	(0.005)	(0.005)	(0.000)	(0.003)	(0.000)	(0.000)	(0.002)
skew	0.918***	1.042***	1.104***	1.062***	1.024***	1.036***	1.056***
	(0.018)	(0.020)	(0.023)	(0.023)	(0.019)	(0.023)	(0.016)
shape	8.440***	5.550***	7.555***	9.412***	3.500***	4.88***	3.674***
	(0.870)	(0.464)	(0.664)	(1.125)	(0.185)	(0.254)	(0.242)
Observations	4,856	4,895	4,936	4,817	4,680	4,900	3,701
Note:							*p<0.1; **p<0.05; ***p<0.01

The new GARCH estimations show that the introduction of the global shock shows some effect in the mean equation parameters; however, the variance equation is mostly unaffected. Additionally, although the global shock proves to be significant for some of the exchange rates considered, its magnitude is minimal for all of them.

The copula estimations shown in Table 10 reflects the minor change in the GARCH models. Changes in both the coefficients and their standard errors are minor across all the copulas estimated. Furthermore, the results here presented lead to qualitatively comparable conclusions as the ones presented in the main specification.

Table 10: Copula dependence parameter estimates with Global Shock

	Dependent variable:					
	COP/USD	MXN/USD	BRL/USD	PEN/USD	CLP/USD	UYU/USD
Gaussian Copula						
θ	-0.21^{***}	-0.19^{***}	-0.18^{***}	-0.13^{***}	-0.18^{***}	-0.07^{***}
	(0.014)	(0.013)	(0.014)	(0.015)	(0.014)	(0.017)
Student-t						
θ	-0.21^{***}	-0.2^{***}	-0.18^{***}	-0.13^{***}	-0.19^{*}	-0.07^{***}
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.017)
ν	20.25	25.21	30	27.32	17.18	30
Clayton						
θ	-0.19^{***}	-0.19^{***}	-0.18^{***}	-0.12^{***}	-0.18^{***}	-0.06^{***}
	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.019)
Gumbel						
θ	-1.14^{***}	-1.13^{***}	-1.10^{***}	-1.07^{***}	-1.12^{***}	-1.04^{***}
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)
Frank						
θ	-1.24^{***}	-1.18^{***}	-1.08^{***}	-0.79^{***}	-1.13^{***}	-0.42^{***}
	(0.089)	(0.088)	(0.089)	(0.090)	(0.089)	(0.10)
Plackett						
θ	0.54^{***}	0.55^{***}	0.59^{***}	0.68^{***}	0.57^{***}	0.83^{***}
	(0.023)	(0.023)	(0.025)	(0.029)	(0.024)	(0.040)
Observations	4,895	4,936	4,817	4,680	4,900	3,701
Note:						*p<0.1; **p<0.05; ***p<0.01

9 Conclusions

This study wondered about the dependence between oil prices and exchange rates in Latin American Countries. Daily oil prices and exchange rates between the 4th of January 2000 and the 31st of December 2018 are analyzed using a copula-GARCH methodology. This methodology allows the capture of complex dependence structures and to model several of the particularities presented by financial time series like excess kurtosis, volatility clusters, and leverage effects.

The results here presented point to the existence of a significant dependence between oil prices and the exchange rates studied. Dependence is more sizable in oil-exporting countries than in their oil-importing counterparts. Nevertheless, it doesn't seem to vary based on the degree of export diversification of these countries. On the other hand, in countries like Uruguay and Peru, were activities like tourism are one of the primary sources of foreign currency, the dependence of exchange rates and oil seems to be weaker.

Additionally, the empirical evidence implies that tail dependence is very low for all oil-price exchange rate pairs here studied. Hence, the dependence is not exacerbated during periods of extreme appreciation or depreciation of the assets. Tail independence has important policy implications since this means that central banks have a less pressing need to intervene in the foreign exchange markets during periods of extensive positive or negative oil price shocks.

Finally, studying dependence through time shows that the comovement between oil prices and exchange rates has evolved from weak to no-dependence between 2000 and 2007 to considerably larger and significant dependence in the years to follow. Nevertheless, the enlargement of dependence seems to be associated with the onset of the 2008 financial crisis and not with changes in the volatility of oil prices.

Future extensions to this work may want to consider including a time-varying component to the copula models to understand further how dependence structures have changed over time (see (Wu et al., 2012)). Furthermore, future studies may be interested in the relationship between oil prices and exchange rates in a multivariate setting. Hence, variables such as interest rates and stock indexes may be included (see (Aloui & Ben-Aïssa, 2016)).

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