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Exchange Rates, Oil Prices and World Stock Returns

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Abstract: This paper examines responses of 14 major currency/USD pairs to two global factors (oil and world equity returns) from January 1999 to July 2017, a period that comprises the global financial crisis and oil price collapse in late 2014. With global equity markets advancing, risk tolerance increases and higher oil prices make “commodity currencies” stronger. GARCH (1, 1) models identify preliminary links and DCC-GARCH modeling strengthens these findings under time-varying correlations: safe-haven currencies depreciate with higher global equity markets and commodity currencies appreciate with oil price gains. In emerging markets, only the South African Rand displays meaningful currency-equity links.

Keywords: exchange rates, oil price returns, world stock returns.

JEL Classification Number: F31, G15, Q43.

1. Introduction

There are numerous examples of varying properties between exchange rates and interest rate differentials in the literature. It has become common to attribute to industrial currencies a persistent forward premium puzzle, which occurs less frequently in emerging markets. Flood and Rose (2002) document more favorable evidence for uncovered interest parity (UIP) for currencies during the turmoil times of the 1990s. Chinn (2006) discusses UIP for emerging markets with longer maturities and Frankel and Poonawala (2010) confirm that the forward market in emerging currencies is less biased than in major currencies. Gilmore and Hayashi (2011) look at monthly data of excess returns of 20 tradable emerging market currencies against the USD from the mid-1990s to 2010 and conclude they differ substantially from major currencies. As for forecasting exercises, Rossi (2013) shows for major currencies that interest rates are not very good predictors of exchange rate changes and suggests that Taylor rule tend to outperform standard predictors such as interest rate differentials (by UIP) or price differentials under the purchasing power parity (PPP) paradigm.

Given the poor performance of interest rate differentials in predicting currency moves, it has become common to focus on risk factors, particularly those derived from equity or commodity markets. On the one hand, the literature linking exchange rates to equity markets includes: Diamandis and Drakos (2011) for four Latin American countries, Kalra (2011), Lin (2012) for Asian currencies, Wong (2017) for four Asian and three major currencies, Andreou et al. (2013) for emerging markets, Chkili and Nguyen (2014) for BRICS countries, Caporale et al. (2014) for the recent financial crisis period, and Cho et al. (2016), who proxy global stock market conditions by MSCI world index returns in local currencies and report higher correlations (on average) for

developed than emerging markets between 1996 and 2009. Another body of work by Chue and Cook (2008) and Chang et al. (2013) examines the degree of exchange rate exposure (at firm level) with causality running from currency to stock returns.

On the other hand, for the links among currency, oil and interest rates, Akram (2009) and Arora and Tanner (2013) offer representative studies, with Basher et al. (2012) focusing on emerging stock markets. Taking into account major commodities certainly makes sense for “commodity currencies”, some of which may be from emerging markets.¹ Although the link between oil price and exchange rate has been widely investigated, the results are mixed. Some empirical evidence contains evidence of cointegration between exchange rate and oil prices with causality running in both directions. Some studies show that an increase in oil price leads to U.S. dollar appreciation: Amano and van Norden (1998); Benassy-Queré et al. (2007); and Ghosh (2011). Others find, however, that increases in oil price cause U.S. dollar depreciation against other currencies: Narayan et al. (2008); Akram (2009); Wu et al. (2012); Turhan et al. (2013); and Turhan et al. (2014).

A very simple approach, without commodity factors, has been recently proposed by Katechos (2011), who suggests interest rate differentials determine the sign of the link between currency and equity markets. When global stock market returns increase the currency with higher interest rate should appreciate against the currency with lower interest rate. As investors experience positive equity returns they borrow from low yield countries and invest in high yield

¹ A recent example from the financial press illustrates the many forces at play in a widely traded emerging-market currency: “The Mexican peso, the most traded of the emerging-market currencies, traded at more than 16 to the dollar Monday for the first time, with worries about Fed tightening exacerbated by renewed declines in oil prices. Although the Bank of Mexico is widely expected to start raising interest rates as soon as the Fed does and has been auctioning dollars to curtail volatility in the exchange market, the peso has continued to depreciate, reacting to oil prices and to positive U.S. economic data that could prompt the Fed into action. Unlike some of its Latin American peers, however, Mexico could benefit from a weaker currency, given that four-fifths of its exports go to the U.S., and manufactured goods account for more than 80% of total exports.” (Harrup, The WSJ, July 21, 2015).

countries, which leads to higher demand of the high yield currency. The currency with higher interest rate will thus appreciate. In this framework, global (all world) equity returns are the only factor explaining currency movements within the GARCH (1, 1) modeling.

We apply this insight on interest rate and equity markets and propose two global risk factors (world equity and oil price returns) assumed to influence currency changes. If the currency is commodity based, such as the Russian Ruble or the Mexican Peso, increases in the price of oil should strengthen the value of these currencies against the USD. This should reinforce the equity-currency link above. Our two-factor approach is also grounded on financial literature, such as: Lustig et al. (2011), who apply a data-driven methodology consistent with the Arbitrage Pricing Theory of Ross (1976) and propose the average currency excess return and the return to carry trade portfolio itself as two risk factors.

The research design of this paper carries a few desirable features. First, when we adopt a direct approach and add interest rate differentials to the mean (or variance) equation in turn for GARCH modeling, we find that interest rate differentials are not statistically significant. This casts doubt on the role of interest rate differentials. Second, adding oil price returns in the mean equation in order to gauge the impact of another global indicator the results appear very consistent with a currency-oil link. Third, given the importance of oil in financial markets, the role of U.S. monetary policy in setting world interest rates, and the time-varying properties across asset classes, we extend the GARCH (1, 1) approach to the DCC-GARCH by Engle (2002). Employing the framework to time-varying correlations helps assessing the dynamic properties of these financial assets, whose time dependence is not constant. This is important since the financial press regularly emphasizes the increases in correlation between asset pairs, particularly between stocks and oil

more recently.² Fourth, due to the mixed evidence regarding industrial and emerging market currencies, we examine not only industrial but also emerging markets currencies, in which carry-trade and risk taking presumably appear at the forefront of investing behavior. Kalra (2011), for example, employs GARCH models for global volatility (VIX and VDAX indices) from 2001 to 2010 on foreign exchange returns in East Asia and finds there is a tendency for these exchange rates to depreciate with increases in global (equity) risk: a “flight to safety” effect.³

Using weekly data from January 1999 to July 2017 for 14 major currencies against the USD, we find evidence in this paper that DCC-GARCH modeling strengthens GARCH (1, 1) findings. Under time-varying correlations, oil price increases usually lead to appreciation of commodity currencies in both industrial and emerging-market currencies. Commodity currencies of industrial and emerging countries respond only, however, to oil price moves. Overall, currency returns appear to follow more closely oil than world equity returns.

