Asymptotic dependence and exchange rate forecasting

Francisco Pinto-Avalos* Michael Bowe† Stuart Hyde‡

Abstract

This paper explores the relationship between commodity and exchange rate returns in terms of their non-linear association and the ability of commodity prices to predict exchange rates. Using a broad sample of commodity exporting economies we document that the forecasting ability of commodity prices lies in the asymptotic dependence relationship between commodity and exchange rate returns at a daily frequency. We argue that the information located in the tail of the distributions is a key component to describe the short-lived relationship between those variables.

Keywords: Exchange rates, commodity prices, asymptotic dependence, forecasting.

EFM Classification: International finance. 610 - Currency Markets and Exchange Rates

JEL Codes: F31, F37, C22, C53.

*Corresponding author and presenter. The University of Manchester. Alliance Manchester Business School, Booth Street West, Manchester, M15 6PB, UK. E-mail: francisco.pintoavalos@manchester.ac.uk

†The University of Manchester. Alliance Manchester Business School, Booth Street West, Manchester, M15 6PB, UK. E-mail: michael.bowe@manchester.ac.uk

‡The University of Manchester. Alliance Manchester Business School, Booth Street West, Manchester, M15 6PB, UK. E-mail: stuart.hyde@manchester.ac.uk

1 Introduction

Recent empirical studies (Ferraro et al. 2015, Foroni et al. 2015) provide evidence that changes in commodity prices contain a degree of predictive power for exchange rate fluctuations. Both the distribution of exchange rates and commodity prices, measured as a log-returns, exhibit heavy tails, indicating the presence of extreme values in their sample distributions. Motivated by the fact, this paper seeks to investigate the existence of an extreme connection between the variables, examining whether asymptotic dependence underpins the predictive ability of commodity prices for exchange rates. We investigate whether the documented predictive ability of commodity prices applies to broad sample of commodity exporting economies, and the frequencies at which it exists.

A number of recent studies analyse the tail behaviour of financial variables.[1] Research focusing on the information contained in the tails of the distribution explores the relationship between two or more variables when linear correlation fails to detect the extent of the association between them. The belief is that the information contained in the tails of the distribution may contribute to explaining the degree of association between the variables. For example, Cumperayot & De Vries (2017) demonstrate that measuring the asymptotic dependence between exchange rates and classic monetary fundamentals allows one to explain how large swings in exchange rates are related to sharp movements in monetary fundamentals.

This paper contributes to the literature on asymptotic dependence and its implications by examining the relationship between exchange rates and commodity prices in a tail dependence framework. We believe it is the first paper to attempt to synthesise these two literatures. We highlight the role of asymptotic dependence as a central component of the ability of commodity prices to predict exchange rates. In particular, our focus is to establish the nature of the additional information contained in the tails of the distribution and its role in exchange rate predictability. Our approach employs multivariate extreme value techniques. We explore the occurrences of large movements in exchange and commodity prices and test if they are asymptotically dependent. Measuring tail dependence enables us to determine the extent to which large movement in exchange rates relate to their underlying fundamentals, in this case, commodity prices. Our empirical approach is particularly relevant when variables are known to exhibit fat-tailed distributions.

Our main results demonstrate that the asymptotic dependence between commodity prices and exchange rates is significant when prices are measured contemporaneously and at a

[1]See Patton (2006) for a survey of studies implementing a copula approach. Patton (2012) surveys the methodology and approaches to modelling the tail behaviour of financial variables.

daily frequency, while it reduces considerably when we use lagged values or data at a lower frequency. Moreover, we also show that the predictive ability of commodity prices is highly significant when we use contemporaneous daily observations. Using lagged or lower frequency observations reduces the ability of commodity prices to forecast exchange rates. We maintain that the nature of the documented asymptotic dependence is a key element in evaluating the relationship between the two variables, and in particular it is the crucial element to incorporate when analysing the ability of commodity prices to predict exchange rates.

2 Related literature

2.1 Exchange rates and Commodity prices

We now contextualise the contribution of this study in relation to the existing literature. Rossi (2013) surveys the large research literature on nominal exchange-rate forecasting, including models using commodity prices, and concludes that the random walk remains a difficult benchmark to outperform (Meese & Rogoff 1983). She reports that linear models appear the most successful and that results vary depending upon the set of predictors, the sample period, the forecast evaluation method, and the forecast horizon. In this vein, several studies focus upon the analysis of the statistical relationship between commodity prices and both real and nominal exchange rates at a variety of frequencies. Conducting in-sample exercises using quarterly frequency observations, Chen & Rogoff (2003) claim strong correlation and cointegration between commodity prices and real exchange rates of several developed country commodity exporters. Further, Cashin et al. (2004) provide evidence of the in-sample predictive power of commodity export prices to explain real exchange rates. They find evidence of correlation and cointegration in around one-third of their sample of 58 economies using observations at the monthly frequency.

Amano & van Norden (1995, 1998*a*,*b*) provide evidence in favour of the ability of commodity prices to explain exchange rates at a monthly frequency using cointegration analysis applied to a subset of advanced economies. The 1995 study presents empirical evidence linking the Canada-US real exchange rate with the terms of trade, reporting that the real exchange rate is cointegrated with terms-of-trade variables (price of commodity exports relative to the price of manufactured imports), and that causality runs from the terms of trade to the exchange rate. Moreover, a simple exchange rate equation performs better than a random walk in post-sample forecasting exercises. In the 1998 study, the authors document a robust and relationship between the real domestic price of oil and real effective exchange rates for Germany, Japan and the United States. They attribute this effect to the real oil price capturing exogenous terms-of-trade shocks and explain why these shocks may determine long-term real exchange rates.

Chen (2002) finds that including commodity prices improves the out-of-sample forecasting ability of fundamental-based models for nominal exchange rates at the monthly frequency in the cases of Australia, Canada and New Zealand. However, the evidence is not completely robust for the entire sample period under analysis. In contrast, Chen et al. (2010) using both in-sample Granger-causality tests with time-varying parameters and out-of-sample forecasting with rolling windows, document that nominal exchange rates (for commodity currencies) help forecast commodity prices, but find no evidence for the reverse impact. Their study analyses nominal exchange rates of Canada, Australia, New Zealand, South Africa, and Chile (each relative to the US dollar) along with export-earnings-weighted commodity prices for each country, at a quarterly frequency. They rationalise their findings in the context of a present value model following Engel & West (2005).

While much of the earlier literature is based on low frequency sampling, some more recent studies investigate the forecasting ability of commodity prices using daily and higher frequency data. Zhang et al. (2016), using daily data from a sample of four economies (Australia, Canada, Chile, Norway), document the in-sample ability of three commodity prices (crude oil, gold, copper) to explain exchange rates. They employ both conditional and unconditional causality measures and consider non-USD exchange rates, noting that the documented relationship is stronger at short horizons and runs mainly in the direction of commodity prices to exchange rates. Similarly, Foroni et al. (2015), using a mixed frequency estimation based on both daily and monthly observations for a sample of advanced economies, show that incorporating commodity prices improves the forecasting ability of fundamentals-based exchange rate models.

Other recent papers extend the analysis to a broader sample of countries at a daily frequency. Ferraro et al. (2015) examine the ability of oil prices to forecast exchange rates in a one-step ahead, out-of-sample exercise for five commodity exporter economies (Australia, Canada, Chile, Norway, and South Africa). However, Akram (2004) shows that the value of the Norwegian krone value against a European basket of currencies is not correlated with the oil price. Kohlscheen et al. (2017) find a strong correlation between changes in the nominal exchange rate and a daily index of export commodity prices for 11 countries using a panel dataset.[2] Both studies provide evidence of the forecasting ability of contemporaneous

[2] Australia, Canada, Norway, Brazil, Chile, Colombia, Mexico, Peru, South Africa, Russia and Malaysia.

commodity prices to beat a RW model in out-of-sample exercises using observations at a daily frequency, while they also show that the forecasting ability tends to be weaker using monthly data, and completely disappears at a quarterly frequency. In addition, both studies find that only contemporaneous commodity prices outperform the RW model and confirm that there is little evidence of out-of-sample prediction using lagged commodity prices. In particular, Ferraro et al. (2015) argue that any forecasting ability comes from the short-lived relationship between commodity prices and exchange rates, therefore, including contemporaneous observations at a daily frequency is a crucial component in capturing the relationship between these variables.

2.2 Higher moments in exchange rate distributions

An alternative line of literature analyses the role of higher moments in the exchange rate distribution by modelling tail relationships using extreme value theory, often adopting a copula methodology. Patton (2006) studies the tail behaviour of the Japanese yen and the German mark. His results indicate exchange rate movements located in the tails of the distribution are asymmetric, and that the degree of association between these currencies tends to be higher during periods of currency depreciation in comparison to episodes of appreciation. Similarly, Yang & Hamori (2014) also find asymmetric effects during periods of appreciation and depreciation when analysing the tail behaviour of the Euro, Japanese yen and British pound in relation to the gold price. Using a time-varying copula approach to analyse the tail relationship between the Japanese Yen and the Euro, Dias & Embrechts (2010) argue that time-varying estimation provides additional information about the tail dependence between the variables. While this literature exploits information in the tails for examining the relationship between exchange rates and other financial assets, Cumperayot & De Vries (2017) explore the ability of monetary fundamentals to forecast exchange rates. Their main results show that information located in the tails of the distributions of exchange rates and monetary fundamentals contributes to explaining the relationship between the variables.

This paper seeks to synthesis these two literatures, and to the best of our knowledge, our research is the first to study the link between exchange rates and commodity prices in such a tail dependence framework. The novelty of our contribution lies in measuring the degree of asymptotic dependence and how this relationship contributes to explain the ability of commodity prices in forecasting exchange rates. This analysis of the tail behaviour of exchange rates and commodity prices may be highly relevant in terms of policy considerations for the subset of commodity exporting economies which document a close relationship between exchange rates and commodity prices.

3 Commodity exporter economies

Commodity price shocks play a key role in the transmission of global shocks to domestic economies. As discussed by Agénor & da Silva (2019), the effect of commodity prices is particularly relevant for the economic outlook of commodity exporting economies. On the one hand, in the short run, a negative commodity price shock reduces the export revenues which translates to a lower foreign currency inflows (typically U.S. dollars) arriving into the commodity exporting economy. As a result, the exchange rate of those economies tends to depreciate. On the other hand, in long run, a negative commodity price shock is interpreted as a worsening in the economic outlook of the commodity exporting economies. The deterioration in future economic expectations in commodity exporting countries discourages investment in those countries, as a result capital flows tend to run from these economies and their exchange rate tends to depreciate.

As pointed out by the International Monetary Fund (2017), the relationship between exchange rates and commodity prices is especially sensitive in the case of commodity exporting economies. It is particularly important to understand commodity price shocks as an element which conveys information into commodity exporting economies and ends up generating changes to the value of their currencies. This relationship has been particularly notorious during the commodity price super-cycle taking place from the 2000's. De Gregorio (2012) shows that, during prolonged episodes of high commodity prices, commodity exporting economies exhibit large and persistent current account deficits due to the massive capital inflows which aim to invest in the commodity sector. In this case, massive capital inflows lead exchange rate appreciations. Following this logic, shocks generated in commodity markets produce changes in the domestic economic expectations of commodity exporting economies. Then, that change in the future outlook of the commodity sector drive capital flows movements which finally impact exchange rates. The relationship between commodity prices and capital flows is consistent with the finding of related papers, such as Reinhart & Reinhart (2009) and Byrne & Fiess (2016).

Given our focus on the relationship between commodity prices and exchange rates, the sample of countries we include in this paper satisfy two conditions: (1) commodities must represent a significant proportion of the country's exports, and (2) countries must have a free floating exchange rate regime.Therefore, the sample of economies we include in the analysis is identified to be among the commodity exporting economies (International Monetary Fund 2012). Moreover, in general, the exports of these countries are both poorly diversified and mainly consist upon one or two main commodities. Countries with poorly diversified exports develop a high degree of economic dependence upon commodities. In addition, all of the countries in the sample have adopted a free floating exchange rate regime.

Table 1 reports some descriptive statistics of the economies included in the sample. For each country in the sample the table shows a set of commodity related indicators during three different periods of time: 2000-2005, 2006-2011, and 2012-2017. The indicators highlight the relevance of commodity exports for the economies of the sample. As we observe, commodity exports represent a high percentage of the total exports for all of the countries. Moreover, the commodity sector is a highly relevant one for the whole economy. On average, around 15% of GDP is represented by the commodity sector. Additionally, the table also shows the main product exported by each country, which represent a high proportion of the commodity exports. All in all, the information exhibited in table 1 puts in perspective the relevance the commodity exports for the countries under analysis. It is worth noting that, although, oil seems to be less relevant for the case of Brazil, that country is one of the top ten oil producers around the globe and it is the biggest oil producer in the region.[3] The oil industry in Brazil is also important for domestic investment and attracts foreign capital into the country.

3.1 Some empirical facts about returns

It is a well established empirical fact that the returns of many asset classes tend to follow leptokurtic distributions. This distribution characterised by higher kurtosis and a greater likelihood of observing extreme values in comparison to the normal distribution. As a result, distributions describing returns tend to exhibit fat tails which is indicative of this higher probability of observing extreme values. This fat-tailed phenomena also characterises exchange rate log-returns and commodity log-returns. Indeed, evidence on the growing degree of financialisation of commodity markets since the 2000's (Buyuksahin & Robe 2014, UNCTAD 2011) shows that commodities have been actively included in investment portfolios. Thus, commodity returns, interpreted as another financial asset, may be expected to exhibit fat-tailed distributions.

