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Wavering Interactions between Commodity Futures Prices and USD Exchange Rates

Submitted by

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Doctor of Business Administration in Finance

Doctoral Dissertation Paper

Wavering Interactions between Commodity Futures Prices and US Dollar Exchange Rates

Monika Sywak
(Sacred Heart University)

Abstract:

This paper examines the intricate impact of commodity futures prices on US dollar exchange rates. The daily data on returns on futures and on USD are tested with Bayesian VAR, multiple breakpoint regression and two-state Markov switching. The tested commodity futures include West Texas Intermediate and Brent crude oil, as well as copper and gold. The tests imply that changes in commodity returns inversely affect USD exchange rates. This relationship is not uniform across the tested commodity futures and is affected by market risk. The relationships between crude oil futures prices and USD exchange rates are normally negative but they become positive at stressful market conditions. The relationships between copper prices and USD exchange rates are inverse at normal market periods; they turn positive at times of financial distress. The relationships between returns on gold futures and on USD are very unstable.

Keywords: commodity prices; exchange rates; multiple breakpoint regression; USD exchange rates.

JEL Classification: C58, F31, G13.

April 2017

Dissertation Mentor: Lucjan T. Orlowski, Ph. D.
I. Introduction

Our study examines the interplay between returns on selected commodities and the US dollar (USD) exchange rates. Our initial hypothesis is that shocks in commodity futures settlement prices inversely affect the values of USD in foreign currencies. In other words, rising commodity futures prices result in USD depreciation and declining prices in USD appreciation. Based on key findings in the prior literature, we assume that the impact of commodity futures prices on the exchange rate varies significantly in time. This causal impact is particularly sensitive to financial market risk conditions. Specifically, at normal market periods the USD depreciation is associated with rising commodity prices, while at times of financial distress, i.e. under high market risk conditions, the USD appreciation corresponds with higher commodity futures prices.

We focus our analysis on two crude oil and two metal one-month futures settlement prices that have been widely discussed in the literature as more or less significantly related to exchange rate movements. Specifically, the commodities included in our exercise are: West Texas Intermediate (WTI) and Brent crude oil, copper and gold. The returns on commodity futures are expressed as changes in logs of their settlement prices. The returns on USD are expressed by two measures: as changes in logs of USD value in euro (EUR) and USD Trade Weighted exchange rates (TWEX). We test causal interactions and impulse responses between commodity futures prices and exchange rates. We employ linear multiple breakpoint regression to examine their changes over time. We assume that returns on crude oil futures and the exchange rates are very sensitive to market risk conditions. Our underlying assumption is that at normal, low market risk periods the two pairs of returns display an inverse relationships, while at turbulent times their relationship becomes positive. As suggested by several recent studies (Lizardo/Mollick, 2010; Ding/Vo, 2012; Reboredo, 2012), these relationships hold well for all examined commodity spot
and futures prices in relation to USD in EUR and TWEX, albeit mainly in the aftermath of the recent financial crisis, i.e. in the presence of massive liquidity injections to financial markets.

In line with several prior studies we assume that there is a prevalent causal impact of changes in commodity prices on the USD exchange rate (Lizardo/Mollick, 2010; Ding/Vo, 2012; Fratzscher, et al., 2014).

We begin with a survey of pertinent literature in Section II. In Section III we analyze bivariate causal relationships between returns on commodity futures prices and on USD exchange rates by testing them with Bayesian vector autoregression (BVAR) with impulse response functions. In Section IV we devise an underlying analytical model and test it empirically with Bai-Perron multiple breakpoint (MBP) regressions. MBP enables us to identify discernible phases in the changeable relationships between commodity futures and the exchange rates. In Section V we check robustness of these tests and gain insights on their time varying patterns by estimating Two-State Markov Switching Models (MSM). The concluding Section VI contains a summary of our key findings.

II. Survey of Pertinent Literature

The literature examining the relationships between commodity spot as well as futures prices and USD exchange rates is extensive and it seems to follow two research streams. The first of them is consistent with our analytical assumptions and empirical findings assuming a causal impact of changes in commodity prices on the exchange rate. The second stream follows reversed causal effects, assuming a prevalent impact of changes in the USD exchange rate on commodity prices.

The causal effects of changes in commodity prices on exchange rates are evidenced among others by Lizardo/Mollick (2010). They show that crude oil prices significantly and continuously
explain changes in the USD exchange rate. Reboredo (2012), Ding/Vo (2012) and Chiang, et al. (2014) expand this analysis by demonstrating that such causal impact became stronger during the recent financial crisis. We add to this debate by showing reversals in such inference. While at normal periods increasing commodity futures prices entail the USD depreciation, they result in the USD appreciation at times of financial distress. In our analysis, this direct relationship is transmitted via higher market risk during turbulent market conditions that lead to the USD appreciation.

There is a notable distinction between short-run and long-run effects of changes in commodity futures prices on the exchange rate. Among others, Bénassy-Quéré et al., (2005) argue that oil prices significantly and inversely affect the USD exchange rate in the short-run, but their relationship becomes direct in the long-run. Yet, their analysis is based on monthly data ending in 2004 and may not hold for the more recent period much affected by the recent global financial crisis and its resolution policies. In a newer study, Allegret et al., (2015) show that real currency appreciation following demand-driven rise in oil prices affects only selected countries and their exchange rates and they argue that the proportional role of individual macroeconomic and institutional factors affecting oil prices has changed over time.

There are several studies supporting the second stream of the literature that assumes prevalence of a causal impact of changes in the USD exchange rate on commodity prices. Based on historical evidence of co-movements between oil prices and exchange rates, Zhang et al. (2008) as well as Zhang (2013) show that changes in the USD exchange rate inversely affect changes in oil prices. However, they also show that sudden surges in exchange rate volatility have no impact on fluctuations in oil prices. Similarly, Wu et al., (2012) and Beckmann/Czudaj (2013) provide some evidence that the USD depreciation against major currencies results in a corresponding
increase in oil prices, although this functional relationship is subject to right-skewness, i.e. prevalence of positive over negative shocks, as well as leptokurtosis (tail risks). In a similar vein, Sari, et al., (2010) provide evidence of short run responses of changes in metal future prices and weaker response of oil prices to fluctuations in USD exchange rates.