2. The Data

² For example, the subtitle of this article from a time period covered in this research summarizes this point: “Ties that bind oil and dollar snap: Traditionally, crude fell when greenback rose, but global influences have changed relationship (Berthelsen, The WSJ, March 7, 2012). In the academic press, it has become more common to report univariate and multivariate GARCH models across financial markets. Algieri (2014) does so for classes of GARCH models and also for diagonal BEKK parametrizations to find positive effects of S&P 500 on commodity returns and for negative effects of U.S./EURO on commodity returns. Another example is Creti et al. (2014), who apply a multivariate co-spectral analysis and, for this reason, develop measures of dependence by coherence function rather than the correlation function in the time domain.

³ Our sample contains the two most famous “safe-haven” currencies: CHF and JPY. Ranaldo and Soderling (2010) document that these currencies appreciate against the USD when U.S. stock prices decrease and U.S. bond prices and FX volatility increase. Habib and Stracca (2012) identify factors for currencies to be associated with this status based on the notion that if global risk aversion is high the value of portfolio of risky assets fall and the value of safe-haven currencies appreciates. Mollick and Assefa (2013) report, under monthly data from 1986 to 2009, strongly negative interest rate differentials for JPY (-2.78%) and CHF (-2.22%) relative to USD.

All data collected in this study are weekly data sourced from *Datastream* from January 1 1999 to July 1 2017.⁴ The data include 14 currency pairs: 8 for industrial countries (CHF, JPY, GBP, AUD, NZD, EUR, CAD, NOK) and 6 for emerging countries (KRW, INR, ZAR, BRL, RUB, MXN). Each currency pair consists of exchange rates quoted as one USD dollar expressed in units of local currency. The choice of the USD as reference follows from its relevance as major world currency. All major currencies of industrial currencies are included and representative currencies of emerging markets are included as well!

For the exchange rate an increase means USD appreciation. On interest rate differentials, we collect the overnight interest rates for all countries (and U.S.) and then calculate the average of overnight interest rates (weekly) over the period for all countries. The weekly return of FTSE all world index⁵ is used as the world stock market indices measured in each of the currencies examined. Also, we consider oil price per barrel, West Texas Intermediate (WTI) as the oil price in this study. The reasons for using the prices of the West Texas Intermediate (WTI) are two-fold. First, they are the most widely used indices in North America and all the currencies in this paper are expressed relative to the USD. Second, when firms use hedging instruments the vast majority use futures, forwards and other derivative contracts based on the WTI.

Panels A and B of Table 1 represent the descriptive statistics of FTSE in local currency returns, as well as currency and oil price returns, respectively. FTSE in Brazilian and Russian local currencies have the highest average weekly returns (0.17%), while FTSE in Switzerland local currency shows the lowest weekly returns. Moreover, the average weekly return for some

⁴ We also use the daily data in our analysis but we find that for some currencies (AUD, NZD, KRW, INR and BRL) there is serial correlation between error terms. By using weekly data we find that serial correlation is much less frequent and we prefer to focus on the weekly frequency sample.

⁵ The global stock index to capture the weekly return is the FTSE, all world index, which consists of 2,700 large and mid-cap stocks worldwide and has been used before by Katechos (2011).

industrial currencies is negative over the period. In contrast, the average weekly return is positive for emerging currencies (except KRW), indicating currency depreciation (USD strength). Among all currencies, BRL and RUB have the highest average weekly return with 0.001 for both, as well as high standard deviations (0.024 and 0.017) relative to mean returns.

[INSERT TABLE 1 ABOUT HERE]

Figure 1 presents the charts for the exchange rate in levels (graphs at left) and their calculated returns (graphs at right) for some industrial and emerging countries, respectively. Industrial currencies and all emerging currencies depreciate strongly against USD during the 2008-2009 financial crises. In returns, the figures show that all the currencies which depreciate against USD experienced most fluctuations during the financial crises period.

[INSERT FIGURE 1 ABOUT HERE]

Figure 2 presents the oil price and FTSE all world behavior over the period. The levels of WTI oil index show a slight downturn after the technology bubble, but a rapid rise and fall during the financial crisis. Oil price return in Table 1 is 0.0014 on average (with standard deviation of 0.053). For illustrative comparisons, the Euro has lower mean and standard deviation (zero and 0.0142, respectively), as well as FTSE returns in Euro currency (0.0006 and 0.024, respectively). Over the sample, oil has higher returns and more volatility than currency and equity markets. The global stock index to capture the weekly return is the FTSE, all world index, which consists of 2,700 large and mid-cap stocks worldwide and has been used before by Katechos (2011). FTSE all world dramatically fall and experience the highest volatility during 2008-2009. The methodology will assess the impact on currencies when another global factor (world equity returns) is taken into account. In late 2014 there is an oil price collapse (following OPEC decisions

not to change production) that places WTI oil in the \$ 40-50 range while stocks fluctuated strongly and end the sample period strongly on the upside worldwide.

[INSERT FIGURE 2 ABOUT HERE]

3. Empirical Methodologies

The first model used in this study is GARCH (1, 1) with exchange rates, stock, and WTI oil price series in (natural logarithm) returns. Return series are always stationary. This property bodes well for estimation purposes below. We then estimate at weekly frequency the relationship among exchange rate returns, global stock returns and oil price returns in the mean equation as follows:

$$RET_EX_t = b_0 + \sum_{i=1}^l L_{t-i} a_i RET_EX_{t-i} + b_1 RET_FTSE_t + b_2 RET_WTI_t + \varepsilon_t \quad (1)$$

$$h_t^2 = c + \alpha \varepsilon_{t-k}^2 + \beta h_{t-1}^2 + \lambda D \quad (2),$$

where: RET_EX_t is the weekly pair of currency returns, RET_FTSE_t is the all world stock returns in local currencies (to avoid currency value appearing in both sides of the equation) at time t and RET_WTI_t is WTI weekly returns. L_{t-i} is the coefficient capturing the lag of currency returns. ε_t is the error term which has zero mean and Eq. (2) presents its conditional variance. We include a dummy variable (D) for crisis which appears in the variance equation: D is equal to one if the observations are in crisis period (December 2007 to June 2009 as defined by NBER in the U.S.), and zero otherwise. It captures a period of major financial turmoil in the U.S. with obvious effects on many financial markets.

Under the null of $b_1 = 0$, global equity returns have no role in explaining mean returns of exchange rates. Following Kanas (2013, 2014) for analysis of U.S. stock returns, the a -terms in the mean equation are those necessary to achieve white noise processes, assuming a maximum lag-length of 6 weeks. In order to choose the proper number of lags for the mean equation we rely on statistical significance at the 10% level of the “ a ” terms, together with information criteria. If no lags of exchange rate returns are significant and absent oil price returns in the mean equation, we revert to the specification in Katchos (2011) with only stock returns in (RHS). We apply white noise tests to verify absence of serial correlation. LBSQ (5) and (20) stand for the Ljung-Box statistic of 5th and 20th order, respectively applied to the squared standardized residuals. If the p -value is significant, there is serial correlation in the errors, which casts doubt on the specification for inference. All statistical interpretation is based on semi-robust standard errors.