As an illustration, figure 1 plots the histograms of the US dollar - Chilean peso (USDCLP) exchange rate in log-returns (left-hand side panel) and the copper price in log-returns (right-

[3]According to the U.S. Energy Information Administration (EIA). See table in appendix A for more details about the World's Top Oil Producers.

hand side panel). The data corresponds to daily observations from Jan-2000 to July-2018. Each plot includes a theoretical normal distribution (red line) for comparison purposes. As the figures show, in both cases, the empirical distributions of the exchange rate and the copper returns differ from a normal distribution showing a positive excess of kurtosis and a high number of extreme observations far from the mean. Thus, this preliminary evidence suggests that the log-returns of this commodity and this exchange rate in particular follow fat-tailed distributions. This conclusion is also valid for the rest of the exchange rates and commodity log-returns under analysis as we formally show in section 5.

Additionally, figure 2 shows a scatter plot of the USDCLP (y-axis) and the copper price (x-axis), both in log-returns, using daily data from Jan-2000 to July-2018. As we observe, there is a negative relationship between the log-returns of both variables. Importantly, this negative relationship corresponds to the expected relationship in the asymptotic dependence analysis introduced below.[4]

4 Methodology

4.1 Forecasting model

In order to test the forecasting ability of commodity prices we carry out the standard forecasting evaluation exercise adopted in the literature which is briefly described below.

Our candidate model is a simple OLS regression for each country in which there is only one explanatory variable: a country-specific commodity price. Table 1 reports the country-specific commodity for each country. Equation (1) gives the forecasting model. The dependent variable corresponds to exchange rate log-returns, while the independent variable corresponds to the country-specific commodity log-returns. Particularly, Δs^f_{t+h} corresponds to the exchange rate log-return h-periods-ahead forecast. We estimate equation (1) using a sample window of length R ($R = 2419$ observations), from 03/01/2000 to 09/04/2009, corresponding to the half the total sample T ($T = 4838$ observations) and we produce h-steps ahead forecasts. We then roll forward the window one observation, re-estimate equation (1) over the window 04/01/2000 to 10/04/2009 and generate new h-step ahead forecasts. We repeat this process up to $T - h$ to produce forecasts for the full out-of-sample period. Following the methodology proposed by Meese & Rogoff (1983), we use perfect foresight data,

[4] In this study the nominal exchange rate is defined as the value of one U.S. dollar in terms of the domestic currency.

meaning that we include realised values of commodity returns in the forecasting exercises. For this reason, the approach is also known as a *pseudo* out-of-sample forecasting, since in real life situations it is not possible to know tomorrow's value of commodity returns. We set short-term forecast horizons at $h = 1, 2, 3, 4, 5, 10$ periods ahead. Following the exchange rate forecasting literature, related studies using daily observation mostly focus on short-term horizons (e.g.: Ferraro et al. (2015) and Kohlscheen et al. (2017) use 1-step ahead forecast using daily commodity prices), while others studies using lower frequency observation, quarterly or annual observations, set longer forecast horizons (see Rossi (2013)).

$$\Delta s_{t+h}^{f} = \widehat{\alpha}_t + \widehat{\beta}_t \Delta p_{t+h}, \quad t = R, R+1, ..., T-h. \tag{1}$$

We select the RW model as a benchmark against which to contrast our commodity-based forecasts. According to Rossi (2013), the RW model without drift is the toughest benchmark to beat in out-of-sample forecast exercises.

In order assess the out-of-sample forecasting ability of the models, we statistically compare the root mean square forecast error (RMSE) of both models using the Diebold-Mariano (DM) test. Giacomini & White (2006) show that the DM test is valid to compare the out-of-sample forecasts of two nested models when the length of the estimation windows is constant. As a robustness check we also evaluate the forecasting ability of the models using the Clark-West (CW) test. The CW test corrects the RMSE taking in account noise that may be generated due to parameter uncertainty.

4.2 Fat-tailed distribution in returns: Tail indexes

Before considering the extent of asymptotic dependence between two random variables, we need to demonstrate that the variables under analysis exhibit heavy-tail distributions.

In order to test whether exchange rates and commodity returns follow fat-tailed distributions we implement two non-parametric approaches: the Hill tail index (Hill 1975) and a tail index indicator (Dekkers et al. 1989) shown in equations (2) and (3), respectively.

$$\widehat{H} = \frac{1}{k} \sum_{i}^{k} log\left(\frac{X_{(i)}}{X_{(k)}}\right) \tag{2}$$

$$\widehat{\gamma} = 1 + H + \frac{1}{2}\left(\frac{\frac{M}{H}}{H - \frac{M}{H}}\right), \tag{3}$$

These non-parametric indicators consider order statistics of a random variable X of length n, such that X is sorted in descending order as follows $X_{(1)} \geq X_{(2)} \geq \ldots \geq X_{(n)}$. Then, the indicators only include the information located above the threshold represented by $X_{(k)}$, where k corresponds the number of observations above the threshold. The variance of both indicators is asymptotically normally distributed and given by $\widehat{H}^2$ and $1 + \widehat{\gamma}^2$ for the $\widehat{H}$ and $\widehat{\gamma}$ estimator, respectively. When tail indices display positive values and the confidence bands do not include zero, the indicators suggest that statistically log-returns follow a heavy-tail distribution.

The Hill tail index is an unbiased estimator and it is also more efficient in comparison to other alternative tail index indicators as pointed out by Tsay (2010) and Cumperayot & De Vries (2017). However, the indicator assumes that the data comes from a fat-tailed distribution. In contrast, the $\widehat{\gamma}$ tail index indicator is more flexible since it does not assume *a priori* any specific distribution in the data.

4.3 Asymptotic dependence

In order to analyse the information contained in the tail of the log-returns distribution (i.e. extreme values) and how those observations are related in a multidimensional framework the related literature focuses on the concept of tail dependence. Tail dependence measures the probability that extreme values of one random variable occur given that extreme values of another random variable simultaneously happen. In other words, it is a measure of the joint probability that large changes in two random variables take place simultaneously. Previous studies provide a variety of procedures to estimate the tail dependence of two random variables. A common approach in finance focuses on modelling the whole join distribution of two or more variables using the copula methodology. Under that approach, the idea is to model the entire dependence structure between two random variables. The asymptotic dependence method we implement in this paper, also known as the limit copula, is a more specific way to analyse the probability of occurrence of large movements in two variables and it is also an alternative and simplified standard procedure to model only the tail behaviour of two random variables.

The relevance of the asymptotic dependence analysis is due to its contribution to explain the relationship between two variables by taking in account the link between them based on the information contained in the tails of the distribution. This is particularly relevant when two (or more) variables seem to show a low degree of correlation, but most of the relationship is driven by the information contained in the tails. For instance, this is the case of exchange rate log-returns and commodity log-returns, as we show in figure 2, where most of the observations in the scatter plot tend to concentrate around the origin with no clear pattern, however, there are some observations, located in the tails of the distribution, which help explain the negative relationship between those variables.

Based on this logic, it may happen that, in the most extreme case where the correlation between two variables is close to zero, the variables can still hold an asymptotic dependence relationship. In such a case, the information contained in the tails of the distributions is crucial in describing the link between two variables. On the contrary, two random variables exhibiting heavily-tailed distributions may not be asymptotically dependent. If that is case, then, extreme values of those variables are not linked between each other and the occurrence of extreme values are due to pure noise, or a third factor, rather than because of the relationship between those variables.

In order to test the extreme relationship between exchange rate and commodity returns we implement the non-parametric Asymptotic Dependence Indicator (ADI) proposed by de Haan & Ferreira (2007) shown in equation (4). The $\widehat{S}(k)$ asymptotic dependence measure is a counter indicator which takes the value of 1 when two random variables (X and Y) are simultaneously higher than a given threshold X_k and Y_k for the variables X and Y, respectively. Note that the threshold may differ between the two variables, meaning that each variable is compared against its own threshold. k represents the number of observations above the threshold.[5]

$$\widehat{S}(k) = \frac{1}{k} \sum_{i=1}^{n} \mathbf{1}_{\{X_i \geq X_k, Y_i \geq Y_k\}} \tag{4}$$

The $\widehat{S}(k)$ asymptotic dependence measure indicates that two random variables are asymptotically dependent when $\widehat{S}(k)$ is positive (no greater than 1, by construction) and the confidence bands exclude zero. By definition, the specific value of the $\widehat{S}(k)$ asymptotic indicator is interpreted as a probability of observing that a pair of observations of two random variables lies above a given threshold simultaneously.

The advantage of this indicator lies in its simplicity and also because it can be implemented even when the scale of the variables under analysis is different. The literature also offers alternative asymptotic measures, such the one proposed by Poon et al. (2004). This

[5]Even though the threshold may be different between variables, k or the chosen percentile for the threshold must be the same for both variables.

measure allows capturing the extreme linkage between two random variables by identifying asymptotic dependence relationships and also by quantifying its degree of association. A disadvantage of this approach is that the two random variables included in the analysis need to be measured in the same scale. Additionally, as Fernandez (2008) notes, the Poon et al. (2004)'s measure tends to provide biased results since it tends to reject the null hypothesis of asymptotic dependence. In this sense, Fernandez (2008) concludes that the copula analysis, and therefore the empirical copula analysis which corresponds to the de Haan & Ferreira (2007) indicator implemented here, is a more suitable approach to measure the degree of asymptotic dependence between two random variables.

5 Results

This section reports the results of the out-of-sample forecast and the asymptotic dependence measure. The data corresponds to daily observations of nominal exchange rates and commodity prices, both measured in log-returns, from 01/Jan/2000 to 18/Jul/2018. The countries under analysis and the country-specific commodity prices are shown in table 1. The nominal exchange rate is defined using the U.S. dollar as the base currency.

5.1 Out-of-sample forecasts

This section describes the results of the out-of-sample exercises using the forecasting model introduced in equation 1.

Commodity-based models vs. random walk models

Table 2 presents the RMSE ratio between the commodity-based model (numerator) and a RW model without drift (denominator) for the countries under analysis (in rows) and for different forecast horizons (in columns). The results show that in all cases and for every forecast horizon the commodity-based model forecasts better than the driftless RW model. In addition, the Diebold-Mariano test indicates that the MSFE of the commodity-based model is statistically lower, at 1% level, than the MSFE of the driftless RW model.

Similarly, as table 3 shows, the conclusions remain the same when comparing the forecasting ability of the commodity-based models against a RW model with drift. In this case, the commodity-based models forecast better than a RW model with drift and the difference in predictive power is statistically significant at 1% according to the Diebold-Mariano test.

Our results are consistent with previous findings. For instance, Ferraro et al. (2015) and Kohlscheen et al. (2017) show that commodity-based models also beat the RW model, both with and without drift, using daily observations.

5.2 Robustness tests

In order to test the statistical robustness of our results, we assess the forecasting ability of the commodity-based models using the Clark-West test as an alternative statistical measure. Tables 4 and 5 report the RMSE ratios using the driftless RW model and the RW with drift, respectively. As the tables show, our results remain valid, meaning that the commodity-based models produce lower MSFEs in comparison to the RW model with and without drift and that difference is statistically significant at 1%.

Further we also test the robustness of our results by implementing the same out-of-sample forecasting exercises but using an alternative definition of the base currency. Tables 6 and 7 show the results using the euro (EUR) and the pound sterling (GBP), as the currency base, respectively. From the results, it is possible to hold that the findings generally remain the same even after using an alternative base currency definition. The forecasting ability of commodity-based models is still significant even when the US dollar is not the base currency. Some minor exceptions appear in the case of Peru when the base currency is GBP or EUR, and also in the case of South Africa using EUR as the base currency where the evidence is only marginally significant at 10% level. Overall, the results of this robustness exercise show that the forecasting ability of commodity prices is not only limited to the dollar as a base currency, thus its predictive power goes beyond a mere dollar effect.

In addition, our results are robust to unobservable global factor affecting both exchange rates and commodity returns. In order to test for the the effect of that potential factor we replicate the out-of-sample exercise using exchange rate returns which are orthogonal to the change in the VIX index. We include the VIX index since it is variable available at daily frequency which accounts for global risk aversion which may be affecting both exchange rates and commodity returns. Table 8 shows the results. As we can see, after controlling for the effect of a global common factor, the conclusion remains the same even and we can hold that commodity returns forecast better than a random walk model without drift for all the countries in the sample.

5.2.1 Lagged commodity prices

In order to perform a *truly* out-of-sample exercise we use lagged commodity prices rather than contemporaneous prices and replace equation (1) with equation (5).

$$\Delta s_{t+h}^{f} = \widehat{\alpha}_t + \widehat{\beta}_t \Delta p_t, \quad t = R, R+1, ..., T-h. \tag{5}$$

We estimate equation (5) using a sample window of length R ($R = 2419$ observations), from 04/01/2000 to 10/04/2009, corresponding to the half the total sample T ($T = 4838$ observations) and we produce h-steps ahead forecasts. We then roll forward the window one observation, re-estimate equation (5) over the window 05/01/2000 to 11/04/2009 and generate new h-step ahead forecasts. We repeat this process up to $T-h$ to produce forecasts for the full out-of-sample period.

Table 9 depicts the results comparing the commodity-based models with a RW without drift. As the results show, the forecasting ability of commodity prices disappears when the explanatory variable is replaced by its lagged values. This evidence shows that the commodity-based model using lagged commodity prices cannot beat the driftless RW.