As a compromise to the discussion about prevalence of causal effects in the relationships between commodity (spot and futures) prices and USD exchange rate, Fratzscher et al., (2014) argue that there is a pronounced causality between oil prices and USD exchange rate in both directions. Nevertheless, they concur that the USD depreciation is brought about by positive shocks in oil prices and this directional effect has been prevalent. They further prove that the negative correlation between oil prices and USD exchange rates has become recently become stronger due to higher market risk triggered by the recent financial crisis. As a result, crude oil and its derivatives have gained importance as global financial assets. In an earlier study, Breitenfellner/Cuaresma (2008) also demonstrated an increasing association between oil prices and exchange rates, attributing it to improved accuracy of forecasts of both commodity prices and exchange rate. The strengthening impact of commodity prices on exchange rates and on other macroeconomic variables stemming from greater stability of their changes and improved forecast accuracy is also proven by Joëts, et al., (2015).

In sum, the literature seems to imply increasing inference of changes in commodity futures prices on the USD exchange rate. Under normal, low risk market conditions, this relationship is inverse, i.e. increasing commodity prices entail USD depreciation, and decreasing prices are associated with the USD appreciation. This functional relationship becomes direct during turbulent, high market risk times. We test the causal effects, varied intensity and stability of these
functional interactions between commodity futures prices and USD exchange rate in subsequent sections.

III. Causal Interactions between Commodity Prices and Exchange Rates

Before devising a model examining association between commodity futures prices and the USD exchange rates, we intend to analyze causal directions and transmission of shocks between these variables. For this purpose, we employ Bayesian vector autoregression (BVAR) analysis and the corresponding impulse reaction functions on our two crude oil and metal prices and separately, USD in EUR and trade weighted USD exchange rates.

As a basis for BVAR and subsequent tests in our study, we use daily data on futures settlement prices and average exchange rates for a sample period January 5, 1999 – August 12, 2016 (4401 observations). The beginning of our sample period is determined by the inception of EUR in January 1999. The data are obtained from Bloomberg and Federal Reserve Bank of St. Louis – Federal Reserve Economic Data (FRED). All variables in our empirical exercises are stationary, as they are entered in changes in logs, i.e. captured as percent returns. The order of our BVAR tests is optimized for the number of response lags by minimizing the Akaike information criterion (AIC) at different lag specifications. AIC results suggest a BVAR optimization with 2 lagged terms in each of the examined cases. Our BVAR(2) tests assume Monte Carlo distribution of error terms. From BVAR(2) tests, we derive un-accumulated impulse responses that are shown in Figures 1a and 1b.

….. insert Figures 1a and 1b around here …..

The results shown in Figure 1a indicate that the change in logs of USD value in EUR responds inversely to one-standard deviation shocks in commodity futures prices, as displayed in the upper-
row diagrams. The opposite causal reactions of commodity prices to the exchange rate are indiscernible (the lower-row diagrams). Brent prices’ response is stronger than that of WTI prices. The responses of metal futures, i.e. copper and gold, are stronger than those for crude oil futures. As shown by impulse response functions in Figure 1b, the causal reactions of futures prices to the USD trade weighted exchange rate are almost identical to the responses to USD in EUR.

We note that our BVAR tests and impulse response functions are consistent with the directional inference suggested by Lizardo/Mollick (2010), Ding/Vo (2012) and Reboredo (2012). Moreover, our causal interactions are reversed to those implied by Zhang, et al., (2008), Wu et al., (2012) as well as Beckmann/Czekaj (2013), all of whom showing prevalence of a casual inference from nominal USD exchange rates to oil prices. They also demonstrate that these responses are sensitive to sample periods, market risk conditions and testing (data generating) specifications.

In sum, we detect pronounced and rather instantaneous inverse responses of exchange rates to changes in commodity futures prices. Specifically, positive shocks in all four commodity prices entail a USD depreciation, with a one-day lag. Recognizing the prevalence of such causal reactions, we devise an underlying analytical function for further, more specific empirical tests.

IV. The Underlying Model

Taking into consideration the transmission of shocks from commodity futures prices to the USD exchange rates, we devise the following functional relationship that is a basis for the remainder of our analysis:
$$\Delta \log e_t = \beta_0 + \beta_1 \Delta \log(CP_t) + \epsilon_t$$

(1)

with $\Delta e_t$ representing changes in USD values in EUR or in the USD trade-weighted exchange rate and $\Delta \log(CP_t)$ reflecting percent changes in commodity futures settlement prices.

We fundamentally agree that the relationships between commodity futures prices and USD exchange rates are not uniform over time. They are particularly sensitive to market risk and market liquidity conditions, among other influential factors which in-depth examination is beyond the scope of our analysis. In order to account for different patterns in the relationship prescribed by Eq. 1 at tranquil vs. turbulent markets, we introduce the Chicago Board Options Exchange VIX market volatility variable into the examined functional relationships in the following form. We augment Eq. 1 with a dummy variable $DVIX$ that assumes the value of 1 at turbulent market periods when VIX exceeds the threshold of 24 and 0 for the tranquil market days of VIX remaining below the threshold. We have identified the VIX threshold of 24 by running the Bai-Perron Threshold estimation of the stochastic VIX series for the entire sample period, permitting just one structural break. The threshold test has identified 3350 tranquil market days, i.e. VIX oscillating below the obtained threshold, and 1050 days of turbulent markets.

The modified functional relationship that accounts for market turbulence by adding the $DVIX$ variable is represented by:

$$\Delta \log e_t = \beta_0 + \beta_1 \Delta \log(CP_t) + \beta_2 DVIX + \beta_3 \Delta \log(CP_t) * DVIX + \epsilon_t$$

(2)

The interactive term $\Delta \log(CP) \times DVIX$ represents the impact of log changes in commodity prices on the exchange rates during elevated market risk periods. It is plausible to expect that at times of high market risk that might be exacerbated by increasing futures prices, there are significant capital inflows to USD denominated assets. As a result, rising commodity prices are associated with the USD appreciation at times of financial distress, thus the value of the estimated $\hat{\beta}_3$ is likely to be positive.