In addition, it is also possible that the correlation among the financial assets is time-varying, which is not captured by the models in (1) – (2). The second model used in this study is Dynamic Conditional Correlation (DCC) – GARCH developed by Engle (2002). The DCC-GARCH allows for the estimation of time-varying correlation coefficients of standardized residuals and hence controls for heteroskedasticity. The estimation results from the DCC-GARCH model enable us to track the conditional changes in correlations among the variables (currency returns, stock returns and oil price returns) even when the markets suffer large shocks during the period of study. The mean equations of bivariate DCC-GARCH in our study are as follows:⁶

$$RET_EX_t = a_0 + \sum_{i=1}^l L_{t-i} a_i RET_EX_{t-i} + b_1 RET_FTSE_{t-1} + \varepsilon_t$$

⁶ There is another bivariate equation linking oil to world equity markets, but the emphasis in this paper is on currency returns affected by the two global factors, which makes the focus on the two equations in (3).

$$RET_EX_t = a_0 + \sum_{i=1}^l L_{t-i} a_i RET_EX_{t-1} + b_2 RET_WTI_{t-1} + \varepsilon_t \quad (3),$$

where: RET_EX_t is weekly return of local currencies against US dollars, RET_WTI_{t-1} is WTI weekly return. L_{t-i} is the lag of dependent variable and ε_t is a error term with a conditional variance matrix.

$$H_t = D_t R_t D_t \quad (4),$$

where: D_t is the 2×2 diagonal matrix of time-varying standard deviation from univariate GARCH models with $\sqrt{h_{ii,t}}$ on the i th diagonal, $i=1$ and 2 ; R_t is the 2×2 time-varying correlation matrix.

Recent applications of this model include: Lehkonen and Heimonen (2014) for local and U.S. stock markets, Turhan et al. (2014) for oil and exchange rates, and Jain and Biswal (2016) for gold, crude oil and Indian currency and stock markets. Based on the DCC-GARCH model proposed by Engle (2002) we have a two stage estimation of the conditional covariance matrix. In the first stage we are looking for getting the standard deviations, $\sqrt{h_{ii,t}}$ ⁷. In the second stage of DCC model, the residuals of the first stage, ε_{it} , are transformed by $\sqrt{h_{ii,t}}$ as $u_{it} = \varepsilon_{it} / \sqrt{h_{ii,t}}$, which are used to estimate the parameters of the dynamic conditional correlation. Eq. (5) represents the correlation in DCC:

$$Q_t = (1-a-b)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \quad (5),$$

⁷ $h_{ii,t} = c_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} + \lambda D$, $i=1, 2$ for all countries. In order to address the effect of the financial crisis on our results and consequently control for structural breaks, we create a dummy variable for the 2008-2009 crisis and insert it in the variance equation.

where $Q_t = (q_{ij,t})$ is the $n \times n$ time varying covariance matrix of u_t , $\bar{Q} = E(u_t u_t')$ is the $n \times n$ unconditional variance matrix of u_t , and a and b are nonnegative scalar parameters satisfying $(a+b) < 1$. See Engle (2002) for details.

4. Results

4.1. GARCH (1, 1) Results

Table 2 presents the GARCH (1, 1) results for industrial countries. Panel A and B present the conditional mean and variance results, respectively and Panel C contains the misspecification tests of the model. As discussed in the methodology section, we choose the proper number of lags based on data dependent procedures yielding two lags for CAD, one for JPY and zero for other industrial countries. The coefficient of FTSE is positive and significant at 1% level for all industrial countries. It follows that increases in (local currency) FTSE returns lead to appreciation of USD.

When oil prices are included as another global factor, we find a negative and statistically significant relationship between oil price returns and exchange rate returns. This suggests that when oil price increases USD depreciates against local currencies. The most striking point about the magnitude of the coefficient is that its value is greater for the majority of commodity based (AUD, NZD, NOK, CAD) currencies than non-commodity (CHF, JPY, GBP and EUR) based currencies. NOK has the largest negative WTI coefficient at -0.09, statistically significant at 1%. Safe-haven currencies (CHF and JPY) have the smallest at -0.04, also statistically significant at 1%.

The crisis dummy in the variance equation is positive and statistically significant in all cases, indicating more volatility during the financial crisis. Also, α and β are significant for all industrial countries and the sum of α and β is less than one for all, which indicates that volatility shocks are persistent: CHF is a little less at 0.613. Also, Table 2 reports the results for Ljung-Box test of order 5 and 20 with no serial correlation at 5 or 20 weeks for all industrial currencies.

[INSERT TABLE 2 ABOUT HERE]

Table 3 reports the GARCH (1, 1) results for emerging countries. The FTSE coefficients for all except INR suggest that when the global stock market return goes up, local currencies depreciate against USD. Our most likely explanation for emerging markets is that occasional turbulences in currency increases global equity returns denominated in local currency, thus weakening the exchange rate: coefficients are 0.528 for ZAR and 0.498 for BRL. But, in general, the effect of FTSE as the global stock market indices on the local exchange returns of emerging currencies is not as clear as in industrial countries. Yet there is a negative and significant relationship between oil price and exchange returns of all emerging currencies, except for INR. Most significant are the oil coefficients for BRL (-0.092) and ZAR (-0.081), both statistically significant at the 1% level, along the lines of a strong commodity-currency link.

These results of the GARCH (1, 1) suggest that when oil price goes up in world markets USD depreciate against local currencies, controlling for equity markets. Yet, the equity-currency relationship is not present at all for 1 emerging market (INR) or is contrary to the expected sign for the other 5 emerging market currencies. In addition, the results for variance equation are satisfactory for all except for INR because the sum of α and β is slightly larger than one violating the stationary condition for that currency pair. On white noise tests, the p-values suggest there is

no serial correlation in the error terms, except for some currencies (KRW and RUB) for 5 lags but only at the 10% significance level.

[INSERT TABLE 3 ABOUT HERE]

4.2. DCC-GARCH Results

One possibility not captured in the models above is that the correlation among asset classes varies over time. Table 4 presents the bivariate DCC-GARCH results for industrial countries. Panels A and B present the conditional mean and variance results, respectively. Panel C reports the dynamic correlation and Panel D contains the misspecification tests of the model. Table 4A contains the bivariate DCC-GARCH results between currency and WTI returns. Based on these results, the time-varying correlation coefficient of standardized residuals between exchange rate and WTI in Panel C is significantly negative for all currencies except for JPY. These results are consistent with increases in oil price leading to USD depreciation and vice versa. More importantly, the time varying relation is stronger for commodity based currencies: CAD (-0.430), NOK (-0.335), NZD (-0.239), and all statistically significant at the 1% level, with CHF (-0.129) statistically significant at the 5% level. Dynamic correlation for GBP and EUR are negative, statistically significant, and broadly similar for these two currency pairs: -0.166 (GBP) and -0.185 (EUR).