On the contrary, when testing the commodity-based model using lagged commodity prices against a RW model with drift the evidence supports the forecasting ability of lagged commodity prices. Table 10 shows that the commodity based model using lagged commodity prices forecast better than a RW with drift and the results are statistically significant.

The evidence of the forecasting ability of our commodity-based model is closely related to the findings of Ferraro et al. (2015) and Kohlscheen et al. (2017). They similarly highlight that lagged commodity prices exhibit a lower forecasting ability in comparison to contemporaneous values. In particular, the forecasting evidence of commodity prices disappears when the benchmark is the driftless RW, while they show that there is still some evidence in favor of commodity-based models to forecast better than the RW with drift.

5.2.2 Using low frequency data

In this section we analyse the forecasting ability of commodity based models using low frequency observations. Following the standard procedure adopted in Ferraro et al. (2015), we compute monthly and quarterly observations using the end-of-sample daily frequency. According to Rossi (2013), using end-of-sample observations implies a harder task in finding forecasting ability in comparison to computing a monthly or quarterly average from daily observations.

Table 11 presents the results using contemporaneous commodity prices at monthly frequency and the driftless RW model as a benchmark. As can be observed, the forecasting ability of the commodity-based model decreases in comparison to the daily data case for most of the countries in our analysis. In general terms, there is no statistical evidence, or it is only marginally significant at 10%, in favour of commodity prices. However, there is still some predictive ability of commodity prices at 5% level of significance for the cases of Canada, Chile and Norway.

We observe similar results when comparing the predictive ability of our commodity-based model against a RW model with drift. As table 12 shows, the predictive ability of commodity prices tends to reduce when comparing to the RW model with drift. Even though the reduction in the forecasting ability decreases in comparison to daily frequency, there is still a couple of highly significant cases, such as Canada and Norway, where commodity prices forecast better that the RW with drift. However, as we previously noted, the statistical significance in those cases comes from the fact the benchmark model, the RW with drift, it is not the toughest benchmark to beat (Rossi 2013).

As with the daily observations previously, we then carry out a *truly* out-of-sample forecast exercise, by including lagged commodity prices as the main explanatory variable, estimating equation (5). Tables 13 and 14 present the results using the driftless RW model and the RW model with drift, respectively. We find that the forecasting ability of the commodity-based model completely disappears no matter which benchmark model we use. As shown, there is no statistical significance in favour of lagged commodity prices to forecast better than the benchmarks at a monthly frequency and this applies to every country under analysis.

In addition, replicating the previous exercises but using quarterly observations we reach the same conclusions. First, by using contemporaneous commodity price observations, the forecasting ability of commodity-based models reduces even further relative to the daily and monthly frequency estimations, this holds for both benchmarks, the RW model without drift (table 15) and RW with drift (table 16). An exception occurs in the case of Chile where the predictive power of commodity prices is still highly significant. Second, the forecasting ability of lagged commodity prices complete disappears for all countries in comparison to daily and monthly frequency. This evidence holds either the benchmark model is defined as a driftless RW (table 17) or a RW with drift (table 18).

The results of this section highlight the relevance of the data frequency in forecasting exchange rates using commodity-based models. We demonstrate that in reducing the frequency of the data, from daily to monthly or quarterly observations, the forecasting ability of the commodity prices decreases in both *pseudo* out-of-sample and *truly* out-of-sample exercises. The results hold no matter the benchmark model we use, either the driftless RW or the RW with drift. Our results are consistent with recent studies (Ferraro et al. (2015) and Kohlscheen et al. (2017)) and reinforce the idea that using observations at a daily frequency is a crucial element to capture the relationship between the variables. As we show, contemporaneous commodity prices exhibit a higher forecasting ability in comparison to lagged commodity prices. Thus, there is a short-lived relationship between the variables which is mostly captured based on the contemporaneous relationship between commodity prices and exchange rates. Moreover, by lowering the data frequency the relationship between the variables tends to vanish and, as a result, the forecasting power of commodity-based models also decreases. This evidence highlights the relevance of daily observation in forecasting exchange rates. In this sense, commodity price shocks affecting exchange rates are transitory and tend to dilute over time when economic agents internalise new information. Therefore, low frequency observations are not able to capture those transitory information, consequently commodity prices at a lower frequency are not useful in predicting exchange rates.

5.3 Fat-tailed distributions of log-returns

Table 19 reports the results of the Hill tail index defined in equation (2) for the case of both the lower and upper log-returns tails, representing the most negative and positive log returns, respectively. Confidence intervals at 95% level are also included in parenthesis. As shown, for all cases and also for both upper and lower tails the indicator is positive and statistically different from zero meaning that the distribution of log-returns of each variable follows a fat-tailed distribution.

A more conservative evaluation of fat-tailed distributions is carried out using the Dekkers et al. (1989) index. Table 20 presents the results of the $\widehat{\gamma}$ tail index estimator introduced in equation (3). As the table shows, most currencies and commodity prices exhibit heavily-tailed distributions in both tails. Some exemptions appear in the case of upper tail for the case of the Canadian dollar, the Norwegian krone and the copper price, while an exception also appears in the lower tail for the the South African Rand. Despite the occurrence of those exceptions, we can interpret the $\widehat{\gamma}$ tail index estimator as a more strict measure to capture the amount of information contained in the tails of the distribution.

Overall, these results allows us to conclude that there is information in the tails of the distribution which can be explored further by carrying out our asymptotic dependence analysis in next section.

5.4 Asymptotic dependence

This section introduces the results of the asymptotic dependence measure based on de Haan & Ferreira (2007). It is relevant to define some important cases under analysis before describing the results. As we discuss in section 4, the ADI measures the asymptotic dependence between a pair of random variables. In this study, there are 4 cases to analyse corresponding to the combination of the two tails of each of the two random variables under analysis. Particularly, we compute the ADI using nominal exchange rates and commodity prices, both in log-returns, therefore, the four cases under analysis are the following:

- **Case 1**: Nominal exchange rate appreciation (lower tail of exchange rate log-return distribution) and increase in country-specific commodity price (upper tail of commodity log-return distribution).
- **Case 2**: Nominal exchange rate depreciation (upper tail of exchange rate log-return distribution) and reduction in country-specific commodity price (lower tail of commodity log-return distribution).
- **Case 3**: Nominal exchange rate appreciation (lower tail of exchange rate log-return distribution) and reduction in country-specific commodity price (lower tail of commodity log-return distribution).
- **Case 4**: Nominal exchange rate depreciation (upper tail of exchange rate log-return distribution) and increase in country-specific commodity price (upper tail of commodity log-return distribution).

5.4.1 Asymptotic dependence using contemporaneous commodity prices

Table 21 reports the ADI estimation using daily contemporaneous commodity prices from Jan-2000 to Jul-2018. Confidence bands are computed by bootstrap method using 5000 resampling iterations. As the table shows, the asymptotic dependence index is positive and statistically significant for all countries in cases 1 and 2. On the contrary, for cases 3 and 4, the index reduces in magnitude for all of the countries and becomes statistically non-significant in most of the countries.

Results are in line with the theoretical relationship between commodity prices and exchange rates. As we discuss in section 3, commodity price shocks generate changes in commodity exporting economies which ultimately cause impacts on exchange rates. In particular, a sharp decrease (increase) in the price of the country-specific exported commodity is associated with a deterioration (improvement) in the economic outlook of that commodity exporter economy, as a result, a massive surge of capital flows flies from (enter to) the economy and, as a consequence of this sudden deterioration (improvement) in economic confidence, a sharp depreciation (appreciation) of the nominal exchange rate takes place.

Following this logic, the asymptotic dependence only makes sense when the variables are negatively related such as in cases 1 (exchange rate appreciation and increase in commodity price) and case 2 (exchange rate depreciation and a reduction in the commodity price). Moreover, this expected negative relationship between the variables is empirically supported in the data as we preliminary show in section 3.1. Importantly, cases 3 and 4 report low values for ADI and, in general, show no statistical significance for most of the countries.

Our asymptotic dependence measure is robust to a set of alternative specifications. First, the ADI is robust to commodity and exchange rates returns that are orthogonal to the VIX index. As table 22 shows, cases 1 and 2 are statistically significant even after controlling for the effect of common risk aversion, captured by the VIX index. This mean that the asymptotic dependence measure goes beyond a mere risk factor that may move both exchange rates and commodity returns. As expected, cases 3 and 4 are close to zero or statistically non-significant.

Second, as commodity prices and exchange rates are measured in U.S. dollars, we also show that the asymptotic relationship between the variables does not only reflect a dollar effect. Tables 23 and 24 show the ADI defining the exchange rate using Euros and Pound Sterling as a currency base, respectively. As we can see, the asymptotic dependence between exchange rates and commodity returns remains significant for cases 1 and 2, while cases 3 and 4 are close to zero or statistically non-significant.

Third, due to the nature of time-series of log-returs, it may be the case that the effect of heteroskedasticity in log-returns biases the result of the asymptotic dependence analysis. Following the literature, we estimate our ADI measure controlling for the potential issue of heteroskedastic in log-returns. To do so, we estimate our ADI measure using standardised residual, which a are free of heteroskedasticity issues, for both commodity and exchange rate returns. In order to compute the standardised residual we model the univariate conditional variance for each return using a GARCH(1,1) model. As table 25 shows, the results after controlling for heteroskedasticity remains the same, cases 1 and 2 are statistically significant and they show an asymptotic dependence relationship around 10% on average, while cases 3 and 4 are much lower, close to zero, or statistically non-significant.

5.4.2 Interpretation of tail dependence between commodity prices and exchange rates

The interpretation of the asymptotic dependence measure is based on the effect of unexpected news over commodity markets. The arrival of unexpected news, or economic surprises, affecting commodities markets generates sharp changes in commodity prices which are transmitted, to some degree, to the commodity exporter economies impacting their exchange rates.

It is widely accepted that news has a significant impact on asset return volatility. Consequently, episodes characterised by the frequent arrival of unexpected news are associated with changes in asset prices and periods of high volatility of returns. Some studies show the same logic also applies to commodity markets (Caporale et al. 2017; Frankel & Hardouvelis 1985; Roache & Rossi 2010) where the arrival of news has a significant impact on commodity price volatility. According to these studies, unexpected news affecting commodity markets represents the main driver of large fluctuations in commodity prices. As a result, large fluctuations in commodity prices translate to leptokurtic commodity log-return distributions where extreme observations are more likely to take place generating fat tails in the log-returns distributions.

Following the discussion about the transmission channel of external shocks into the domestic economy (see section 3), large swings in commodity prices, which are driven by unexpected news in commodity markets, convey information to commodity exporting economies by changing the perception of investors about the economic outlook of commodity exporting economics, affecting capital flows and, ultimately, generating changes in domestic currencies. In particular, the proposed measure of tail dependence allows us to quantify how extreme values of exchange rates log-returns are related to extreme values of commodity log-returns. Consequently, the relationship in the tails of the distribution provide us with an idea of how much of the arrival of unexpected news in commodity markets are transmitted to exchange rates. This point of view is also consistent with Ferraro et al. (2015) who interpret commodity price shocks as the mechanism conveying information about macroeconomic news that may affect exchange rates.

As an illustration of the above mechanism we provide an example using the copper price and the Chilean exchange rate. In the particular case of the copper market, China's copper demand is considered as an important driver of the international copper price. The economic activity in that country is closely related to changes in the copper price, therefore, news, or economic surprises, about the current economic situation of China tend to impact the price of cooper. Thus, it is expected that news, or surprises about economic activity in China, generate a significant effect on copper price. Figure 3 shows the asymptotic dependence indicator for the case of large decreases in copper prices and large depreciations in the Chilean exchange rate (blue line), while the shaded grey areas correspond to those periods when negative economic news (negative economic surprises) take place in China.[6] As we can see from figure 3, during episodes of negative economic surprises in China, we observe an increase in our asymptotic dependence measure, meaning that bad news (or negative surprises) in China are associated to large decreases in copper price, which, in turn, are linked to large depreciation of the Chilean exchange rate. Therefore, it is possible to argue that, at least, some part of the news (or economic surprises) affecting the copper market are also transmitted to the Chilean exchange rate, via the copper price. Although China is a relevant global agent affecting the copper market, it is worth noting that there is no perfect correlation between events in figure 3 and our asymptotic dependence measure, this is mainly because surprises about economic activity in China only represent a fraction of the shocks affecting the copper market with other elements also playing a role in explaining changes in the international price of copper.

5.4.3 Asymptotic dependence using lagged commodity prices

Table 26 shows the ADI estimation using one period lagged commodity prices at a daily frequency. The results show that for cases 1 and 2 the asymptotic dependence considerably reduces in magnitude in comparison to the case of contemporaneous commodity prices and, for the case of some countries, the indicator is no statistically different to zero. In cases 3 and 4 there is certain significance for some countries, however the ADI tends to be low around 5% on average, and importantly, tends to be as low as cases 1 and 2. All in all, the statistical significance of asymptotic dependence between nominal exchange rates and lagged commodity prices at daily frequency is rather than weak, specially compared with the cases 1 and 2 of ADI using contemporaneous commodity prices.

5.4.4 Asymptotic dependence using low frequency data

Table 27 presents a comparison of the the asymptotic dependence between exchange rates and contemporaneous commodity prices computed at daily, monthly and quarterly frequency. As can be seen, most of the asymptotic dependence tends to vanish at a monthly frequency

[6] The asymptotic dependence indicator shown in this example corresponds to the ADI case 2 described on page 16. The China surprise index corresponds to the Citigroup China Economic Surprise Index obtained from Bloomberg.

and only few countries (Chile, Norway, Russia, and South Africa) still show at least some degree of statistical significance in cases 1 or 2, while no significance at all in cases 3 and 4.