We have conducted a number of empirical tests of the functional relationships represented by Eq. 2. The results of the linear MBP estimations as well as non-parametric MSM tests are shown and discussed in the subsequent sections. We choose only the most robust estimations that are optimized by minimizing the Akaike information criterion.

V. Multiple Breakpoint Regression Tests

We test the functional relationships between the exchange rates and futures price with the Bai-Perron multiple breakpoints (MBP) regressions in order to identify possible discernible phases in individual functional relationships. The estimation results for the tests of the USD in EUR as a function of commodity futures prices based on Eq. 2 are shown in Tables 1a and 1b.

The results shown in Table 1a reflect the MBP estimation of the USD in EUR exchange rate as a function of crude oil prices. There are four discernible periods, separated by three breakpoints for both WTI and Brent prices. Incidentally, the timing of these breakpoints is almost identical in both cases and the results are quite similar. There is no significant relationship between crude oil
prices and USD in EUR exchange rate in the early period, i.e. in Phase 1 that begins January 5, 1999 and end January 22 (for Brent) and January 23 (for WTI) of 2003. In Phase 2 capturing the period between late January 2003 and mid-March 2009, there is an inverse, statistically significant relationship between both crude oil prices and the USD in EUR exchange rate. Specifically, an increase in oil futures prices is associated with the USD depreciation, although the estimated values of \( \hat{\beta}_1 \) coefficients are both rather low. The same coefficient assumes a considerably higher absolute value in Phase 3 that covers the period of crisis resolution policies, notably, the vast liquidity injections by central banks to financial markets (Orlowski, 2015). There is a strong inverse relationship between crude oil prices and the USD value in EUR during this period. More recently in Phase IV, the same inverse relationship is considerably weaker, as suggested by lower estimated values of \( \hat{\beta}_1 \).

The interactive term is significant only during the most recent period, i.e. in Phase IV. Its estimated \( \hat{\beta}_3 \) coefficient is positive and equally strong for both WTI and Brent series implying that increasing oil prices at times of financial distress prescribed by VIX exceeding 24 are associated with USD appreciation. This suggests that rising oil prices tend to exacerbate global equity market risk that triggers capital flows to less risky USD denominated securities, thus leads to the USD appreciation. Similar effects are not detected for the preceding sample periods.

Similar results are obtained in the MBP estimation of the relationship between the USD in EUR and metals prices shown in Table 1B. The MBP estimation identifies five discernible periods for the copper series and four for the gold series. The timing of breakpoints is different in this case. Nevertheless, the absolute values of the estimated \( \hat{\beta}_1 \) coefficients are high during the post-crisis sub-periods. Notably, these inverse relationships were strong for both copper and gold series in
Phase 2, i.e. during mid-April 2002 to early September 2005 period, which roughly corresponds with the monetary expansion pursued by the Federal Reserve at that time. Unlike in the case of crude oil, the interactive term for both metals was positive and very significant during the 2002-2005 period and also during the most recent period. Evidently, at times of elevated market risk, rising copper and gold prices lead to the USD appreciation, reflecting global risk mitigating efforts through investments in USD denominated assets.

….. insert Tables 2a and 2b around here …..

In order to insulate the factors specific to the euro and the euro-denominated assets from our analytical framework, we examine the relationship between commodity prices and the USD trade weighted exchange rate. The results of the MBP regression tests for changes in logs of USD trade weighted exchange rate as a function of WTI and Brent crude oil prices are shown in Table 2A. The tests identify three breakpoints (four distinctive phases) for WTI series and just one breakpoint (two phases) for Brent. Phase I for the WTI series, capturing a January 5, 1999 – January 23, 2003 subperiod, shown no relationship of crude oil prices and the USD exchange rate. In Phases II and III, we observe an inverse relationship between the tested variables. This relationship is stronger in Phase III than in the preceding period, suggesting a strong association between decreasing WTI prices (from their peak in early July 2008) and USD appreciation. During the most recent period of October 5, 2012 – August 12, 2016 (Phase IV), this inverse relationship becomes somewhat weaker, as implied by the lower estimated absolute value of \( \hat{\beta}_1 \). The interactive term \( \hat{\beta}_3 \) is significant only in the most recent period. Its positive value suggests a combination of rising (declining) WTI prices and USD appreciation (depreciation) at times of financial distress.
It is worth noting that the $\hat{\beta}_3$ for the Brent series is significant only in the early period (Phase I, i.e. a January 5, 1999 – August 16, 2007 sub-period). There is no discernible impact of turbulent market conditions on the association between the Brent price and the USD trade weighted exchange rate during the second sub-period. The estimated $\hat{\beta}_3$ coefficients for WTI and Brent show an opposite directional influence during the entire sample period, with the impact of stressful market conditions on the examined relationship becoming stronger for WTI and weaker for Brent over time.

The results of the MBP estimations of Eq. 2 for USD trade weighted exchange rate as a function of copper and gold futures settlement prices are shown in Table 2B. The relationship between copper prices and the exchange rate is not significant during the earliest sub-period, i.e. in Phase I. It is statistically significant with a negative sign during the remaining sub-periods, indicating a pronounced inverse relationships in Phases II (August 6, 2002 – May 18, 2005) and IV (March 19, 2008 – November 23, 2012) and a weaker association in Phases III and V. Turbulent market conditions have a significant positive effect on the relationship between copper and USD trade weighted exchange rate in Phases II and V and these results are fully consistent with the MBP estimation of the USD in EUR exchange rate series in Table 1B. A similar consistency takes place in estimation of gold prices and exchange rates. However this time, in the case of the USD trade weighted exchange rate, there is a statistically significant reversal in the impact of turbulent markets on the examined relationship between Phases I and II. During the episodes of high market risk, higher gold prices were associated with the USD depreciation in Phase I, while they became linked with the USD appreciation in Phase II and again in Phase IV, but not during the eve and the peak of the financial crisis captured by Phase III.
In sum, our tests show prevalence of an inverse relationship between commodity prices and USD exchange rates. However, during the most recent period, i.e. in the aftermath of global financial crisis, their relationships switches from negative to significantly positive during episodes of high market risk, i.e. when VIX exceeds the obtained threshold of 24. The normal inverse relationship between increasing (decreasing) commodity prices and USD depreciation (appreciation) switches to their positive co-movement at times of financial distress, with a reversed interaction between gold price and USD trade weighted exchange rate during the early sample period of 1999-2002.