In the variance equation, the crisis dummy is significantly positive for all currencies except for CHF, while α and β are significant for all currencies and the sum of α and β is close to one for all, which indicates that volatility shocks are very persistent. Also, all errors are white noise as confirmed by tests of panel D in Table 4A.

[INSERT TABLES 4A and 4B ABOUT HERE]

Table 4B contains the bivariate DCC-GARCH results between currency returns and global FTSE of industrial countries. There is a positive and significant time varying relationship between exchange rate and FTSE for all non-commodity based currencies: CHF (0.582), JPY (0.685), EUR (0.396) and GBP (0.309), all statistically significant at the 1% level. While the links appear to be stronger for the “safe-haven” currencies of CHF and JPY, if FTSE in local currencies goes up the USD appreciates against the local currencies of non-commodity based industrial currencies and vice versa. However, the time varying relationships between exchange rates and FTSE are not statistically significant for any of the commodity based currencies.

Table 5 presents the bivariate DCC-GARCH (1, 1) results for emerging countries. Based on the results of Table 5A, there is a negative and significant dynamic correlation in Panel C between local currency and WTI for all except for INR. Oil price increases lead to appreciation of these currencies against USD. These are consistent with our priors: increases in oil prices co-move with stronger local currencies that are commodity-based: ZAR, BRL, RUB and MXN, as well as KRW which is not a typical commodity currency. Table 5B displays the bivariate DCC-GARCH results between currency returns and global FTSE for emerging countries. The dynamic relationship between local currency and FTSE is positive and significant only for ZAR (0.607). The difference with GARCH (1, 1) results is that the MXN, BRL, RUB and KRW coefficients are not statistically significant in dynamic correlations with stock returns. The results again indicate that the time varying relationships between exchange rates and FTSE are not statistically significant for any of the commodity based currencies except ZAR.

[INSERT TABLES 5A and 5B ABOUT HERE]

In Figures 3 and 4, we graph the dynamic conditional correlations of the models estimated in Tables 4 and 5 for industrial and emerging countries, respectively. For industrial currencies the time-varying correlations between currency and WTI returns is consistently negative over the period, especially for the four “commodity currencies” of AUD, CAD, NOK and NZD.⁸ It is clear that in the commodity currencies there is a movement downward in the dynamic correlations around the financial crisis in 2008, only reverting back for AUD and NZD. During the financial crisis the USD strengthens against other currencies but also the price of oil falls with soft world demand. For these four currencies, the dynamic correlations therefore become more significantly negative. The movement to the downside in the dynamic correlations is also present in four emerging markets: BRL, KRW, RUB, ZAR, although reverting back for BRL and ZAR, which was also displayed for some commodity currencies of industrial countries (AUD and NZD).

The time-varying correlations between currency of industrial countries and FTSE returns appear steadier over time. In particular, the safe-haven currencies of Swiss Franc and Japanese Yen remain highly correlated with global equity returns with dynamic correlations of 0.582 and 0.685, respectively. As global equities improve, risk tolerance increases and these safe-haven currencies depreciate against the U.S. dollar. Currencies that pay close to the USD, such as GBP and EUR, also have positive dynamic correlations of around 0.30 to 0.40 but no such significant correlations are found for the commodity currencies which respond to oil prices. For emerging markets, there is a movement towards more correlation to the upside between FTSE and emerging currencies. For ZAR, in particular, we report dynamic correlations varying from -0.4 to up to 0.8.

[INSERT FIGURES 3 AND 4ABOUT HERE]

⁸ This is much less so for EUR and GBP (currencies that pay roughly the same as USD over the period) and close to zero or even positive for the safe-haven currencies of JPY and CHF.

5. Concluding Remarks

This paper examines the fact that when equities move up worldwide, this may increase risk taking and lead to carry-trade activities: borrowing at lower interest rates and lending at higher interest rates. This could increase demand for higher interest rate currencies against USD. We extend the proposition by Katechos (2011) with only one global factor (world stock returns) as determinant of currency movements in several directions. First, oil price returns (another global financial indicator) support a currency-commodity link with commodity currencies strengthening with higher oil prices. This is very clear for CAD, NOK, NZD and AUD in industrial currencies and for BRL, KRW, ZAR, RUB and MXN in emerging markets. Second, emerging market currencies provide an interesting contrast to major currencies of the world. In the DCC-GARCH estimations reported herein, the time-varying coefficients between currency and global equity returns are weaker for all commodity currencies of industrial countries and almost all emerging market currencies. This does not bode well for the increase in risk tolerance leading to higher demand for high-paying currencies. Overall, the results in this paper cast doubt on interest rate differentials as the driving force of currency movements and are consistent with another type of global factors (oil price movements) providing a more accurate explanation of currency movements.

In recent years expansionary monetary policies have been conducted by major central banks of the world. Recent studies have addressed some of these channels. Huang et al. (2016) look at the effects of real interest rates on major U.S. stock markets, controlling for WTI oil prices and the value of the USD against major currencies, while Wan and Kao (2015) emphasize threshold effects among financial assets, such as: real interest rates, currency and oil. Further work

may shed light on how these factors (particularly very low or negative real interest rates) impact currency and other global markets.

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Fig.1. Exchange rates of some industrial and emerging countries.

Notes: Weekly data from January 1999 to July 2017. Actual (graphs at left) and calculated returns (graphs at right).

Fig. 2. Oil price in U.S. dollars (WTI) and FTSE (WORLD).

Notes: Weekly data from January 1999 to July 2017. Actual (graphs at left) and calculated returns (graphs at right).

Fig. 3. Mean level shifts in the dynamic correlations estimated by DCC GARCH between exchange rates (local currencies against USD), FTSE (in local currencies) of industrial countries and WTI (in USD).

Fig.4. Mean level shifts in the dynamic correlations estimated by DCC GARCH between exchange rates (local currencies against USD), FTSE (in local currencies) of emerging countries and WTI (in USD).