Similarly, in the case of quarterly frequency and contemporaneous observations, there is no statistically significant asymptotic dependence between exchange rate and contemporaneous commodity prices for any of the countries in the sample. This set of results contrasts with the evidence provided in Cumperayot & De Vries (2017) since they show that the asymptotic dependence between classical monetary fundamentals and exchange rates is still present when the data frequency is reduced to quarterly observations. On the contrary, in our case, commodity price shocks measured at lower frequency, either monthly or quarterly, tend show no effect on large exchange rate movements.

In the same way, using lagged commodity prices and low frequency data (see table 28) we observe similar results: the asymptotic dependence evidence complete disappears at both frequencies, monthly and quarterly, for all of the countries in the sample.

5.4.5 Relationship between exchange rate forecasting ability and asymptotic dependence

Our results allow us to draw two main conclusions. First, timing plays a key role in describing the relationship between exchange rates and commodity prices. As we show, the forecasting ability of commodity prices and also the asymptotic dependence between the variables tend to be short-lived meaning that only contemporaneous observations can capture that relationship. As we show, both, the out-of-sample forecasting ability of commodity prices and the asymptotic dependence between exchange rates and commodity prices are highly significant in contemporaneous terms, while both tend to disappear when lagged commodity prices are included in the analysis.

Second, the relationship between commodity prices and exchange rate is transitory. As we show, the forecasting ability of commodity prices and the asymptotic dependence between the variables is highly significant when observations are included at a daily frequency. On the contrary, the forecasting ability and the asymptotic dependence tend to disappear when lower frequencies are included either using monthly or quarterly observations.

The interpretation of our results lies in the nature of the news affecting commodity markets. As we previously discuss, large swings in commodity prices are driven by unexpected news arriving to that market. Our ADI measure captures how those news, which cause large swings in commodity prices, are also related to large movements in exchange rates. Unexpected news are transitory, short-lived and vanish over time as economic agents internalise those surprises.[7] As we document, the asymptotic dependence and the forecasting ability of commodity prices are highly significant using contemporaneous daily observations, while there is a reduction in the statistical significance of both elements when we use lagged or observations at a low frequency. Therefore, we argue that the information contained in the tails of the distributions, which reflects the effect of transitory, short-lived news arriving to the commodity markets, is a key component of the forecasting ability of commodity prices. On the contrary, when there is no news transmission from commodity prices to exchange rate (i.e.: no asymptotic dependence) the forecasting ability of commodity prices statistically reduces. Therefore the ability of commodity prices to forecast exchange rates is manly driven by the asymptotic dependence relationship between those variables. In this sense, log-returns located in the tails of the exchange rate and commodity price distributions convey crucial information to describe the relationship between those variables and, more importantly, account for the source of the forecasting ability of commodity prices.

It is worth noting that the proposed transmission mechanism provides a general framework to explain how commodity price shocks are transmitted to exchange rates. We cannot dismiss the possibility that another factor drives both variables, however, if commodities and exchange rate markets are segmented markets then it is less likely that a non-included factor drives our results.[8] In the same vein, demonstrating causality between variables goes beyond the scope of this research.[9] In this study we only focus on the relevance of the asymptotic dependence as a key element of the ability of commodity prices to explain exchange rates in out-of-sample fit tests.

[7]Related literature supports the fact that the effect of unexpected news on financial variables tend to happen in the short run and vanishes over time. For example, Chaboud et al. (2008) show that U.S. macroeconomic news have a significant impact on the Euro and the Japanese yen at a very high frequency (intra-day observation each 3 seconds). While Kilian & Vega (2011) show that U.S. macroeconomic news do not affect oil prices at a monthly frequency.

[8]Some studies show that commodity and exchange rates markets are segmented. For instance, Skiadopoulos (2013), shows that there is no common factor between commodity futures prices and other financial assets such as bonds and equities. From an asset pricing perspective, he concludes that there is no common factor in bonds or equity market which is useful to explain the cross-section returns of commodity futures prices.

[9]Even though the discrepancy regarding causal issues, most of the studies argue that the causal effect goes from commodity prices to exchange rates. Moreover, Ahmed (2019), investigates this issue further based on an event study and high frequency data. He uses the 2019 attack on two Saudi Arabian oil refineries as a natural experiment to provide evidence that, at least in the very short-run, the effect goes from commodity prices (oil in this case) to exchange rates.

6 Conclusions

Based on a sample of nine commodity exporter economies, our empirical results show that the commodity-based model performs better than a driftless RW in out-of-sample forecasting exercises only when commodity prices are included in contemporaneous terms. On the contrary, lagged commodity prices cannot outperform the driftless RW model. The forecasting ability of commodity prices is statistically significant when we use daily observations, conversely, commodity prices at a lower frequency show no forecasting ability.

This evidence supports the idea that the daily relationship between nominal exchange rates and commodity prices is short-lived and transitory. Therefore, the only way to capture that relationship is by including information in daily contemporaneous terms. This evidence is in line with other recent studies, such as Ferraro et al. (2015). The key element behind the forecasting ability of commodity prices lies in the information transmitted from commodity price shocks to exchange rates. We argue that commodity price shocks convey information by generating changes in the outlook of the commodity exporter economies causing capital flow movements which, ultimately, impact the domestic currency of commodity exporter economies.

As we note, unexpected news in the commodity market are those shocks who cause a stronger impact on exchange rates. Our asymptotic dependence measure quantify the degree of relation between large swings of commodity prices and exchange rate. As we document, at daily frequency and using contemporaneous observation, the asymptotic dependence is statistically significant meaning that in this case most of the information conveyed by commodity prices is transmitted to exchange rates. On the contrary, at lower frequencies or using lagged commodity prices, we observe no asymptotic dependence between the variables and we also note no forecasting ability of commodity prices. This evidence highlights the relevance of timing in examining the relationship between exchange rates and commodity prices. As we discuss, unexpected news coming from commodity markets are transitory and short-lived, then high frequency data, i.e.: daily contemporaneous observations are a key component to describe the relationship between the variables. Therefore, the reduction of the asymptotic dependence, interpreted as a reduction of the news conveyed by commodity prices, is the reason why we observe no forecasting ability of commodity prices at lower frequencies or using lagged observations. Hence, the ability of commodity prices to predict exchange rates lies in the asymptotic dependence between the variables.

Bibliography

Agénor, P.-R. & da Silva, L. A. P. (2019), *Integrated inflation targeting: Another perspective from the developing world*, BIS Publications, Bank for International Settlements.

Ahmed, R. (2019), 'Currency Commodities and Causality: Some High-Frequency Evidence', *MPRA working paper Paper. University Library of Munich, Germany* .

Akram, Q. F. (2004), 'Oil prices and exchange rates: Norwegian evidence', *Econometrics Journal* **7**(2), 476–504.

Amano, R. A. & van Norden, S. (1995), 'Terms of trade and real exchange rates: the Canadian evidence', *Journal of International Money and Finance* **14**(1), 83–104.

Amano, R. A. & van Norden, S. (1998*a*), 'Exchange Rates and Oil Prices', *Review of International Economics* **6**(4), 683–694.

Amano, R. A. & van Norden, S. (1998*b*), 'Oil prices and the rise and fall of the US real exchange rate', *Journal of International Money and Finance* **17**(2), 299–316.

Buyuksahin, B. & Robe, M. A. (2014), 'Speculators, commodities and cross-market linkages', *Journal of International Money and Finance* **42**(C), 38–70.

Byrne, J. P. & Fiess, N. (2016), 'International capital flows to emerging markets: National and global determinants', *Journal of International Money and Finance* **61**(C), 82–100.

Caporale, G. M., Spagnolo, F. & Spagnolo, N. (2017), 'Macro News and Commodity Returns', *International Journal of Finance & Economics* **22**(1), 68–80.

Cashin, P., Cespedes, L. F. & Sahay, R. (2004), 'Commodity currencies and the real exchange rate', *Journal of Development Economics* **75**(1), 239–268.

Chaboud, A. P., Chernenko, S. V. & Wright, J. H. (2008), 'Trading activity and macroeconomic announcements in high-frequency exchange rate data', *Journal of the European Economic Association* **6**(2-3), 589–596.

Chen, Y. (2002), 'Exchange rates and fundamental: evidence from commodity economies', *Mimeograph, Harvard University* .

Chen, Y.-C., Rogoff, K. S. & Rossi, B. (2010), 'Can Exchange Rates Forecast Commodity Prices?', *The Quarterly Journal of Economics* **125**(3), 1145–1194.

Chen, Y. & Rogoff, K. (2003), 'Commodity currencies', *Journal of International Economics* **60**(1), 133–160.

Cumperayot, P. & De Vries, C. (2017), 'Linking Large Currency Swings to Fundamentals' Shocks', *World Bank-University of Malaya Joint Seminar* .

De Gregorio, J. (2012), Living with capital inflows, *in* Bank for International Settlements, ed., 'Challenges related to capital flows: Latin American perspectives', Vol. 68, Bank for International Settlements, pp. 9–13.

de Haan, L. & Ferreira, A. (2007), *Extreme Value Theory: An Introduction*, Springer Series in Operations Research and Financial Engineering, Springer New York.

Dekkers, A. L. M., Einmahl, J. H. J. & Haan, L. D. (1989), 'A moment estimator for the index of an extreme-value distribution', *The Annals of Statistics* **17**(4), 1833–1855.

Dias, A. & Embrechts, P. (2010), 'Modeling exchange rate dependence dynamics at different time horizons', *Journal of International Money and Finance* **29**(8), 1687–1705.

Engel, C. & West, K. D. (2005), 'Exchange Rates and Fundamentals', *Journal of Political Economy* **113**(3), 485–517.

Fernandez, V. (2008), 'Copula-based measures of dependence structure in assets returns', *Physica A: Statistical Mechanics and its Applications* **387**(14), 3615–3628.

Ferraro, D., Rogoff, K. & Rossi, B. (2015), 'Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates', *Journal of International Money and Finance* **54**(C), 116–141.

Foroni, C., Ravazzolo, F. & Ribeiro, P. J. (2015), 'Forecasting commodity currencies: the role of fundamentals with short-lived predictive content', *Norges Bank Working Papers* .

Frankel, J. & Hardouvelis, G. (1985), 'Commodity prices, money surprises and fed credibility', *Journal of Money, Credit and Banking* **17**(4), 425–38.

Giacomini, R. & White, H. (2006), 'Tests of conditional predictive ability', *Econometrica* **74**(6), 1545–1578.

Hill, B. M. (1975), 'A simple general approach to inference about the tail of a distribution', *The Annals of Statistics* **3**(5), 1163–1174.

International Monetary Fund (2012), 'Macroeconomic Policy Frameworks for Resource-Rich Developing Countries', *IMF papers* .

International Monetary Fund (2017), 'Regional Economic Outlook: Tale of Two Adjustments', *IMF papers* .

Kilian, L. & Vega, C. (2011), 'Do energy prices respond to u.s. macroeconomic news? a test of the hypothesis of predetermined energy prices', *The Review of Economics and Statistics* **93**(2), 660–671.

Kohlscheen, E., Avalos, F., & Schrimpf, A. (2017), 'When the Walk Is Not Random: Commodity Prices and Exchange Rates', *International Journal of Central Banking* **13**(2), 121–158.

Meese, R. A. & Rogoff, K. (1983), 'Empirical exchange rate models of the seventies : Do they fit out of sample?', *Journal of International Economics* **14**(1-2), 3–24.

Patton, A. J. (2006), 'Modelling asymmetric exchange rate dependence', *International Economic Review* **47**(2), 527–556.

Patton, A. J. (2012), 'A review of copula models for economic time series', *Journal of Multivariate Analysis* **110**(C), 4–18.

Poon, S.-H., Rockinger, M. & Tawn, J. (2004), 'Extreme value dependence in financial markets: Diagnostics, models, and financial implications', *Review of Financial Studies* **17**(2), 581–610.

Reinhart, C. & Reinhart, V. (2009), Capital Flow Bonanzas: An Encompassing View of the Past and Present, *in* 'NBER International Seminar on Macroeconomics 2008', NBER Chapters, National Bureau of Economic Research, Inc, pp. 9–62.

Roache, S. K. & Rossi, M. (2010), 'The effects of economic news on commodity prices', *The Quarterly Review of Economics and Finance* **50**(3), 377 – 385.

Rossi, B. (2013), 'Exchange Rate Predictability', *Journal of Economic Literature* **51**(4), 1063–1119.