VI. Two-State Markov Switching Tests

The In order to verify the robustness of the multiple breakpoint regression estimation for the USD exchange rates as a function of commodity prices, we employ a Two-State Markov Switching Model. Its estimation also enables us to show directional changes and stability of either direct or inverse relationships between both pairs of variables during the entire examined sample period.

A two-state Markov switching process to simulate is specified as follows:

The process in State 1 is specified as

\[
\Delta \log e_{t|S=1} = c_1 + \gamma_1 \Delta \log CP_t + \epsilon_{1t}, \quad \epsilon_{1t} \sim \mathcal{N}(0,1) \tag{3}
\]

We expect the process estimated for State (or "Regime") 1 to follow a seemingly different relationship between the returns to the exchange rate and commodity futures prices during the examined sample period to that obtained for State ("Regime") 2. The process reflecting State or Regime 2 is prescribed by
\[ \Delta \log e_{t \Delta s=2} = c_2 + \gamma_2 \Delta \log CP_t + \varepsilon_{2t}, \quad \varepsilon_{2t} \sim N(0,1) \]  

(4)

The corresponding transition probability matrix is specified as:

\[
P = \begin{bmatrix}
    p_{11} & p_{12} \\
    p_{21} & p_{22}
\end{bmatrix}
\]

(5)

The results of the Markov switching estimation for change in log of the USD in EUR exchange rate as a function of changes in log of WTI and Brent futures prices are shown in Table 3. The estimations are augmented with a log sigma as a common term.

..... insert Table 3 around here .....  

The obtained States or Regimes from the Markov switching estimations for the WTI and Brent series are somewhat different. In the case of WTI futures prices, Regime I indicates a rather weak, positive relationship (a low \( \hat{\gamma}_1 \)) between changes in logs of the USD in EUR exchange rate and changes in logs in these prices. Regime II reflects episodes of a strong positive relationship between these two variables, as implied by a high, positive value of \( \hat{\gamma}_2 \). The obtained regimes suggest that most of observed daily changes in WTI and USD in EUR are directly related, switching between mild and strong positive co-movements. The constant transition probabilities and the expected daily durations indicate that Regime I (i.e. a milder relationship) dominates the process. The probability of staying in this stage on any given day is 78 percent and switching to Regime II is only 22 percent. The expected duration of Regime I is 4.6 days, longer than just 2 days expected for Regime II. In hindsight, the relationship between WTI futures prices and USD in EUR exchange rate is predominantly positive, although not very strong.
The regimes for Brent futures are more divergent. Regime I is prescribed by an inverse, albeit statistically insignificant co-movement. Regime II reflects a strong, positive relationship. However, the more ambiguous relationship prescribed by Regime I overwhelmingly dominates the process with its 99 percent probability of remaining in it on any given day and its expected duration of 205 days. Evidently, the co-movement between Brent futures and USD in EUR exchange rate is normally not robust, although it becomes stronger and significant at less prevalent times prescribed by Regime II.

Estimations of Markov switching processes for changes in (logs of) USD in EUR exchange rate as a function of changes in (logs of) copper and gold futures prices are shown in Table 4. The relationship between copper futures prices and the exchange rate is mainly positive. Regime I depicts a weaker and Regime II considerably stronger positive interactions. Both $\hat{\gamma}_1$ and $\hat{\gamma}_2$ coefficients are statistically significant. Regime I dominates the process with a low 23 percent probability of switching and the longer expected duration of 3.6 days. In the case of gold, Regime I reflects a negative, although statistically insignificant co-movement with the exchange rate. Regime II represents a significant, positive relationship between both variables and this relationship dominates the process with a longer expected duration of 49 days. The switching probabilities for both regimes are very low - only 3 percent for Regime I and 2 percent for Regime II. It can be therefore argued that both copper and gold futures prices are positively related to the USD value in EUR and this direct co-movement is stronger for gold.

...... insert Table 4 around here ..... 

One of the key, rather unexpected findings of our study are observed in Table 5 that shows relationships between changes in (logs of) USD trade weighted exchange rate and changes in (logs of) crude oil futures prices. In a contrast to results in Table 3, this relationship is mainly inverse
for both WTI and Brent. In both cases Regime I reflects a milder inverse co-movement, while Regime II shows considerably stronger inverse relationships. All regime trajectories are statistically significant. The dispersion of results found in Tables 3 and 5 implies a significant negative impact of crude oil futures prices on USD values transmitted via other currencies included in the USD trade weighted basket, primarily via the British Pound. In both WTI and Brent cases, Regimes I, i.e. those reflecting somewhat milder inverse interactions, dominate the process with their longer expected duration and lower switching probability.

….. insert Table 5 around here …..

A similar reversal from positive to inverse interactions is observed in estimations of changes in USD trade weighted exchange rate as a function of copper and gold futures prices shown in Table 6. Both regimes in the case of copper futures prices in relation to the USD trade weighted exchange rate indicate prevalence of an inverse relationships, in contrast to the direct relationship for the USD in EUR series. Regime II implies a milder inverse co-movement and Regime I a considerably stronger inverse relationship. However, Regime II is dominant with its longer expected duration and a bit higher probability of remaining in it. The Markov switching relationship for gold futures prices is dominated by Regime I reflecting a milder inverse relationship. All obtained estimated $\hat{\gamma}$ coefficient in Table 6 are statistically significant.