Table 1 - Descriptive statistics of sample**A. FTSE**

	N	Mean	Median	Min	Max	Std	Skewness	Kurtosis
FTSE_AUD	965	0.0004	0.0014	-0.075	0.066	0.019	-0.147	3.517
FTSE_NZD	965	0.0003	0.0015	-0.104	0.072	0.022	-0.274	3.843
FTSE_CHF	965	0.0002	0.0022	-0.233	0.115	0.028	-1.035	11.092
FTSE_GBP	965	0.0009	0.0022	-0.182	0.094	0.023	-0.752	8.113
FTSE_JPY	965	0.0006	0.0028	-0.283	0.155	0.031	-1.229	13.149
FTSE_EUR	965	0.0006	0.0024	-0.202	0.105	0.024	-0.756	8.836
FTSE_CAD	965	0.0004	0.0017	-0.133	0.083	0.020	-0.546	6.226
FTSE_NOK	965	0.0007	0.0024	-0.183	0.101	0.023	-0.539	8.289
FTSE_MXN	965	0.0012	0.0016	-0.102	0.120	0.020	-0.021	6.091
FTSE_KRW	965	0.0006	0.0014	-0.158	0.098	0.020	-0.615	8.477
FTSE_INR	965	0.0010	0.0019	-0.196	0.116	0.022	-0.904	11.765
FTSE_ZAR	965	0.0014	0.0023	-0.120	0.111	0.024	0.117	5.350
FTSE_RUB	965	0.0017	0.0026	-0.214	0.128	0.024	-0.482	11.498
FTSE_BRL	965	0.0017	0.0010	-0.133	0.225	0.025	1.008	13.903
FTSE_WORLD	965	0.0006	0.0026	-0.224	0.115	0.024	-1.183	13.006

B. Currency & Oil

	N	Mean	Median	Min	Max	Std	Skewness	Kurtosis
CHF	965	-0.0004	-0.0002	-0.173	0.121	0.016	-0.925	20.125
JPY	965	0.0000	0.0003	-0.085	0.054	0.015	-0.344	4.632
GBP	965	0.0003	-0.0002	-0.053	0.087	0.013	0.704	7.239
AUD	965	-0.0002	-0.0013	-0.070	0.178	0.018	1.543	15.501
NZD	965	-0.0003	-0.0017	-0.067	0.120	0.019	0.835	6.720
EUR	965	0.0000	-0.0003	-0.053	0.056	0.014	0.195	3.706
CAD	965	-0.0002	-0.0006	-0.046	0.091	0.012	0.802	8.298
NOK	965	0.0001	-0.0009	-0.070	0.064	0.016	0.334	3.844
KRW	965	-0.0001	-0.0005	-0.098	0.070	0.013	-0.027	10.790
INR	965	0.0004	0.0000	-0.047	0.045	0.008	0.259	7.511
ZAR	965	0.0008	-0.0004	-0.113	0.113	0.023	0.579	5.714
BRL	965	0.0010	-0.0008	-0.113	0.198	0.024	1.652	14.832
RUB	965	0.0010	0.0001	-0.087	0.111	0.017	1.243	12.745
MXN	965	0.0006	-0.0003	-0.060	0.158	0.016	1.600	17.307
WTI	965	0.0014	0.0045	-0.312	0.359	0.053	-0.338	7.611

Notes: Weekly data from January 1999 to July 2017.

Table 2 - GARCH results for industrial countries

	CHF	JPY	GBP	AUD	NZD	EUR	CAD	NOK
Panel A: Conditional mean								
a1	-	-0.007	-	-	-	-	-0.007	-
	-	(0.025)	-	-	-	-	(0.033)	-
a2	-	-	-	-	-	-	-0.068**	-
	-	-	-	-	-	-	(0.033)	-
FTSE	0.352***	0.340***	0.180***	0.253***	0.352***	0.252***	0.042*	0.283***
	(0.032)	(0.017)	(0.020)	(0.030)	(0.030)	(0.020)	(0.022)	(0.023)
WTI	-0.040***	-0.040***	-0.042***	-0.077***	-0.068***	-0.049***	-0.065***	-0.090***
	(0.013)	(0.007)	(0.008)	(0.012)	(0.013)	(0.009)	(0.008)	(0.010)
Panel B: Conditional variance								
D	0.897**	0.874**	1.024**	1.192**	1.325**	1.406**	1.594***	1.103***
	(0.357)	(0.438)	(0.483)	(0.589)	(0.557)	(0.583)	(0.427)	(0.385)
α	0.189	0.076***	0.081***	0.147***	0.118***	0.070***	0.100***	0.064***
	(0.160)	(0.020)	(0.020)	(0.046)	(0.043)	(0.022)	(0.031)	(0.022)
β	0.613***	0.881***	0.876***	0.776***	0.758***	0.902***	0.818***	0.867***
	(0.234)	(0.026)	(0.034)	(0.050)	(0.080)	(0.031)	(0.058)	(0.054)
$\alpha + \beta$	0.613	0.957	0.957	0.923	0.876	0.972	0.918	0.931
Panel C: Misspecification tests								
N	965	964	965	965	965	965	963	965
LBSQ (5)	2.6366	1.2173	4.6892	4.2918	2.0779	4.5298	2.1231	5.4842
	[0.7558]	[0.9432]	[0.455]	[0.5082]	[0.8383]	[0.4759]	[0.8319]	[0.3597]
LBS(20)	17.117	14.2361	16.8676	26.2996	13.8749	12.9316	27.0833	16.263
	[0.6454]	[0.8183]	[0.6616]	[0.1561]	[0.8368]	[0.8803]	[0.1361]	[0.7002]

Notes: Weekly data from January 1999 to July 2017. D is a dummy variable which is equal to one if the observations are in crisis period (December 2007 to June 2009 as defined by NBER in the U.S.), and zero otherwise. LBSQ (5) and LBSQ (20) are Ljung – Box Q –statistics on the residuals. Standard errors in parentheses and p-values in square brackets. *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Table 3 - GARCH results for emerging countries

	KRW	INR	ZAR	BRL	RUB	MXN
Panel A: Conditional mean						
a1	-	0.113***	-	-	0.059	-
	-	(0.039)	-	-	(0.040)	-
a2	-	0.116***	-	-	0.103**	-
	-	(0.042)	-	-	(0.043)	-
a3	-	-0.015	-	-	0.139***	-
	-	(0.036)	-	-	(0.050)	-
a4	-	-0.006	-	-	-	-
	-	(0.041)	-	-	-	-
a5	-	0.043	-	-	-	-
	-	(0.036)	-	-	-	-
FTSE	0.060***	-0.004	0.528***	0.498***	0.016*	0.128***
	(0.022)	(0.007)	(0.039)	(0.066)	(0.009)	(0.032)
WTI	-0.038***	0.000	-0.081***	-0.092***	-0.012**	-0.049***
	(0.008)	(0.003)	(0.017)	(0.016)	(0.005)	(0.012)
Panel B: Conditional variance						
D	1.566***	2.440***	1.389***	1.040**	3.837***	2.049**
	(0.437)	(0.776)	(0.462)	(0.453)	(1.111)	(0.980)
α	0.149***	0.135***	0.076***	0.122***	0.141*	0.060*
	(0.038)	(0.042)	(0.027)	(0.033)	(0.081)	(0.031)
β	0.764***	0.867***	0.825***	0.786***	0.874***	0.910***
	(0.055)	(0.036)	(0.052)	(0.051)	(0.060)	(0.045)
$\alpha + \beta$	0.913	1.002	0.901	0.908	1.015	0.910
Panel C: Misspecification tests						
N	965	960	965	965	962	965
LBSQ (5)	10.1369	3.748	4.6791	5.8865	9.6791	2.0338
	[0.0714]	[0.5862]	[0.4563]	[0.3174]	[0.0849]	[0.8444]
LBS(20)	28.2667	16.1821	20.1665	26.589	19.981	19.6394
	[0.1032]	[0.7053]	[0.4476]	[0.1472]	[0.4591]	[0.4807]