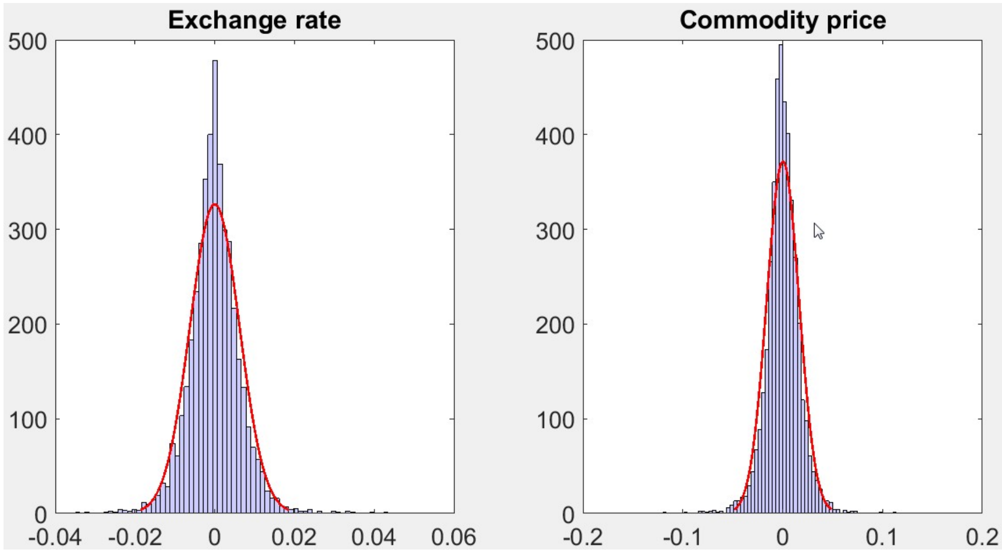
Skiadopoulos, G. (2013), 'Advances in the commodity futures literature: A review', *The Journal of Derivatives* **20**(3), 85–96.

Tsay, R. S. (2010), *Analysis of Financial Time Series*, Wiley series in probability and statistics, 3 edn, Wiley.

UNCTAD (2011), 'Price Formation in Financialized Commodity Markets', *United Nations Publication* **UNCTAD/GDS/2011/1**.

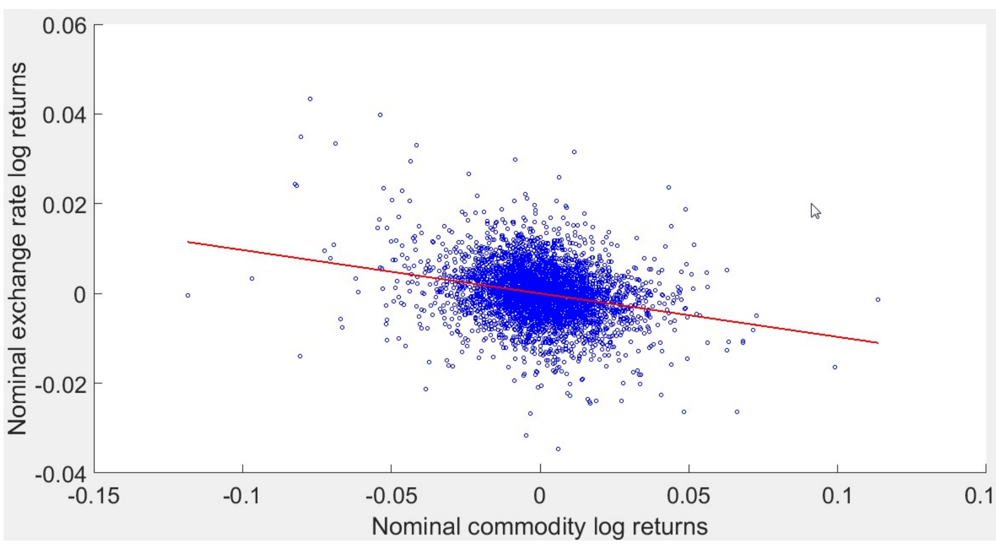
Yang, L. & Hamori, S. (2014), 'Gold prices and exchange rates: a time-varying copula analysis', *Applied Financial Economics* **24**(1), 41–50.

Zhang, H. J., Dufour, J.-M. & Galbraith, J. W. (2016), 'Exchange rates and commodity prices: Measuring causality at multiple horizons', *Journal of Empirical Finance* **36**(C), 100–120.



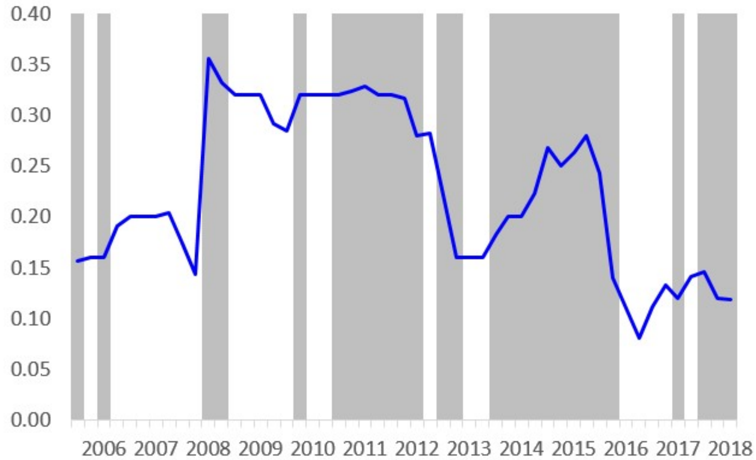
Note: Estimation sample corresponds to daily data from 01/Jan/2000 to 18/Jul/2018.

Figure 1: Chilean peso and copper price (both in log-returns)



Note: Estimation sample corresponds to daily data from 01/Jan/2000 to 18/Jul/2018.

Figure 2: Chilean peso and copper price (both in log-returns)



Notes: (1) Asymtotic dependence indicator (ADI) plotted in blue in the left-hand side axis. Shaded area corresponds to periods when the China economic surprise index exhibit negative economic surprises. (2) Asymptotic dependence computed using 1000 daily observations and 2.5% as the tail percentile (25 observations over the threshold). (4) Estimation sample corresponds to daily data from 01/Jan/2000 to 18/Jul/2018. (5) The China surprise index corresponds to the Citigroup China Economic Surprise Index obtained from Bloomberg.

Figure 3: Asymptotic dependence and China economic surprise index

Table 1: Commodity exporter economies

	Main Export	Commodity exports (% of total exports)			Commodity exports (% of GDP)			Main commodity export (% of commodity exports)		
		2000-2005	2006-2011	2012-2017	2000-2005	2006-2011	2012-2017	2000-2005	2006-2011	2012-2017
Brazil	Oil	46	58	64	5	6	6	9	16	13
Canada	Oil	36	49	50	11	12	12	22	33	37
Chile	Copper	84	87	86	24	31	23	55	70	63
Colombia	Oil	65	71	81	9	11	11	43	46	55
Mexico	Oil	18	26	21	4	7	7	59	59	42
Norway	Oil	79	82	80	25	26	22	64	54	44
Peru	Copper	83	88	89	13	23	18	42	49	46
Russia	Oil	76	83	81	22	20	18	57	64	63
S. Africa	Precious metals	49	55	57	9	12	14	51	62	59

Note: This table reports the mean percentage value of exports for each of three periods: 2000-2005, 2006-2011, and 2012-2017 for each country. Each period corresponds to the average values within those years. **Source**: United Nations Conference on Trade and Development (UNCTAD) website (https://unctadstat.unctad.org/EN/Index.html).

Table 2: Contemporaneous commodity prices vs. RW model without drift

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	0.919***	0.92***	0.92***	0.919***	0.919***	0.919***
stat	-4.867	-4.821	-4.818	-4.844	-4.841	-4.824
Canada	0.812***	0.812***	0.812***	0.813***	0.813***	0.813***
stat	-6.945	-6.928	-6.921	-6.907	-6.900	-6.862
Chile	0.905***	0.905***	0.905***	0.906***	0.907***	0.909***
stat	-3.792	-3.800	-3.808	-3.835	-3.880	-4.036
Colombia	0.856***	0.856***	0.856***	0.855***	0.854***	0.854***
stat	-5.112	-5.116	-5.123	-5.135	-5.173	-5.189
Mexico	0.905***	0.905***	0.905***	0.905***	0.904***	0.904***
stat	-5.595	-5.595	-5.592	-5.588	-5.567	-5.545
Norway	0.88***	0.88***	0.88***	0.88***	0.88***	0.881***
stat	-5.375	-5.353	-5.347	-5.337	-5.329	-5.271
Peru	0.976***	0.976***	0.976***	0.976***	0.976***	0.976***
stat	-4.113	-4.090	-4.090	-4.101	-4.105	-4.059
Russia	0.857***	0.857***	0.857***	0.857***	0.858***	0.858***
stat	-4.879	-4.878	-4.882	-4.885	-4.888	-4.905
S. Africa	0.944***	0.944***	0.944***	0.944***	0.944***	0.943***
stat	-4.015	-4.042	-4.045	-4.057	-4.061	-4.089

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 3: Contemporaneous commodity prices vs. RW model with drift

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	0.892***	0.892***	0.892***	0.892***	0.892***	0.892***
stat	-5.644	-5.616	-5.604	-5.624	-5.621	-5.607
Canada	0.783***	0.783***	0.783***	0.783***	0.783***	0.783***
stat	-7.380	-7.375	-7.375	-7.371	-7.372	-7.343
Chile	0.881***	0.881***	0.881***	0.881***	0.882***	0.88***
stat	-4.303	-4.315	-4.304	-4.331	-4.336	-4.377
Colombia	0.824***	0.824***	0.824***	0.823***	0.822***	0.822***
stat	-5.509	-5.514	-5.526	-5.556	-5.609	-5.596
Mexico	0.875***	0.874***	0.874***	0.875***	0.873***	0.874***
stat	-6.614	-6.621	-6.610	-6.608	-6.600	-6.560
Norway	0.849***	0.848***	0.849***	0.849***	0.849***	0.85***
stat	-6.430	-6.413	-6.406	-6.397	-6.391	-6.326
Peru	0.952***	0.952***	0.952***	0.952***	0.952***	0.952***
stat	-4.510	-4.484	-4.495	-4.500	-4.510	-4.490
Russia	0.841***	0.841***	0.841***	0.841***	0.841***	0.842***
stat	-4.872	-4.870	-4.876	-4.877	-4.880	-4.895
S. Africa	0.917***	0.917***	0.916***	0.916***	0.916***	0.916***
stat	-5.585	-5.573	-5.579	-5.603	-5.615	-5.636

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW with drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 4: Contemporaneous commodity prices vs. RW model without drift

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	0.919***	0.92***	0.92***	0.919***	0.919***	0.919***
stat	9.894	9.816	9.816	9.852	9.855	9.811
Canada	0.812***	0.812***	0.812***	0.813***	0.813***	0.813***
stat	12.284	12.267	12.264	12.245	12.234	12.176
Chile	0.905***	0.905***	0.905***	0.906***	0.907***	0.909***
stat	7.201	7.224	7.286	7.347	7.379	7.666
Colombia	0.856***	0.856***	0.856***	0.855***	0.854***	0.854***
stat	7.985	8.000	8.014	8.037	8.083	8.087
Mexico	0.905***	0.905***	0.905***	0.905***	0.904***	0.904***
stat	9.341	9.343	9.341	9.334	9.312	9.285
Norway	0.88***	0.88***	0.88***	0.88***	0.88***	0.881***
stat	12.157	12.139	12.137	12.132	12.125	12.067
Peru	0.976***	0.976***	0.976***	0.976***	0.976***	0.976***
stat	6.473	6.456	6.457	6.471	6.474	6.415
Russia	0.857***	0.857***	0.857***	0.857***	0.858***	0.858***
stat	7.917	7.923	7.937	7.944	7.951	7.969
S. Africa	0.944***	0.944***	0.944***	0.944***	0.944***	0.943***
stat	8.284	8.311	8.318	8.330	8.340	8.381

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Clark-West test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 5: Contemporaneous commodity prices vs. RW model with drift

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	0.892***	0.892***	0.892***	0.892***	0.892***	0.892***
stat	10.464	10.425	10.409	10.439	10.444	10.412
Canada	0.783***	0.783***	0.783***	0.783***	0.783***	0.783***
stat	12.575	12.577	12.580	12.580	12.579	12.542
Chile	0.881***	0.881***	0.881***	0.881***	0.882***	0.88***
stat	6.763	6.772	6.765	6.802	6.816	6.919
Colombia	0.824***	0.824***	0.824***	0.823***	0.822***	0.822***
stat	8.549	8.565	8.582	8.623	8.675	8.641
Mexico	0.875***	0.874***	0.874***	0.875***	0.873***	0.874***
stat	10.731	10.738	10.729	10.726	10.720	10.679
Norway	0.849***	0.848***	0.849***	0.849***	0.849***	0.85***
stat	13.058	13.045	13.041	13.039	13.034	12.962
Peru	0.952***	0.952***	0.952***	0.952***	0.952***	0.952***
stat	7.766	7.744	7.755	7.760	7.771	7.753
Russia	0.841***	0.841***	0.841***	0.841***	0.841***	0.842***
stat	7.353	7.352	7.366	7.366	7.372	7.376
S. Africa	0.917***	0.917***	0.916***	0.916***	0.916***	0.916***
stat	10.635	10.628	10.639	10.645	10.658	10.623

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW with drift. (4) Stat. corresponds to the statistic of the Clark-West test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 6: Contemporaneous commodity prices vs. RW model without drift, using Euro as a base currency