….. insert Table 6 around here …..

Further insights in stability and reliability of the obtained Markov switching regimes can be derived from Figures 2a-d and 3a-d showing one-step ahead regime probabilities for the USD in EUR and USD trade weighted exchange rates respectively. The regime probabilities path shows in Figure 2a implies an orderly pattern of both regimes in the relationship between WTI futures
and USD in EUR exchange rate. There are only minor discernible switching episodes around the peak of the financial crisis at the end of 2008 and the instability of the euro stemming from the sovereign debt crisis in the euro area in 2012-2013. The switching pattern for Brent futures prices vis-à-vis USD in EUR exchange rate two regimes is rather disorderly, as shown in Figure 2b. The regimes were rather stable only at the early stage of the sample period in 1999-2002. Time distribution of predicted regime probabilities for crude oil futures prices as a function of the USD trade weighted exchange rate shown in Figures 3a and 3b is exactly reverse for WTI and Brent. Both identified regimes for WTI series in relation to USD trade weighted exchange rate are very unstable (Figure 3a), while the regimes for Brent show a remarkable stability (Figure 3b).

….. insert Figures 2a-d and 3a-d around here …..

The patterns of predicted regime switching probabilities for copper and gold futures prices in relation to USD in EUR exchange rate (Figures 2c and 2d) and USD trade weighted exchange rate (Figures 3c and 3d) are very similar. The switching patterns in the case of copper are rather orderly. There are minor switching episodes only in the case of the USD and EUR exchange rate series (Figure 2c) around the peak of the recent crisis and the timing of the euro area sovereign debt crisis. No discernible switching episodes are observed for the copper series as a function of the USD trade weighted exchange rate. In contrast, the patterns for gold series are very unstable in relation to both exchange rates. There are several regime reversals in the case of gold and USD in EUR exchange rate series, particularly during the first half of the entire sample period, i.e. between 1999 and 2007. The pattern for gold in relation to USD trade weighted exchange rate (Figure 3d) is very unsettled through the entire sample period.

In sum, the Markov switching estimations indicate rather unstable interactions between crude oil as well as gold futures prices and USD exchange rates. Stability of the identified regimes
for copper futures prices and both USD exchange rates is considerably better. Both WTI and Brent crude oil futures prices are positively related with USD in EUR values. They are inversely related to the USD values on the basis of the trade weighted exchange rate, being presumably strongly affected by fluctuations in other exchange rates.

VII. A Synthesis

We examine the impact of returns on one-month commodity futures prices on returns on USD exchange rates. Changes in West Texas Intermediate and Brent crude oil futures prices inversely affect the value of US dollar in euro and of the USD trade-weighted exchange rate. The impact of changes in WTI on USD exchange rates becomes positive under turbulent market conditions, i.e. high CBOE VIX. However, this positive effect holds only during the most recent sample period of October 5, 2012 - August 12, 2016. Changes in copper and gold prices are also inversely related to changes in USD values in EUR and the trade-weighted USD exchange rate. We also observe a positive interaction between changes in the two examined metal futures prices and the USD exchange rates during turbulent market conditions, with the exception of the 1999-2002 and 2005-2009 sub-periods.

In essence, market interactions between returns on commodity futures and the exchange rates are not uniform for the examined two crude oil futures, the two metal futures and the USD exchange rates. The relationships between commodity futures prices and the exchange rates are subject to pronounced structural breaks over time. The interplay between these returns is very sensitive to the market risk conditions. At normal market periods, i.e. low market risk conditions, there is a significant inverse relationship between commodity futures prices and exchange rate returns. Generally, it becomes positive at turbulent market times.
These key findings are derived from BVAR and Bai-Perron multiple break points tests. We check their robustness by employing non-parametric Two-State Markov switching testing. We find unstable interactions between crude oil as well as gold futures prices and USD exchange rates. Stability of the identified regimes for copper futures prices and both USD exchange rates is considerably better.

Our empirical exercise is focused only on the four selected commodity futures prices and two measures of USD exchange rates. We recognize a need for further investigation of other commodity futures and exchange rates.
References:


Table 1A. Phases in the relationship between changes in logs of USD in EUR exchange rate as a function of crude oil futures settlement prices - the Bai-Perron multiple break-point regression estimation results of Eq. 2.

<table>
<thead>
<tr>
<th>Phases based on break points</th>
<th>Changes in the USD in EUR exchange rate as a function of changes in log of WTI price</th>
<th>Phases based on break points</th>
<th>Changes in USD in EUR exchange rate as a function of changes in log of Brent price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Const term $\hat{\beta}_0$</td>
<td>$\hat{\beta}_1$ coefficient</td>
<td>$\hat{\beta}_2$ coefficient</td>
</tr>
<tr>
<td>Phase I 1/05/1999 - 1/23/2003 (998 obs)</td>
<td>0.001 (1.41)</td>
<td>0.015 (1.29)</td>
<td>-0.001 (-1.56)</td>
</tr>
<tr>
<td>Phase II 1/24/2003 - 3/18/2009 (1535 obs)</td>
<td>-0.001 (-0.78)</td>
<td>-0.042*** (-4.88)</td>
<td>0.001 (0.22)</td>
</tr>
<tr>
<td>Phase III 3/19/2009 - 3/22/2013 (1012 obs)</td>
<td>0.001 (0.52)</td>
<td>-1.151*** (-10.82)</td>
<td>-0.001 (-0.10)</td>
</tr>
<tr>
<td>Phase IV 3/25/2013 - 8/12/2016 (855 obs)</td>
<td>0.002 (0.88)</td>
<td>-0.035*** (-3.89)</td>
<td>0.001 (0.09)</td>
</tr>
</tbody>
</table>

Diagnostic statistics:
F-statistics
Log likelh.
AIC
DW

| 23.529 | 22.495 |
| 16166 | 16159 |
| -7.341 | -7.338 |
| 1.981 | 1.984 |

Notes: t-statistics in parentheses; *** denotes significance at 1%, ** at 5%, * at 10%. Daily data for a sample period January 5, 1999 – August 12, 2016 (4401 observations).