Notes: Weekly data from January 1999 to July 2017. D is a dummy variable which is equal to one if the observations are in crisis period (December 2007 to June 2009 as defined by NBER in the U.S.), and zero otherwise. LBSQ (5) and LBSQ (20) are Ljung – Box Q –statistics on the residuals. Standard errors in parentheses and p-values in square brackets. *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Table 4A - Bivariate DCC - GARCH results for industrial countries (EX & WTI)

	CHF	WTI	JPY	WTI	GBP	WTI	AUD	WTI
Panel A: Conditional mean								
a1	0.00625 (0.0202)	0.144 (0.105)	- -	- -	- -	- -	0.000268 (0.0105)	-0.0898 (0.101)
a2	- -	- -	- -	- -	-0.00832 (0.00802)	0.0538 (0.149)	- -	- -
a3	- -	- -	-0.0138 (0.00853)	-0.0325 (0.116)	- -	- -	- -	- -
a4	- -	- -	- -	- -	- -	- -	- -	- -
Panel B: Conditional variance								
D	0.440 (0.292)	0.695 (0.494)	0.891** (0.360)	0.660 (0.445)	0.895* (0.492)	0.530 (0.440)	0.920* (0.480)	0.391 (0.463)
α	0.257 (0.218)	0.0892*** (0.0220)	0.0637** (0.0255)	0.0861*** (0.0216)	0.0761*** (0.0203)	0.0937*** (0.0235)	0.120*** (0.0366)	0.0992*** (0.0248)
β	0.531* (0.289)	0.870*** (0.0328)	0.855*** (0.0535)	0.867*** (0.0340)	0.887*** (0.0295)	0.858*** (0.0373)	0.801*** (0.0449)	0.851*** (0.0393)
$\alpha + \beta$	0.531	0.959	0.918	0.953	0.963	0.951	0.921	0.95
Panel C: Dynamic Correlations								
EX & WTI	-0.129** (0.0537)		-0.0163 (0.0530)		-0.166*** (0.0407)		-0.374*** (0.135)	
Panel D: Misspecification tests								
N	964	964	962	962	963	963	964	964
LBSQ (5)	4.6945 [0.4543]	3.497 [0.6238]	1.7364 [0.8843]	2.5547 [0.7682]	4.49 [0.4812]	2.6372 [0.7557]	1.1721 [0.9475]	3.2545 [0.6608]
LBS(20)	22.8379 [0.2968]	22.5648 [0.3107]	19.7818 [0.4717]	22.4052 [0.3189]	14.4065 [0.8093]	18.8282 [0.533]	22.5549 [0.3112]	22.0517 [0.3377]

Table 4A (Continued)

	NZD	WTI	EUR	WTI	CAD	WTI	NOK	WTI
Panel A: Conditional mean								
a1	-	-	-0.00807	-0.00358	-0.00986	-0.153	-0.0155	-0.00804
	-	-	(0.00966)	(0.133)	(0.00689)	(0.147)	(0.00996)	(0.103)
a2	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
a3	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
a4	0.0114	-0.0133	-	-	-	-	-	-
	(0.0112)	(0.0889)	-	-	-	-	-	-
Panel B: Conditional variance								
D	0.977**	0.557	0.643***	0.536	1.619***	0.588	0.631**	0.0939***
	(0.419)	(0.444)	(0.0880)	(0.467)	(0.416)	(0.457)	(0.309)	(0.0226)
α	0.0714***	0.0904***	0.00477	0.0944***	0.0952***	0.0996***	0.0478***	0.864***
	(0.0258)	(0.0233)	(0.00829)	(0.0238)	(0.0240)	(0.0264)	(0.0137)	(0.0347)
β	0.822***	0.858***	0.962***	0.859***	0.853***	0.853***	0.896***	0.463
	(0.0520)	(0.0391)	(0.0168)	(0.0372)	(0.0366)	(0.0402)	(0.0326)	(0.464)
$\alpha + \beta$	0.893	0.948	0.962	0.953	0.948	0.952	0.943	0.864
Panel C: Dynamic Correlations								
EX & WTI	-0.239***		-0.185***		-0.430***		-0.335***	
	(0.293)		(0.0533)		(0.0926)		(0.0558)	
Panel D: Misspecification tests								
N	961	961	964	964	964	964	964	964
LBSQ (5)	1.3129	4.3509	3.7761	3.4659	3.9797	3.4507	2.3937	3.385
	[0.9336]	[0.5001]	[0.5821]	[0.6286]	[0.5523]	[0.6309]	[0.7924]	[0.6409]
LBS(20)	13.8047	24.9344	22.5229	22.4355	23.755	22.0206	17.1255	22.3375
	[0.8403]	[0.204]	[0.3128]	[0.3174]	[0.3241]	[0.3394]	[0.6448]	[0.3225]

Notes: Weekly data from January 1999 to July 2017. For all countries the mean equation (for currency returns) is $RET_EX_t = a_0 + \sum_{i=1}^L L_{t-i} a_i RET_EX_{t-1} + b_2 RET_WTI_{t-1} + \varepsilon_t$ and the variance equation is $h_{iit} = c_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{iit-1} + \lambda$ crisis dummy, $i=1, 2$. Another mean equation reported to its right has RET_WTI as dependent variable with similar autoregressive structure. Reported in each column of Panel A as L_{t-i} is the coefficient of the lag of dependent variable. D is a dummy variable which is equal to one if the observations are in crisis period (December 2007 to June 2009 as defined by NBER in the U.S.), and zero otherwise. LBSQ (5) and LBSQ (20) are Ljung – Box Q –statistics on the residuals. Standard errors in parentheses and p-values in square brackets. *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Table 4B - Bivariate DCC - GARCH results for industrial countries (EX & FTSE)