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	0.969***	0.968***	0.968***	0.969***	0.969***	0.968***
stat	-3.043	-3.051	-3.055	-3.014	-3.007	-3.053
Canada	0.953***	0.954***	0.954***	0.954***	0.954***	0.954***
stat	-3.408	-3.407	-3.414	-3.400	-3.409	-3.385
Chile	0.995***	0.995***	0.995**	0.995**	0.995**	0.995**
stat	-2.660	-2.578	-2.546	-2.507	-2.506	-2.465
Colombia	0.973***	0.973***	0.973***	0.974***	0.974***	0.975***
stat	-3.245	-3.255	-3.268	-3.259	-3.253	-3.269
Mexico	0.98***	0.98***	0.98***	0.98***	0.98***	0.981***
stat	-2.774	-2.768	-2.773	-2.777	-2.792	-2.800
Norway	0.913***	0.913***	0.913***	0.913***	0.913***	0.913***
stat	-4.784	-4.781	-4.783	-4.793	-4.795	-4.751
Peru	0.995	0.995	0.995	0.995	0.995	0.994
stat	-0.736	-0.731	-0.696	-0.684	-0.658	-0.785
Russia	0.952***	0.953***	0.953***	0.953***	0.954***	0.955***
stat	-3.346	-3.341	-3.342	-3.348	-3.347	-3.357
S. Africa	0.995*	0.995*	0.995*	0.994*	0.994**	0.994**
stat	-1.868	-1.868	-1.912	-1.940	-1.963	-2.040

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: EUR. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 7: Contemporaneous commodity prices vs. RW model without drift, using Pound Sterling as a base currency

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	0.983**	0.983**	0.983**	0.983**	0.983**	0.983**
stat	−2.212	−2.201	−2.197	−2.205	−2.196	−2.190
Canada	0.968***	0.968***	0.968***	0.968***	0.969***	0.969***
stat	−2.875	−2.851	−2.850	−2.844	−2.824	−2.772
Chile	0.993**	0.993**	0.993**	0.993**	0.993**	0.993**
stat	−2.513	−2.454	−2.426	−2.421	−2.428	−2.297
Colombia	0.975***	0.975***	0.975***	0.975***	0.975***	0.975***
stat	−3.094	−3.095	−3.100	−3.108	−3.105	−3.108
Mexico	0.988**	0.988**	0.988**	0.988**	0.988**	0.988**
stat	−2.264	−2.257	−2.260	−2.263	−2.252	−2.250
Norway	0.963***	0.963***	0.963***	0.963***	0.963***	0.964***
stat	−3.005	−2.988	−2.991	−3.007	−2.997	−2.934
Peru	1.002	1.002	1.002	1.002	1.003	1.002
stat	0.383	0.311	0.296	0.345	0.457	0.369
Russia	0.96***	0.961***	0.961***	0.961***	0.962***	0.962***
stat	−3.051	−3.038	−3.035	−3.033	−3.021	−3.025
S. Africa	0.985***	0.985***	0.985***	0.985***	0.985***	0.985***
stat	−3.580	−3.617	−3.642	−3.663	−3.681	−3.765

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: GBP. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 8: Contemporaneous commodity prices vs. RW model without drift, using exchange returns orthogonal to VIX index

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	0.964***	0.965***	0.965***	0.964***	0.964***	0.964***
stat	-3.063	-2.964	-2.961	-3.020	-3.012	-3.017
Canada	0.85***	0.85***	0.851***	0.851***	0.851***	0.852***
stat	-6.386	-6.367	-6.359	-6.342	-6.333	-6.286
Chile	0.926***	0.926***	0.926***	0.926***	0.927***	0.928***
stat	-3.970	-3.967	-3.969	-3.977	-4.007	-4.138
Colombia	0.892***	0.892***	0.892***	0.892***	0.891***	0.892***
stat	-4.840	-4.844	-4.852	-4.859	-4.892	-4.899
Mexico	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***
stat	-4.680	-4.683	-4.681	-4.678	-4.656	-4.631
Norway	0.9***	0.9***	0.9***	0.9***	0.901***	0.901***
stat	-4.848	-4.825	-4.818	-4.808	-4.798	-4.734
Peru	0.981***	0.981***	0.981***	0.981***	0.981***	0.982***
stat	-3.855	-3.833	-3.827	-3.842	-3.843	-3.785
Russia	0.883***	0.883***	0.883***	0.883***	0.883***	0.884***
stat	-4.686	-4.685	-4.691	-4.693	-4.697	-4.719
S. Africa	0.936***	0.935***	0.935***	0.935***	0.935***	0.935***
stat	-4.998	-5.040	-5.052	-5.052	-5.059	-5.079

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) We obtain exchange rate returns orthogonal to the VIX index by running the following regression per country: $s_t = \alpha_0 + \alpha_1 d(VIX) + \nu_t$, where s_t corresponds to the exchange rate log-return, $d(VIX)$ is the change in the VIX index, and α_0 and α_1 are coefficients to be estimated. We interpret the error term of above regression (ν_t) as the exchange rate log-returns that are orthogonal to changes in the VIX. (3) Base currency: USD. (4) Benchmark model: RW without drift. (5) Stat. corresponds to the statistic of the Diebold-Mariano test. (6) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (7) Columns correspond to the selected forecast horizons. (8) Perfect foresight information. Realised observations of explanatory variable. (9) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 9: Lagged commodity prices vs. RW model without drift

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	1.002	1.003*	1.002	1.003**	1.002*	1.002
stat	1.140	1.732	1.414	2.176	1.671	1.464
Canada	1.001	1.001	1.003***	1.001	1.001*	1.002*
stat	0.329	0.578	2.703	1.322	1.683	1.804
Chile	1.002	1.002*	1.001	0.999	1.002	1.001
stat	1.389	1.769	0.276	-0.143	0.680	0.440
Colombia	0.999	1.003***	1.001	1.002***	1.002***	1.002***
stat	-0.907	3.019	1.454	2.667	2.595	2.790
Mexico	1.003	1.003**	1.006***	1.001	1.001	1.001
stat	1.122	2.170	3.216	1.087	1.020	1.089
Norway	0.998	1.001	1	1.001	1	1.002*
stat	-0.384	1.278	0.537	0.782	0.678	1.895
Peru	1.005***	1.001	1.001	1.002	1	1.001
stat	3.035	1.111	0.867	1.225	0.149	1.170
Russia	0.992*	1	0.998**	1.002	1.001	1.001
stat	-1.682	0.311	-2.468	1.227	0.771	0.668
S. Africa	1.001	1.001	1.001	1.001	1.001	1.001
stat	0.664	0.734	0.614	0.606	0.573	0.478

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Lagged observations of explanatory variable. (8) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 10: Lagged commodity prices vs. RW model with drift

	h=1	h=2	h=3	h=4	h=5	h=10
Brazil	0.972***	0.973***	0.972***	0.973***	0.972***	0.972***
stat	-3.923	-3.628	-3.764	-3.864	-3.880	-3.793
Canada	0.964***	0.964***	0.966***	0.964***	0.964***	0.964***
stat	-4.177	-4.206	-4.326	-4.376	-4.426	-4.242
Chile	0.975***	0.975***	0.974***	0.972***	0.974***	0.968***
stat	-3.228	-2.834	-3.215	-3.207	-4.228	-3.374
Colombia	0.962***	0.966***	0.964***	0.964***	0.964***	0.964***
stat	-3.858	-3.463	-3.787	-3.633	-3.634	-3.609
Mexico	0.969***	0.97***	0.973***	0.967***	0.967***	0.968***
stat	-3.866	-3.776	-3.655	-4.199	-4.278	-4.109
Norway	0.963***	0.965***	0.965***	0.965***	0.964***	0.967***
stat	-4.588	-5.268	-5.278	-5.249	-5.240	-5.070
Peru	0.98**	0.977***	0.976***	0.978***	0.975***	0.976***
stat	-2.519	-2.751	-2.818	-2.723	-2.954	-2.826
Russia	0.973***	0.981***	0.979***	0.982***	0.982***	0.982***
stat	-2.864	-3.414	-3.267	-3.004	-3.004	-2.773
S. Africa	0.972***	0.972***	0.972***	0.971***	0.971***	0.973***
stat	-4.927	-4.611	-4.999	-4.995	-5.046	-4.543

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW with drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Lagged observations of explanatory variable. (8) Sample: Daily data from 01/Jan/2000 to 18/Jul/2018.

Table 11: Contemporaneous commodity prices vs. RW model without drift

	h=1	h=2	h=3	h=4	h=5	h=10	h=11	h=12
Brazil	0.873	0.881	0.878	0.872	0.873	0.88	0.877	0.873
stat	-1.494	-1.326	-1.361	-1.405	-1.402	-1.302	-1.328	-1.396
Canada	0.734**	0.755**	0.732**	0.706**	0.706**	0.699**	0.699**	0.699**
stat	-2.563	-2.089	-2.200	-2.257	-2.269	-2.299	-2.276	-2.274
Chile	0.69**	0.689**	0.688**	0.679**	0.667**	0.659**	0.658**	0.655**
stat	-2.228	-2.194	-2.161	-2.256	-2.382	-2.304	-2.300	-2.327
Colombia	0.802*	0.802*	0.799*	0.799*	0.807*	0.824*	0.826*	0.838*
stat	-1.749	-1.701	-1.737	-1.806	-1.826	-1.897	-1.895	-1.954
Mexico	0.912	0.916	0.91	0.91	0.907	0.916	0.916	0.912
stat	-1.000	-0.938	-0.984	-0.988	-1.021	-0.955	-0.938	-0.978
Norway	0.726**	0.734**	0.735**	0.729**	0.727**	0.731**	0.733**	0.733**
stat	-2.082	-1.976	-1.983	-2.011	-2.042	-1.990	-1.992	-2.030
Peru	0.931	0.932	0.926	0.929	0.937	0.927	0.931	0.932
stat	-1.356	-1.332	-1.458	-1.423	-1.215	-1.526	-1.458	-1.490
Russia	0.653	0.667	0.671	0.676	0.678	0.696*	0.699*	0.706*
stat	-1.621	-1.592	-1.605	-1.614	-1.634	-1.647	-1.651	-1.680
S. Africa	0.89*	0.899	0.897	0.895	0.899	0.894	0.903	0.892
stat	-1.772	-1.581	-1.542	-1.562	-1.474	-1.370	-1.269	-1.453

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Monthly data from Jan/2000 to Jun/2018.

Table 12: Contemporaneous commodity prices vs. RW model with drift

	h=1	h=2	h=3	h=4	h=5	h=10	h=11	h=12
Brazil	0.844**	0.851*	0.848*	0.84*	0.842*	0.847*	0.844*	0.84*
stat	-2.052	-1.856	-1.876	-1.952	-1.930	-1.856	-1.853	-1.926
Canada	0.7***	0.72**	0.699***	0.671***	0.672***	0.663***	0.664***	0.662***
stat	-3.065	-2.565	-2.658	-2.728	-2.736	-2.793	-2.765	-2.763
Chile	0.65**	0.65**	0.65**	0.641**	0.63**	0.621**	0.62**	0.617**
stat	-2.361	-2.311	-2.265	-2.348	-2.460	-2.367	-2.363	-2.382
Colombia	0.787**	0.786**	0.784**	0.782**	0.791**	0.806**	0.809**	0.821**
stat	-2.088	-2.025	-2.050	-2.124	-2.136	-2.191	-2.156	-2.223
Mexico	0.855	0.863	0.858	0.859	0.855	0.866	0.868	0.866
stat	-1.617	-1.493	-1.532	-1.532	-1.557	-1.497	-1.446	-1.463
Norway	0.693***	0.701**	0.701**	0.695***	0.693***	0.697***	0.698***	0.698***
stat	-2.673	-2.546	-2.569	-2.604	-2.650	-2.619	-2.634	-2.671
Peru	0.926	0.928	0.924	0.926	0.93	0.915	0.918	0.919
stat	-1.056	-1.027	-1.056	-1.033	-0.938	-1.123	-1.084	-1.083
Russia	0.621**	0.636**	0.64**	0.644**	0.646**	0.665**	0.668**	0.675**
stat	-2.054	-2.009	-2.031	-2.052	-2.084	-2.116	-2.120	-2.164
S. Africa	0.846*	0.857*	0.856	0.854	0.858	0.853	0.861	0.851
stat	-1.825	-1.648	-1.617	-1.637	-1.574	-1.465	-1.401	-1.515

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW with drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Monthly data from Jan/2000 to Jun/2018.

Table 13: Lagged commodity prices vs. RW model without drift

	h=1	h=2	h=3	h=4	h=5	h=10	h=11	h=12
Brazil	1.016	0.962	1.014	1.037	1.041	1.024	1.037	1.039
stat	0.926	−0.523	0.322	1.452	1.032	0.931	1.362	1.430
Canada	1.044*	1.029	1.047	1.024**	1.059	1.025*	1.026	1.05*
stat	1.773	1.242	0.903	2.455	1.306	1.820	1.584	1.810
Chile	1.031	1.023	1.018	1.021	1.017*	1.026	1.027	1.013
stat	1.185	1.523	1.036	0.856	1.647	1.029	1.286	1.111
Colombia	1.019*	1.018	1.046	1.045*	1.053	1.019	1.028	1.019**
stat	1.887	0.438	0.559	1.840	1.169	1.058	1.454	2.023
Mexico	1.035	1.025	1.016	1.002	1.037	1.004	0.971	1.019
stat	0.824	1.316	0.355	0.144	0.977	0.252	−1.153	1.374
Norway	1.025**	1.025	1.002	1.019	1.051*	1.019*	1.021	1.028
stat	2.082	0.933	0.113	1.535	1.897	1.723	1.283	1.142
Peru	1.033	1.031	1.005	1.034	1.03	1.03	1.05	1.028
stat	0.701	1.241	0.171	0.941	1.096	0.866	1.349	1.028
Russia	0.936	1.05**	1.042	1.015	1.008	1.007	1.005	0.995
stat	−0.744	2.484	0.794	0.824	0.340	0.278	0.366	−0.354
S. Africa	1.019	1.013	1.015	1.011	1.012	0.968	1.006	0.998
stat	0.521	0.562	0.524	0.432	0.396	−0.675	0.257	−0.092

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Lagged observations of explanatory variable. (8) Sample: Monthly data from Jan/2000 to Jun/2018.