Source: Authors’ own estimation based on Bloomberg and the Federal Reserve Bank of St. Louis FRED daily data.
Table 1B. Phases in the relationship between changes in logs of USD in EUR exchange rate as a function of copper and gold futures settlement prices - the Bai-Perron multiple break-point regression estimation results of Eq. 2.

<table>
<thead>
<tr>
<th>Phases based on break points</th>
<th>Changes in USD in EUR exchange rate as a function of changes in log of copper prices</th>
<th>Phases based on break points</th>
<th>Changes in USD in EUR exchange rate as a function of gold prices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Const term ( \hat{\beta}_0 )</td>
<td>( \hat{\beta}_1 ) coefficient</td>
<td>( \hat{\beta}_2 ) coefficient</td>
</tr>
<tr>
<td>Phase I 1/05/1999 - 5/16/2002 (835 obs)</td>
<td>0.001 (1.49)</td>
<td>0.018 (0.75)</td>
<td>-0.001 (-0.95)</td>
</tr>
<tr>
<td>Phase II 5/28/2002 - 5/16/2002 (736 obs)</td>
<td>-0.001 (-1.40)</td>
<td>-0.121*** (-7.81)</td>
<td>-0.001 (-0.97)</td>
</tr>
<tr>
<td>Phase III 5/20/2005 - 3/18/2008 (710 obs)</td>
<td>0.001 (0.70)</td>
<td>-0.013*** (-2.58)</td>
<td>-0.002 (-0.37)</td>
</tr>
<tr>
<td>Phase IV 3/19/2008 - 3/23/2013 (1266 obs)</td>
<td>0.001 (0.78)</td>
<td>-0.187*** (-11.68)</td>
<td>-0.001 (-0.17)</td>
</tr>
<tr>
<td>Phase V 3/27/2013 - 8/12/2016 (853 obs)</td>
<td>0.001 (0.69)</td>
<td>-0.093*** (-5.81)</td>
<td>-0.001 (-0.09)</td>
</tr>
</tbody>
</table>

**Diagnostic statistics:**
- F-statistics:
  - 27.893
  - 16246
- Log likelh.:
  - -7.375
  - 1969
- AIC:
  - 59.471
  - 16403
- DW:
  - -7.449
  - 2.011

Notes and Source as in Table 1a.
**Table 2A.** Phases in the relationship between changes in logs of USD trade weighted exchange rate as a function of crude oil futures settlement prices - the Bai-Perron multiple break-point regression estimation results of Eq. 2.

<table>
<thead>
<tr>
<th>Phases based on break points</th>
<th>Changes in the USD trade weighted exchange rate as a function of changes in log of WTI price</th>
<th>Phases based on break points</th>
<th>Changes in USD trade weighted exchange rate as a function of changes in log of Brent price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Const term $\hat{\beta}_0$</td>
<td>$\hat{\beta}_1$ coefficient</td>
<td>$\hat{\beta}_2$ coefficient</td>
</tr>
<tr>
<td>Phase I 1/05/1999 - 1/23/2003 (998 obs)</td>
<td>0.001 (1.41)</td>
<td>0.001 (0.07)</td>
<td>-0.001 (-0.44)</td>
</tr>
<tr>
<td>Phase II 1/24/2003 - 3/18/2009 (1535 obs)</td>
<td>-0.001 (-0.99)</td>
<td>-0.042*** (-6.14)</td>
<td>0.001 (0.79)</td>
</tr>
<tr>
<td>Phase III 3/19/2009 - 10/4/2012 (896 obs)</td>
<td>-0.001 (-0.33)</td>
<td>-0.119*** (-11.00)</td>
<td>-0.001 (-0.16)</td>
</tr>
<tr>
<td>Phase IV 10/5/2012 - 8/12/2016 (971 obs)</td>
<td>0.001 (1.54)</td>
<td>-0.051*** (-8.11)</td>
<td>0.001 (0.96)</td>
</tr>
<tr>
<td>Diagnostic statistics:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-statistics</td>
<td>33.829</td>
<td>50.526</td>
<td></td>
</tr>
<tr>
<td>Log likelh.</td>
<td>17664</td>
<td>17594</td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>-8.022</td>
<td>-7.994</td>
<td></td>
</tr>
<tr>
<td>DW</td>
<td>2.035</td>
<td>2.047</td>
<td></td>
</tr>
</tbody>
</table>