	CHF	FTSE	JPY	FTSE	GBP	FTSE	AUD	FTSE
Panel A: Conditional mean								
a1	-0.0465** (0.0211)	-0.107* (0.0622)	-0.0437** (0.0205)	0.0286 (0.0690)	-0.0244 (0.0196)	0.0691 (0.0576)	-0.0541* (0.0276)	0.0241 (0.0326)
a2	- -	- -	- -	- -	- -	- -	- -	- -
Panel B: Conditional variance								
D	0.507** (0.254)	1.290*** (0.271)	1.153*** (0.377)	1.791*** (0.486)	1.237** (0.503)	1.615*** (0.549)	1.278** (0.571)	0.948*** (0.289)
α	0.000169 (0.00203)	0.244*** (0.0743)	0.0847*** (0.0218)	0.103*** (0.0374)	0.0687*** (0.0197)	0.120** (0.0573)	0.123*** (0.0368)	0.104*** (0.0311)
β	0.982*** (0.0169)	0.6583** (0.0254)	0.857*** (0.0317)	0.833*** (0.0636)	0.894*** (0.0315)	0.821*** (0.0835)	0.796*** (0.0496)	0.821*** (0.0533)
$\alpha + \beta$	0.982	0.902	0.941	0.936	0.962	0.941	0.919	0.925
Panel C: Dynamic Correlations								
EX & FTSE	0.582*** (0.0640)		0.685*** (0.0722)		0.309*** (0.0772)		0.390 (0.339)	
Panel D: Misspecification tests								
N	964	964	964	964	963	963	964	964
LBSQ (5)	9.504 [0.1906]	5.2897 [0.3816]	0.7398 [0.9807]	2.6949 [0.7469]	3.8949 [0.5647]	6.2216 [0.2853]	0.9808 [0.9641]	1.3003 [0.9349]
LBS(20)	28.9826 [0.8881]	16.5523 [0.6818]	18.5946 [0.5483]	17.042 [0.6502]	13.2565 [0.8661]	16.3399 [0.6953]	24.0114 [0.2419]	17.6002 [0.6137]

Table 4B (Continued)

	NZD	FTSE	EUR	FTSE	CAD	FTSE	NOK	FTSE
Panel A: Conditional mean								
a1	-0.0637** (0.0279)	0.0560 (0.0357)	-0.0358* (0.0192)	-0.00561 (0.0572)	-0.0543*** (0.0153)	-0.0485 (0.0457)	-0.0384 (0.0235)	-0.0410 (0.0433)
a2	- -	- -	- -	- -	- -	- -	-0.0242 (0.0244)	0.0699 (0.0443)
Panel B: Conditional variance								
D	1.214*** (0.455)	1.016*** (0.312)	0.649*** (0.0800)	1.694*** (0.622)	1.859*** (0.507)	1.324*** (0.444)	1.009*** (0.377)	1.605** (0.644)
α	0.0925*** (0.0295)	0.0862* (0.0486)	0.00303 (0.00731)	0.119*** (0.0352)	0.109*** (0.0320)	0.0789*** (0.0236)	0.0566*** (0.0183)	0.0706*** (0.0225)
β	0.790*** (0.0582)	0.814*** (0.139)	0.965*** (0.0194)	0.823*** (0.0501)	0.841*** (0.0477)	0.864*** (0.0359)	0.891*** (0.0445)	0.888*** (0.0382)
$\alpha + \beta$	0.882	0.9	0.965	0.942	0.95	0.942	0.947	0.958
Panel C: Dynamic Correlations								
EX & FTSE	0.473 (0.328)		0.396*** (0.0687)		0.0832 (0.354)		0.379 (0.205)	
Panel D: Misspecification tests								
N	964	964	964	964	964	964	963	963
LBSQ (5)	1.5223 [0.9105]	0.9513 [0.9664]	3.6088 [0.607]	4.4901 [0.4812]	4.4254 [0.4899]	3.8432 [0.5722]	2.415 [0.7892]	1.8407 [0.8707]
LBS(20)	13.9414 [0.8335]	10.767 [0.952]	21.4908 [0.3688]	18.5227 [0.553]	33.8603 [0.1271]	18.8673 [0.5305]	17.0078 [0.6525]	13.0862 [0.8737]

Notes: Weekly data from January 1999 to July 2017. For all countries the mean equation (for currency returns) is $RET_EX_t = a_0 + \sum_{i=1}^L L_{t-i} a_i RET_EX_{t-1} + b_2 RET_WTI_{t-1} + \varepsilon_t$ and the variance equation is $h_{iit} = c_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{iit-1} + \lambda$ crisis dummy, $i=1, 2$. Another mean equation reported to its right has RET_WTI as dependent variable with similar autoregressive structure. Reported in each column of Panel A as L_{t-i} is the coefficient of the lag of dependent variable. D is a dummy variable which is equal to one if the observations are in crisis period (December 2007 to June 2009 as defined by NBER in the U.S.), and zero otherwise. LBSQ (5) and LBSQ (20) are Ljung – Box Q –statistics on the residuals. Standard errors in parentheses and p-values in square brackets. *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Table 5A - Bivariate DCC - GARCH results for emerging countries (EX & WTI)

	KRW	WTI	INR	WTI	ZAR	WTI	BRL	WTI	RUB	WTI	MXN	WTI
Panel A: Conditional mean												
a1	0.00372 (0.00641)	-0.0957 (0.153)	0.000722 (0.00276)	0.133 (0.148)	-0.0120 (0.0150)	-0.0485 (0.0713)	-0.0122 (0.0122)	0.0305 (0.0784)	-0.0344** (0.0143)	-0.0149 (0.109)	-0.00286 (0.00943)	0.104 (0.115)
a2	- -	- -	0.000508 (0.00231)	-0.0170 (0.165)	2.45e-05 (0.0138)	-0.00214 (0.0780)	-0.00212 (0.0124)	-0.204*** (0.0685)	0.0118 (0.0134)	-0.210** (0.0990)	- -	- -
a3	- -	- -	0.00286 (0.00235)	-0.221 (0.138)	-0.0273** (0.0139)	-0.0356 (0.0707)	- -	- -	-0.0324*** (0.0125)	-0.0496 (0.108)	- -	- -
a4	- -	- -	0.00319 (0.00299)	0.150 (0.147)	0.00748 (0.0136)	-0.0302 (0.0666)	- -	- -	- -	- -	- -	- -
a5	- -	- -	- -	- -	-0.0184 (0.0141)	0.0314 (0.0748)	- -	- -	- -	- -	- -	- -
Panel B: Conditional variance												
D	1.590*** (0.452)	0.705* (0.420)	2.456*** (0.797)	0.709 (0.455)	1.007** (0.497)	0.646 (0.442)	0.533 (0.498)	0.478 (0.407)	0.401** (0.186)	0.703 (0.447)	1.929* (1.139)	0.665 (0.447)
α	0.149*** (0.0369)	0.0869*** (0.0235)	0.142*** (0.0429)	0.0909*** (0.0227)	0.119*** (0.0329)	0.0975*** (0.0244)	0.199*** (0.0425)	0.104*** (0.0280)	0.0125 (0.00819)	0.0864*** (0.0235)	0.0820** (0.0340)	0.0907*** (0.0218)
β	0.772*** (0.0541)	0.862*** (0.0392)	0.863*** (0.0351)	0.863*** (0.0359)	0.858*** (0.0325)	0.855*** (0.0352)	0.762*** (0.0386)	0.840*** (0.0440)	0.897*** (0.179)	0.867*** (0.0358)	0.891*** (0.0353)	0.865*** (0.0328)
$\alpha + \beta$	0.921	0.948	1.005	0.953	0.977	0.952	0.961	0.944	0.897	0.953	0.973	0.955
Panel C: Dynamic Correlations												
EX & WTI	-0.287*** (0.0721)		-0.177 (0.182)		-0.275** (0.121)		-0.372* (0.232)		-0.387*** (0.0656)		-0.233*** (0.0570)	
Panel D: Misspecification tests												
N	964	964	961	961	960	960	963	963	962	962	964	964
LBSQ (5)	4.8785 [0.4309]	3.3069 [0.6528]	6.4582 [0.2641]	1.5837 [0.9032]	4.9601 [0.4208]	1.9702 [0.8533]	3.8773 [0.5672]	1.9783 [0.8521]	16.0439 [0.0067]	1.1349 [0.951]	3.1837 [0.6717]	3.6176 [0.6057]
LBS(20)	20.2466 [0.4426]	22.8027 [0.2986]	19.7399 [0.4743]	18.6785 [0.5428]	20.2772 [0.4407]	19.838 [0.4681]	26.684 [0.1444]	16.035 [0.7144]	19.104 [0.6522]	16.009 [0.716]	18.0458 [0.5844]	22.8628 [0.2956]