Table 14: Lagged commodity prices vs. RW model with drift

	h=1	h=2	h=3	h=4	h=5	h=10	h=11	h=12
Brazil	0.982	0.929	0.977	1	1.001	0.986	0.997	0.999
stat	-0.456	-1.619	-0.617	-0.009	0.008	-0.326	-0.056	-0.016
Canada	0.996	0.981	0.994	0.973	1.006	0.972	0.973	0.996
stat	-0.211	-0.662	-0.106	-0.726	0.103	-0.716	-0.920	-0.161
Chile	0.973	0.966	0.961	0.963	0.96	0.967	0.968	0.954
stat	-1.283	-1.065	-1.166	-0.745	-1.091	-1.092	-1.099	-1.274
Colombia	1	0.999	1.024	1.024	1.029	0.998	1.007	0.998
stat	-0.004	-0.031	0.254	0.383	0.345	-0.038	0.134	-0.040
Mexico	0.975*	0.966	0.958	0.945	0.976	0.951	0.922*	0.968
stat	-1.759	-0.831	-0.523	-1.375	-0.335	-1.271	-1.906	-0.857
Norway	0.978	0.977	0.956	0.972	1.001	0.971	0.972	0.979
stat	-0.883	-1.159	-1.011	-0.843	0.020	-0.837	-0.694	-0.632
Peru	1.028	1.028	1.001	1.026	1.016	1.016	1.035	1.015
stat	0.336	0.312	0.009	0.272	0.196	0.174	0.369	0.158
Russia	0.892	1.001	0.993	0.967	0.963	0.962	0.961*	0.952
stat	-1.584	0.016	-0.098	-0.755	-1.068	-0.998	-1.747	-1.590
S. Africa	0.972	0.966	0.968	0.964	0.966	0.924	0.96	0.953
stat	-0.472	-1.168	-0.983	-0.975	-0.935	-1.376	-1.212	-0.958

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW with drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Lagged observations of explanatory variable. (8) Sample: Monthly data from Jan/2000 to Jun/2018.

Table 15: Contemporaneous commodity prices vs. RW model without drift

	h=1	h=2	h=3	h=4	h=5	h=10	h=11	h=12
Brazil	0.718*	0.718	0.698*	0.709	0.699	0.676*	0.679	0.694
stat	-1.838	-1.519	-1.661	-1.535	-1.608	-1.821	-1.534	-1.500
Canada	0.699**	0.748	0.744	0.723*	0.704*	0.784	0.822	0.847
stat	-2.010	-1.626	-1.493	-1.681	-1.769	-1.162	-0.856	-0.739
Chile	0.608***	0.602***	0.584***	0.602**	0.588**	0.633**	0.716***	0.728**
stat	-2.696	-2.619	-2.579	-2.470	-2.376	-2.045	-2.709	-2.573
Colombia	0.916	0.887	0.858	0.921	0.947	0.948	0.967	0.98
stat	-0.739	-0.955	-1.197	-0.834	-0.763	-1.358	-0.894	-0.394
Mexico	0.91	0.905	0.917	0.931	0.927	0.93	1.055	1.047
stat	-0.478	-0.483	-0.407	-0.359	-0.354	-0.321	0.219	0.191
Norway	0.713	0.721	0.713	0.693	0.698	0.682	0.713	0.661
stat	-1.288	-1.234	-1.146	-1.261	-1.280	-1.070	-0.887	-1.073
Peru	0.861**	0.902**	0.931	0.937	0.95	0.957	0.981	0.99
stat	-1.964	-2.334	-1.529	-1.588	-1.174	-0.642	-0.300	-0.163
Russia	0.543	0.557	0.543	0.572	0.593	0.589*	0.61	0.611
stat	-1.506	-1.491	-1.545	-1.540	-1.566	-1.683	-1.576	-1.557
S. Africa	0.95	0.897	0.87	0.883	0.877	0.821*	0.794*	0.828
stat	-0.493	-0.912	-1.168	-1.056	-1.304	-1.951	-1.789	-1.523

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Quarterly data from Jan/2000 to Jun/2018.

Table 16: Contemporaneous commodity prices vs. RW model with drift

	h=1	h=2	h=3	h=4	h=5	h=10	h=11	h=12
Brazil	0.712*	0.707	0.683*	0.693	0.686*	0.654*	0.68	0.695
stat	-1.843	-1.540	-1.706	-1.624	-1.651	-1.805	-1.472	-1.417
Canada	0.711**	0.747*	0.72*	0.697**	0.668**	0.737	0.8	0.816
stat	-2.223	-1.671	-1.746	-1.991	-2.172	-1.487	-1.087	-1.003
Chile	0.612***	0.599***	0.584***	0.596**	0.588**	0.616**	0.718***	0.732***
stat	-2.744	-2.669	-2.628	-2.513	-2.408	-1.983	-3.042	-2.856
Colombia	0.893	0.866	0.833	0.899	0.918	0.909**	0.95	0.963
stat	-1.047	-1.259	-1.634	-1.221	-1.444	-2.200	-1.165	-0.682
Mexico	0.907	0.918	0.927	0.95	0.957	0.968	1.108	1.102
stat	-0.465	-0.392	-0.338	-0.246	-0.197	-0.142	0.437	0.425
Norway	0.708	0.71	0.686	0.67	0.678	0.656	0.695	0.645
stat	-1.445	-1.422	-1.440	-1.558	-1.567	-1.334	-1.077	-1.280
Peru	0.834**	0.859**	0.867*	0.875*	0.879*	0.874	0.904	0.891
stat	-2.566	-2.254	-1.778	-1.673	-1.651	-1.393	-1.007	-1.156
Russia	0.552*	0.568*	0.554*	0.584*	0.604*	0.602**	0.625*	0.627*
stat	-1.718	-1.694	-1.763	-1.775	-1.834	-2.015	-1.884	-1.853
S. Africa	0.983	0.942	0.911	0.923	0.916*	0.865***	0.849**	0.883
stat	-0.224	-0.792	-1.251	-1.112	-1.744	-2.603	-2.123	-1.558

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW with drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Perfect foresight information. Realised observations of explanatory variable. (8) Sample: Quarterly data from Jan/2000 to Jun/2018.

Table 17: Lagged commodity prices vs. RW model without drift

	h=1	h=2	h=3	h=4	h=5	h=10	h=11	h=12
Brazil	1.076	1.054	1.238	1.056	1.063	1.067*	1.058	1.082
stat	1.536	0.694	1.183	1.238	1.406	1.799	0.729	1.131
Canada	1.044	1.044	1.411	1.136	1.075	1.063	1.146	1.087
stat	0.307	0.715	1.494	1.370	1.614	1.166	0.976	1.311
Chile	1.038	1.097	1.054	1.051	1.111	1.09*	1.039	1.064
stat	0.706	1.292	1.296	1.558	1.383	1.709	0.735	1.242
Colombia	0.979	1.044	1.489	1.028	1.061	1.121	1.041	1.099
stat	-0.478	0.905	1.297	1.167	1.346	1.112	0.669	1.196
Mexico	1.02	1.043	1.018	0.99	1.033	0.942	0.935	1.012
stat	0.500	1.146	0.391	-0.200	0.439	-0.727	-0.997	0.222
Norway	1.012	0.993	1.187	1.071	1.024	1.029	1.057	1.101
stat	0.312	-0.315	1.375	0.866	0.435	0.354	0.498	1.310
Peru	1.061	1.089	1.17	1.118	1.12	1.17	1.155	1.147
stat	0.606	0.847	1.060	0.976	0.957	0.997	1.102	1.163
Russia	1.002	0.924	1.077	1	0.988	1.027	1.014	1.006
stat	0.044	-1.453	1.241	-0.016	-0.374	0.736	0.256	0.200
S. Africa	1.022	1.26	1.086	1.048	1.054	1.12	1.069	1.11
stat	0.356	1.375	1.471	0.877	0.598	0.675	0.567	0.703

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW without drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Lagged commodity prices as the main explanatory variable. (8) Sample: Quarterly data from Jan/2000 to Jun/2018.

Table 18: Lagged commodity prices vs. RW model with drift

	h=1	h=2	h=3	h=4	h=5	h=10	h=11	h=12
Brazil	1.059*	1.031	1.21	1.037	1.048	1.069	1.059	1.082
stat	1.873	0.482	1.165	1.600	1.638	1.221	1.560	1.503
Canada	1.042	1.011	1.361	1.079	1.05**	1.034	1.103	1.038
stat	0.374	0.250	1.566	1.516	2.196	0.872	0.936	1.159
Chile	1.032	1.097	1.042*	1.051***	1.125	1.093	1.044	1.05
stat	0.802	1.242	1.659	2.586	1.376	1.169	1.160	1.376
Colombia	0.956	1.013	1.453	0.997	1.028	1.101	1.022	1.062
stat	−0.672	0.335	1.258	−0.982	0.835	1.075	0.655	0.982
Mexico	1.036	1.055	1.039	1.022*	1.062	0.99	0.984	1.085*
stat	1.582	0.736	1.258	1.728	1.430	−0.149	−0.151	1.802
Norway	0.997	0.957	1.147	1.039	1.006	1.002	1.031	1.068
stat	-0.147	-1.364	1.237	0.533	0.117	0.025	0.420	1.039
Peru	1.011	1.014	1.093	1.035	1.035	1.079	1.04	1.027
stat	0.487	0.611	1.242	1.197	1.052	0.747	0.950	0.825
Russia	1.022	0.942	1.099	1.02	1.009***	1.053	1.041	1.034
stat	0.735	-1.640	1.360	1.477	0.000	1.143	0.971	1.018
S. Africa	1.073	1.32	1.136	1.094	1.112	1.196	1.14	1.205
stat	1.454	1.284	1.411	1.614	1.487	0.983	0.985	1.265

Notes: (1) MSFE ratio between the commodity-based model (numerator) and a RW model (denominator). (2) Base currency: USD. (3) Benchmark model: RW with drift. (4) Stat. corresponds to the statistic of the Diebold-Mariano test. (5) Statistical significance: (*) $p < 0.1$, (**) $p < 0.05$, (***) $p < 0.01$. (6) Columns correspond to the selected forecast horizons. (7) Lagged commodity prices as the main explanatory variable. (8) Sample: Quarterly data from Jan/2000 to Jun/2018.

Table 19: Hill index estimator

	Lower tail	Upper tail
Brazil	0.36 (0.31;0.41)	0.36 (0.31;0.41)
Canada	0.31 (0.27;0.35)	0.33 (0.29;0.38)
Chile	0.28 (0.25;0.32)	0.30 (0.26;0.34)
Colombia	0.38 (0.33;0.43)	0.38 (0.33;0.43)
Mexico	0.35 (0.31;0.40)	0.34 (0.30;0.38)
Peru	0.44 (0.38;0.49)	0.44 (0.39;0.50)
Norway	0.29 (0.25;0.32)	0.32 (0.28;0.36)
Russia	0.46 (0.40;0.52)	0.48 (0.42;0.54)
S. Africa	0.31 (0.27;0.35)	0.33 (0.29;0.37)
Copper	0.34 (0.30;0.39)	0.30 (0.26;0.34)
Gold	0.35 (0.31;0.40)	0.31 (0.27;0.35)
WTI	0.33 (0.29;0.38)	0.32 (0.28;0.37)

Notes: Note: Confidence Intervals at 95% level in parenthesis. Daily log-returns, Jan-2000 to July-2018 (4270 observations approx.). Threshold corresponds to 2.5% of the data (107 obs. approx.).

Table 20: Tail index estimator of Dekkers et al. (1989)

	Lower tail	Upper tail
Brazil	0.16 (0.03;0.30)	0.23 (0.09;0.37)
Canada	0.16 (0.03;0.29)	0.04 (−0.09;0.17)
Chile	0.15 (0.01;0.28)	0.25 (0.11;0.39)
Colombia	0.19 (0.05;0.32)	0.19 (0.06;0.33)
Mexico	0.21 (0.08;0.34)	0.38 (0.24;0.52)
Peru	0.18 (0.05;0.32)	0.34 (0.20;0.48)
Norway	0.24 (0.11;0.37)	0.02 (−0.11;0.15)
Russia	0.23 (0.09;0.36)	0.31 (0.17;0.45)
S. Africa	0.06 (−0.07;0.18)	0.23 (0.10;0.36)
Copper	0.19 (0.06;0.33)	0.12 (−0.02;0.25)
Gold	0.15 (0.02;0.28)	0.26 (0.13;0.39)
WTI	0.19 (0.05;0.33)	0.19 (0.06;0.33)

Notes: Confidence Intervals at 95% level in parenthesis. Daily log-returns, Jan-2000 to July-2018 (4270 observations approx.). Threshold corresponds to 2.5% of the data (107 obs. approx.). **Source**: Author's calculations.