Notes and Source: as in Table 1a.
**Table 2B.** Phases in the relationship between changes in logs of USD trade weighted exchange rate as a function of copper and gold futures settlement prices - the Bai-Perron multiple break-point regression estimation results of Eq. 2.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Const term ( \hat{\beta}_0 )</td>
<td>( \hat{\beta}_1 ) coefficient</td>
<td>( \hat{\beta}_2 ) coefficient</td>
<td>( \hat{\beta}_3 ) coefficient</td>
<td>Const term ( \hat{\beta}_0 )</td>
<td>( \hat{\beta}_1 ) coefficient</td>
<td>( \hat{\beta}_2 ) coefficient</td>
<td>( \hat{\beta}_3 ) coefficient</td>
<td>Const term ( \hat{\beta}_0 )</td>
<td>( \hat{\beta}_1 ) coefficient</td>
<td>( \hat{\beta}_2 ) coefficient</td>
<td>( \hat{\beta}_3 ) coefficient</td>
<td>Const term ( \hat{\beta}_0 )</td>
</tr>
<tr>
<td>Phase I 1/05/1999 - 8/05/2002 (881 obs)</td>
<td>0.001 (0.45)</td>
<td>0.010 (0.78)</td>
<td>0.001 (0.05)</td>
<td>-0.037* (-1.89)</td>
<td>0.001 (1.11)</td>
<td>-0.048*** (-2.65)</td>
<td>0.001 (0.20)</td>
<td>-0.065*** (-2.56)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phase II 8/06/2002 - 5/18/2005 (690 obs)</td>
<td>-0.001 (-0.64)</td>
<td>-0.111*** (-9.39)</td>
<td>-0.001 (-0.76)</td>
<td>0.221*** (7.00)</td>
<td>-0.001 (-0.69)</td>
<td>-0.357*** (-22.90)</td>
<td>-0.001 (-0.99)</td>
<td>0.126*** (4.31)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phase III 5/19/2005 - 3/18/2008 (710 obs)</td>
<td>-0.001 (-1.69)</td>
<td>-0.020*** (-2.94)</td>
<td>0.001 (0.09)</td>
<td>-0.007 (-0.39)</td>
<td>0.001 (0.02)</td>
<td>-0.150*** (-10.27)</td>
<td>0.001 (0.07)</td>
<td>-0.024 (-1.19)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phase IV 3/19/2008 - 11/23/2012 (1183 obs)</td>
<td>0.001 (0.22)</td>
<td>-0.150*** (-12.46)</td>
<td>0.001 (0.06)</td>
<td>0.026* (1.84)</td>
<td>0.001 (0.73)</td>
<td>-0.192*** (-19.27)</td>
<td>0.001 (1.48)</td>
<td>0.132*** (6.69)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phase V 11/26/2012 - 8/12/2016 (936 obs)</td>
<td>0.001 (1.32)</td>
<td>-0.089*** (-7.95)</td>
<td>0.001 (0.01)</td>
<td>0.163*** (4.73)</td>
<td>0.001 (1.32)</td>
<td>-0.089*** (-7.95)</td>
<td>0.001 (0.01)</td>
<td>0.163*** (4.73)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Diagnostic statistics:**

- F-statistics: 40.691
- Log likelh. 17781
- AIC -8.073
- DW 2.021
- AIC 84.596
- DW 17983
- AIC -8.167
- DW 2.078

Notes and Source as in Table 1a.
Table 3: Estimations of Two-State Markov Switching for changes in logs of USD in EUR in relation to changes in WTI and Brent prices (Equations 3, 4 and 5).

<table>
<thead>
<tr>
<th></th>
<th>Changes in USD in EUR ex. rate as a function of changes in WTI price</th>
<th>Changes in USD in EUR ex. rate as a function of changes in Brent price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime I</td>
<td>( \hat{c}_1 = 0.001 ) (0.50)</td>
<td>( \hat{c}_1 = 0.001 ) (0.17)</td>
</tr>
<tr>
<td></td>
<td>( \hat{\gamma}_1 \times 100 = 1.86^{**} ) (2.14)</td>
<td>( \hat{\gamma}_1 \times 100 = -0.54 ) (-0.86)</td>
</tr>
<tr>
<td>Regime II</td>
<td>( \hat{c}_2 = -0.002 ) (-0.83)</td>
<td>( \hat{c}_2 = -0.001 ) (-0.80)</td>
</tr>
<tr>
<td></td>
<td>( \hat{\gamma}_2 \times 100 = 19.79^{***} ) (10.50)</td>
<td>( \hat{\gamma}_2 \times 100 = 15.13^{***} ) (13.56)</td>
</tr>
</tbody>
</table>

Common terms:

<table>
<thead>
<tr>
<th></th>
<th>Log Sigma</th>
<th>Log Sigma</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-5.144^{***} (-419.9)</td>
<td>-5.102^{***} (-457.0)</td>
</tr>
</tbody>
</table>

Diagnostic tests:

<table>
<thead>
<tr>
<th></th>
<th>Log likelihood = 16140</th>
<th>Log likelihood = 16142</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Durbin Watson stats. = 1.977</td>
<td>Durbin Watson stats. = 1.994</td>
</tr>
</tbody>
</table>

Constant transition probabilities, Probability of staying (switching):

<table>
<thead>
<tr>
<th></th>
<th>Regime I</th>
<th>Regime II</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.78 (0.22)</td>
<td>0.99 (0.01)</td>
</tr>
<tr>
<td></td>
<td>0.49 (0.51)</td>
<td>0.01 (0.99)</td>
</tr>
</tbody>
</table>

Constant expected durations:

<table>
<thead>
<tr>
<th></th>
<th>Regime I</th>
<th>Regime II</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4.6 days</td>
<td>205 days</td>
</tr>
<tr>
<td></td>
<td>2.0 days</td>
<td>105 days</td>
</tr>
</tbody>
</table>

Notes: as in Table 1, z-statistics in parentheses.

Source: as in Table 1.
Table 4: Estimations of Two-State Markov Switching for changes in logs of USD in EUR in relation to changes in copper and gold prices (Equations 3, 4 and 5).

<table>
<thead>
<tr>
<th>Regime</th>
<th>Changes in USD in EUR ex. rate as a function of changes in copper price</th>
<th>Changes in USD in EUR ex. rate as a function of changes in gold price</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>$\hat{c}_1 = -0.001 (-0.61)$</td>
<td>$\hat{c}_1 = -0.001** (-2.27)$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\gamma}_1 <em>100= 2.59</em>** (2.66)$</td>
<td>$\hat{\gamma}_1 *100= -2.85 (1.35)$</td>
</tr>
<tr>
<td>II</td>
<td>$\hat{c}_2 = 0.001 (0.34)$</td>
<td>$\hat{c}_2 = 0.001 (0.85)$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\gamma}_2 <em>100= 28.11</em>** (12.37)$</td>
<td>$\hat{\gamma}_2 <em>100= 36.53</em>** (13.56)$</td>
</tr>
</tbody>
</table>

Common terms:

| Log Sigma | $-5.140*** (-424.2)$ | $-5.102*** (-457.0)$ |

Diagnostic tests:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime I</td>
<td>16185</td>
<td>-7.354</td>
</tr>
<tr>
<td>Regime II</td>
<td>16142</td>
<td>-7.334</td>
</tr>
</tbody>
</table>

Constant transition probabilities, Probability of staying (switching):

<table>
<thead>
<tr>
<th>Regime</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.72 (0.23)</td>
</tr>
<tr>
<td>II</td>
<td>0.16 (0.83)</td>
</tr>
</tbody>
</table>

Constant expected durations:

<table>
<thead>
<tr>
<th>Regime</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>3.6 days</td>
</tr>
<tr>
<td>II</td>
<td>1.2 days</td>
</tr>
</tbody>
</table>

Notes: as in Table 1, z-statistics in parentheses.