Notes: Weekly data from January 1999 to July 2017. For all countries the mean equation (for currency returns) is $RET_EX_t = a_0 + \sum_{i=1}^L L_{t-i} a_i RET_EX_{t-1} + b_2 RET_WTI_{t-1} + \varepsilon_t$ and the variance equation is $h_{i,t} = c_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \lambda$ crisis dummy, $i=1, 2$. Another mean equation reported to its right has RET_WTI as dependent variable with similar autoregressive structure. Reported in each column of Panel A as L_{t-i} is the coefficient of the lag of dependent variable. D is a dummy variable which is equal to one if the observations are in crisis period (December 2007 to June 2009 as defined by NBER in the U.S.), and zero otherwise. LBSQ (5) and LBSQ (20) are Ljung – Box Q – statistics on the residuals. Standard errors in parentheses and p-values in square brackets. *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Table 5B - Bivariate DCC - GARCH results for emerging countries (EX & FTSE)

	KRW	FTSE	INR	FTSE	ZAR	FTSE	BRL	FTSE	RUB	FTSE	MXN	FTSE
Panel A: Conditional mean												
a1	-0.0475*** (0.0165)	0.0777 (0.0480)	-0.00250 (0.00688)	0.162** (0.0660)	0.0159 (0.0412)	-0.0346 (0.0383)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)	-0.0205 (0.0263)	-0.0529 (0.0365)
a2	- (0.0378)	- (0.0450)	-0.0111 (0.00787)	0.0896 (0.0624)	- (0.0378)	- (0.0450)	-0.0154 (0.0378)	0.0561 (0.0450)	-0.0154 (0.0378)	0.0561 (0.0450)	- (0.0378)	- (0.0450)
a3	- (0.0378)	- (0.0450)	0.00240 (0.00625)	-0.00595 (0.0693)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)
a4	- (0.0378)	- (0.0450)	0.00128 (0.00710)	-0.0107 (0.0608)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)
a5	- (0.0378)	- (0.0450)	0.00200 (0.00607)	0.00964 (0.0667)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)	- (0.0378)	- (0.0450)
Panel B: Conditional variance												
D	1.592*** (0.470)	1.735*** (0.565)	2.521*** (0.781)	1.623*** (0.475)	1.244*** (0.470)	1.031** (0.481)	0.656 (0.527)	0.848* (0.489)	0.656 (0.527)	0.848* (0.489)	1.920* (1.079)	1.392*** (0.483)
α	0.150*** (0.0379)	0.0733* (0.0394)	0.135*** (0.0414)	0.125** (0.0537)	0.0850*** (0.0234)	0.109*** (0.0352)	0.154*** (0.0310)	0.142*** (0.0496)	0.154*** (0.0310)	0.142*** (0.0496)	0.0818** (0.0327)	0.0882*** (0.0265)
β	0.774*** (0.0536)	0.877*** (0.0666)	0.868*** (0.0354)	0.806*** (0.0739)	0.870*** (0.0372)	0.838*** (0.0458)	0.782*** (0.0354)	0.710*** (0.0963)	0.782*** (0.0354)	0.710*** (0.0963)	0.886*** (0.0367)	0.884*** (0.0305)
$\alpha + \beta$	0.924	0.95	1.003	0.931	0.955	0.947	0.936	0.852	0.936	0.852	0.967	0.972
Panel C: Dynamic Correlations												
EX & FTSE	0.136 (0.131)		0.00743 (0.145)		0.607*** (0.196)		0.511 (0.332)		0.511 (0.332)		1.188 (2.420)	
Panel D: Misspecification tests												
N	964	964	960	960	964	964	963	963	963	963	964	964
LBSQ (5)	3.5019 [0.6231]	1.1438 [0.9502]	3.1598 [0.6754]	1.5919 [0.9022]	6.9272 [0.2261]	5.9344 [0.3127]	5.9364 [0.3125]	7.3938 [0.193]	5.9364 [0.3125]	7.3938 [0.193]	2.158 [0.8269]	1.5836 [0.9032]
LBS(20)	17.2036 [0.6397]	7.7356 [0.9935]	16.2136 [0.7033]	14.8393 [0.7855]	21.8324 [0.3497]	19.7798 [0.4718]	28.518 [0.0977]	20.337 [0.437]	21.518 [0.1977]	20.337 [0.437]	17.2163 [0.6389]	19.1819 [0.51]

Notes: Weekly data from January 1999 to July 2017. For all countries the mean equation (for currency returns) is $RET_EX_t = a_0 + \sum_{i=1}^L L_{t-i} a_i RET_EX_{t-1} + b_1 RET_FTSE_{t-1} + \varepsilon_t$ and the variance equation is $h_{it,t} = c_i + \alpha_i \varepsilon_{it,t-1}^2 + \beta_i h_{it,t-1} + \lambda$ crisis dummy, $i=1, 2$. Another mean equation reported to its right has RET_FTSE in local currency of each country as dependent variable with similar autoregressive structure. Reported in each column of Panel A as L_{t-i} is the coefficient of the lag of dependent variable. D is a dummy variable which is equal to one if the observations are in crisis period (December 2007 to June 2009 as defined by NBER in the U.S.), and zero otherwise. LBSQ (5) and LBSQ (20) are Ljung – Box Q – statistics on the residuals. Standard errors in parentheses and p-values in square brackets. *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.