Source: as in Table 1.
Table 5: Estimations of Two-State Markov Switching for changes in logs of USD trade weighted exchange rate in relation to changes in WTI and Brent prices (Equations 3, 4 and 5).

<table>
<thead>
<tr>
<th>Regime</th>
<th>Changes in USD trade weighted ex. rate as a function of changes in WTI price</th>
<th>Changes in USD trade weighted ex. rate as a function of changes in Brent price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime I</td>
<td>$\hat{c}_1 = -0.001$ (0.65) $\hat{\gamma}_1 <em>100= -0.94</em>** (-2.31)$</td>
<td>$\hat{c}_1 = 0.001$ (1.16) $\hat{\gamma}_1 <em>100= -1.20</em>* (-2.42)$</td>
</tr>
<tr>
<td>Regime II</td>
<td>$\hat{c}_2 = 0.001$ (0.98) $\hat{\gamma}_2 <em>100= -15.71</em>** (-14.18)$</td>
<td>$\hat{c}_2 = -0.001$ (-1.35) $\hat{\gamma}_2 <em>100= -20.03</em>** (15.07)$</td>
</tr>
<tr>
<td>Common terms:</td>
<td>AR(1) $-0.021$ (-1.32) Log Sigma $-5.469*** (-413.0)$</td>
<td>NA $-5.483*** (-447.4)$</td>
</tr>
<tr>
<td>Constant transition probabilities, Probability of staying (switching):</td>
<td>Regime I 0.98 (0.02) 0.85 (0.15)</td>
<td>Regime II 0.95 (0.05) 0.31 (0.69)</td>
</tr>
<tr>
<td>Constant expected durations: Regime I 54 days 6.5 days</td>
<td>Regime II 21 days 1.5 days</td>
<td></td>
</tr>
</tbody>
</table>

Notes: as in Table 1, z-statistics in parentheses.

Source: as in Table 1.
Table 6: Estimations of Two-State Markov Switching for changes in logs of USD trade weighted in relation to changes in copper and gold futures prices (Equations 3, 4 and 5).

<table>
<thead>
<tr>
<th></th>
<th>Changes in USD trade weighted ex. rate as a function of changes in copper price</th>
<th>Changes in USD trade weighted ex. rate as a function of changes in gold price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime I</td>
<td>$\hat{c}_1 = -0.001 \ (0.25)$</td>
<td>$\hat{c}_1 = 0.001 \ (1.47)$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\gamma}_1 \times 100 = -25.76^{***} \ (12.24)$</td>
<td>$\hat{\gamma}_1 \times 100 = -7.28^{***} \ (-6.25)$</td>
</tr>
<tr>
<td>Regime II</td>
<td>$\hat{c}_2 = 0.001 \ (0.49)$</td>
<td>$\hat{c}_2 = 0.001 \ (0.01)$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\gamma}_2 \times 100 = -3.06^{***} \ (-4.13)$</td>
<td>$\hat{\gamma}_2 \times 100 = -40.05^{***} \ (-15.67)$</td>
</tr>
<tr>
<td><strong>Common terms:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Log Sigma</strong></td>
<td>$-5.507^{***} \ (-448.2)$</td>
<td>$-5.579^{***} \ (-452.8)$</td>
</tr>
<tr>
<td><strong>Diagnostic tests:</strong></td>
<td>Log likelihood = 17733</td>
<td>Log likelihood = 18051</td>
</tr>
<tr>
<td></td>
<td>Durbin Watson stats. = 2.036</td>
<td>Durbin Watson stats. = 2.077</td>
</tr>
<tr>
<td><strong>Constant transition probabilities,</strong></td>
<td>Probability of staying (switching):</td>
<td>Probability of staying (switching):</td>
</tr>
<tr>
<td><em>Regime I</em></td>
<td>0.75 (0.25)</td>
<td>0.95 (0.05)</td>
</tr>
<tr>
<td><em>Regime II</em></td>
<td>0.79 (0.21)</td>
<td>0.92 (0.08)</td>
</tr>
<tr>
<td><strong>Constant expected durations:</strong></td>
<td>Regime I = 1.3 days</td>
<td>Regime I = 19 days</td>
</tr>
<tr>
<td></td>
<td>Regime II = 4.8 days</td>
<td>Regime II = 12 days</td>
</tr>
</tbody>
</table>

Notes: as in Table 1, $z$-statistics in parentheses.

Source: as in Table 1.
**Figure 1:** Impulse responses between commodity futures prices and exchange rates.

**1a:** Responses between commodity futures prices and the USD in EUR exchange rate

**1b:** Responses between commodity futures prices and the USD trade weighted exchange rate

Notes: un-accumulated responses to Cholesky one standard deviation shocks generated from BVAR(2). Daily data for a sample period January 5, 1999 – August 12, 2016 (4401 observations).

Source: authors’ own estimation based on Bloomberg and the Federal Reserve Bank of St. Louis FRED data.
Figure 2: Markov switching one-step ahead predicted regime probabilities for the USD in EUR series as a function of commodity futures prices.

2a: for WTI series (in conjunction with results in Table 3)
2b: for Brent series (in conjunction with results in Table 3)
2c: for copper series (in conjunction with results in Table 4)
2d: for gold series (in conjunction with results in Table 4)

Source: authors’ own estimation.
Figure 3: Markov switching one-step ahead predicted regime probabilities for the USD trade weighted exchange rate series as a function of commodity futures prices.

3a: for WTI series (in conjunction with results in Table 5)
3b: for Brent series (in conjunction with results in Table 5)
3c: for copper series (in conjunction with results in Table 6)
3d: for gold series (in conjunction with results in Table 6)

Source: as in Figure 2.