Table 21: ADI using contemporaneous commodity returns

	Case 1	Case 2	Case 3	Case 4
Brazil	0.11 (0.05;0.17)	0.15 (0.08;0.21)	0.05 (0.01;0.09)	0.03 (0.00;0.06)
Canada	0.22 (0.15;0.30)	0.16 (0.09;0.23)	0.02 (−0.01;0.04)	0.00 (−0.01;0.01)
Chile	0.10 (0.05;0.16)	0.19 (0.12;0.26)	0.03 (0.00;0.06)	0.03 (0.00;0.06)
Colombia	0.20 (0.12;0.27)	0.21 (0.14;0.29)	0.01 (−0.01;0.03)	0.01 (−0.01;0.03)
Mexico	0.15 (0.09;0.22)	0.17 (0.10;0.24)	0.01 (−0.01;0.03)	0.01 (−0.01;0.03)
Norway	0.18 (0.11;0.25)	0.19 (0.11;0.26)	0.03 (0.00;0.06)	0.01 (−0.01;0.03)
Peru	0.06 (0.01;0.10)	0.10 (0.04;0.16)	0.06 (0.01;0.10)	0.05 (0.01;0.09)
Russia	0.21 (0.14;0.29)	0.17 (0.10;0.23)	0.01 (−0.01;0.03)	0.01 (−0.01;0.03)
S. Africa	0.09 (0.04;0.14)	0.13 (0.08;0.19)	0.06 (0.02;0.10)	0.06 (0.02;0.10)

Note: Confidence Intervals in parenthesis at 95% level and obtained by bootstrap using 5000 re-sampling iterations. Daily log-returns, Jan-2000 to July-2018 (4270 observations approx.). Threshold corresponds to 2.5% of the data (107 obs. approx.). **Case 1**: NER appreciation (∇S) and increase in comm. price (ΔP_{comm}). **Case 2**: NER depreciation (ΔS) and reduction in comm. price. (∇P_{comm}) **Case 3**: ∇S and ∇P_{comm}. **Case 4**: ΔS and ΔP_{comm}.

Table 22: ADI using contemporaneous commodity returns and exchange rates orthogonal to VIX

	Case 1	Case 2	Case 3	Case 4
Brazil	0.10 (0.04;0.16)	0.14 (0.08;0.20)	0.04 (0.00;0.07)	0.04 (0.00;0.07)
Canada	0.21 (0.14;0.29)	0.12 (0.06;0.18)	0.03 (0.00;0.06)	0.02 (−0.01;0.04)
Chile	0.12 (0.06;0.18)	0.18 (0.11;0.25)	0.03 (0.00;0.06)	0.03 (−0.01;0.06)
Colombia	0.16 (0.09;0.22)	0.16 (0.09;0.23)	0.02 (−0.01;0.04)	0.01 (−0.01;0.03)
Mexico	0.12 (0.06;0.17)	0.10 (0.04;0.15)	0.07 (0.02;0.12)	0.03 (0.00;0.06)
Norway	0.15 (0.09;0.22)	0.14 (0.08;0.21)	0.04 (0.00;0.07)	0.01 (−0.01;0.03)
Peru	0.06 (0.02;0.11)	0.09 (0.04;0.14)	0.05 (0.01;0.09)	0.06 (0.01;0.10)
Russia	0.22 (0.15;0.30)	0.17 (0.10;0.24)	0.01 (−0.01;0.03)	0.01 (−0.01;0.03)
S. Africa	0.09 (0.04;0.14)	0.12 (0.06;0.17)	0.05 (0.01;0.09)	0.03 (0.00;0.07)

Note: Confidence Intervals in parenthesis at 95% level and obtained by bootstrap using 5000 re-sampling iterations. Daily log-returns, Jan-2000 to July-2018 (4270 observations approx.). Threshold corresponds to 2.5% of the data (107 obs. approx.). **Case 1**: NER appreciation (∇S) and increase in comm. price (ΔP_{comm}). **Case 2**: NER depreciation (ΔS) and reduction in comm. price. (∇P_{comm}) **Case 3**: ∇S and ∇P_{comm}. **Case 4**: ΔS and ΔP_{comm}. We obtain exchange rate returns orthogonal to the VIX index by running the following regression per country: $s_t = \alpha_0 + \alpha_1 d(VIX) + \nu_t$, where s_t corresponds to the exchange rate log-return, $d(VIX)$ is the change in the VIX index, and α_0 and α_1 are coefficients to be estimated. We interpret the error term of above regression (ν_t) as the exchange rate log-returns that are orthogonal to changes in the VIX.

Table 23: ADI using contemporaneous commodity returns and exchange rates with EUR as a base currency

	Case 1	Case 2	Case 3	Case 4
Brazil	0.11 (0.05;0.17)	0.10 (0.04;0.16)	0.06 (0.01;0.10)	0.04 (0.00;0.07)
Canada	0.16 (0.09;0.23)	0.10 (0.04;0.15)	0.01 (−0.01;0.03)	0.01 (−0.01;0.03)
Chile	0.05 (0.01;0.09)	0.07 (0.02;0.12)	0.06 (0.02;0.10)	0.06 (0.02;0.11)
Colombia	0.11 (0.05;0.17)	0.15 (0.09;0.22)	0.04 (0.00;0.07)	0.03 (0.00;0.06)
Mexico	0.11 (0.05;0.16)	0.12 (0.05;0.18)	0.04 (0.00;0.07)	0.06 (0.02;0.11)
Norway	0.19 (0.12;0.26)	0.20 (0.13;0.27)	0.03 (0.00;0.06)	0.01 (−0.01;0.03)
Peru	0.05 (0.01;0.09)	0.02 (−0.01;0.04)	0.07 (0.02;0.12)	0.08 (0.03;0.13)
Russia	0.18 (0.11;0.25)	0.15 (0.08;0.22)	0.02 (−0.01;0.04)	0.04 (0.00;0.07)
S. Africa	0.05 (0.01;0.09)	0.10 (0.05;0.15)	0.06 (0.01;0.10)	0.07 (0.02;0.11)

Note: Confidence Intervals in parenthesis at 95% level and obtained by bootstrap using 5000 re-sampling iterations. Daily log-returns, Jan-2000 to July-2018 (4270 observations approx.). Threshold corresponds to 2.5% of the data (107 obs. approx.). **Case 1**: NER appreciation (∇S) and increase in comm. price (ΔP_{comm}). **Case 2**: NER depreciation (ΔS) and reduction in comm. price. (∇P_{comm}) **Case 3**: ∇S and ∇P_{comm}. **Case 4**: ΔS and ΔP_{comm}. Euro as a base currency.

Table 24: ADI using contemporaneous commodity returns and exchange rates with GBP as a base currency

	Case 1	Case 2	Case 3	Case 4
Brazil	0.10 (0.04;0.15)	0.12 (0.06;0.17)	0.05 (0.01;0.10)	0.03 (–0.01;0.06)
Canada	0.13 (0.07;0.18)	0.13 (0.07;0.18)	0.06 (0.02;0.11)	0.01 (–0.01;0.03)
Chile	0.08 (0.03;0.13)	0.10 (0.04;0.15)	0.08 (0.03;0.13)	0.04 (0.01;0.08)
Colombia	0.09 (0.04;0.14)	0.15 (0.09;0.22)	0.06 (0.02;0.11)	0.01 (–0.01;0.03)
Mexico	0.06 (0.01;0.11)	0.12 (0.06;0.18)	0.07 (0.02;0.12)	0.03 (0.00;0.06)
Norway	0.07 (0.03;0.12)	0.13 (0.07;0.18)	0.05 (0.01;0.10)	0.03 (0.00;0.06)
Peru	0.03 (–0.01;0.06)	0.04 (0.00;0.07)	0.12 (0.07;0.18)	0.06 (0.02;0.11)
Russia	0.16 (0.09;0.23)	0.14 (0.08;0.21)	0.08 (0.02;0.13)	0.03 (–0.01;0.06)
S. Africa	0.05 (0.01;0.09)	0.08 (0.03;0.12)	0.06 (0.02;0.10)	0.05 (0.01;0.09)

Note: Confidence Intervals in parenthesis at 95% level and obtained by bootstrap using 5000 re-sampling iterations. Daily log-returns, Jan-2000 to July-2018 (4270 observations approx.). Threshold corresponds to 2.5% of the data (107 obs. approx.). **Case 1**: NER appreciation (∇S) and increase in comm. price (ΔP_{comm}). **Case 2**: NER depreciation (ΔS) and reduction in comm. price. (∇P_{comm}) **Case 3**: ∇S and ∇P_{comm}. **Case 4**: ΔS and ΔP_{comm}. Pound Sterling as a base currency.

Table 25: ADI using contemporaneous commodity returns and controlling for heteroskedasticity in log-returns

	Case 1	Case 2	Case 3	Case 4
Brazil	0.06 (0.02;0.11)	0.04 (0.00;0.08)	0.03 (0.00;0.06)	0.06 (0.01;0.10)
Canada	0.08 (0.03;0.13)	0.11 (0.05;0.17)	0.00 (0.00;0.00)	0.01 (–0.01;0.03)
Chile	0.05 (0.01;0.09)	0.14 (0.07;0.21)	0.02 (–0.01;0.04)	0.01 (–0.01;0.03)
Colombia	0.05 (0.01;0.09)	0.11 (0.05;0.17)	0.05 (0.01;0.09)	0.03 (0.00;0.06)
Mexico	0.04 (0.00;0.07)	0.09 (0.04;0.14)	0.01 (–0.01;0.03)	0.03 (–0.01;0.06)
Norway	0.08 (0.03;0.13)	0.09 (0.04;0.14)	0.00 (0.00;0.00)	0.02 (–0.01;0.04)
Peru	0.06 (0.02;0.11)	0.07 (0.03;0.12)	0.01 (–0.01;0.03)	0.03 (0.00;0.06)
Russia	0.13 (0.06;0.19)	0.13 (0.07;0.20)	0.02 (–0.01;0.04)	0.04 (0.00;0.07)
S. Africa	0.11 (0.05;0.16)	0.14 (0.08;0.20)	0.01 (–0.01;0.02)	0.03 (0.00;0.05)

Note: Confidence Intervals in parenthesis at 95% level and obtained by bootstrap using 5000 re-sampling iterations. Daily log-returns, Jan-2000 to July-2018 (4270 observations approx.). Threshold corresponds to 2.5% of the data (107 obs. approx.). **Case 1**: NER appreciation (∇S) and increase in comm. price (ΔP_{comm}). **Case 2**: NER depreciation (ΔS) and reduction in comm. price. (∇P_{comm}) **Case 3**: ∇S and ∇P_{comm}. **Case 4**: ΔS and ΔP_{comm}. Exchange rates and commodity returns corresponds to the standardised residual obtained from a *GARCH(1,1)* where the conditional variance is modelled as $\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2$. u_t corresponds to the residuals of the mean equation for returns, and the standardised residuals are computed as $\varepsilon_t = u_t/\sigma_t$.

Table 26: ADI using lagged commodity returns

	Case 1	Case 2	Case 3	Case 4
Brazil	0.06 (0.01;0.10)	0.07 (0.02;0.12)	0.14 (0.07;0.21)	0.02 (−0.01;0.05)
Canada	0.06 (0.02;0.11)	0.07 (0.03;0.12)	0.05 (0.01;0.10)	0.03 (0.00;0.06)
Chile	0.03 (0.00;0.06)	0.10 (0.05;0.16)	0.06 (0.01;0.10)	0.06 (0.01;0.10)
Colombia	0.04 (0.00;0.08)	0.07 (0.02;0.11)	0.06 (0.01;0.10)	0.06 (0.01;0.10)
Mexico	0.07 (0.02;0.12)	0.04 (0.00;0.09)	0.11 (0.05;0.16)	0.06 (0.02;0.11)
Norway	0.05 (0.01;0.10)	0.10 (0.04;0.15)	0.04 (0.00;0.09)	0.03 (0.00;0.06)
Peru	0.06 (0.01;0.10)	0.06 (0.02;0.11)	0.04 (0.00;0.08)	0.05 (0.01;0.08)
Russia	0.09 (0.04;0.14)	0.05 (0.01;0.10)	0.04 (0.01;0.08)	0.04 (0.00;0.07)
S. Africa	0.05 (0.01;0.09)	0.03 (−0.01;0.06)	0.07 (0.02;0.11)	0.05 (0.01;0.09)

Note: Confidence Intervals in parenthesis at 95% level and obtained by bootstrap using 5000 re-sampling iterations. Daily log-returns, Jan-2000 to July-2018 (4270 observations approx.). Threshold corresponds to 2.5% of the data (107 obs. approx.). **Case 1**: NER appreciation (∇S) and increase in comm. price (ΔP_{comm}). **Case 2**: NER depreciation (ΔS) and reduction in comm. price. (∇P_{comm}) **Case 3**: ∇S and ∇P_{comm}. **Case 4**: ΔS and ΔP_{comm}.

Table 27: ADI using contemporaneous commodity returns at different frequencies

	Daily				Monthly				Quarterly			
	C1	C2	C3	C4	C1	C2	C3	C4	C1	C2	C3	C4
Brazil	0.11	0.15	0.05	--	--	--	--	--	--	--	--	--
Canada	0.22	0.16	--	--	--	--	--	--	--	--	--	--
Chile	0.10	0.19	--	--	--	0.60	--	--	--	--	--	--
Colombia	0.20	0.21	--	--	--	--	--	--	--	--	--	--
Mexico	0.15	0.17	--	--	--	--	--	--	--	--	--	--
Norway	0.18	0.19	--	--	--	0.40	--	--	--	--	--	--
Peru	0.06	0.10	0.06	0.05	--	--	--	--	--	--	--	--
Russia	0.21	0.17	--	--	0.40	--	--	--	--	--	--	--
S. Africa	0.09	0.13	0.06	0.06	--	0.40	--	--	--	--	--	--

Note: Asymptotic dependence index computed at different frequencies using log-returns from Jan-2000 to July-2018. "−−" indicates no statistical significance at 5%. **Case 1**: NER appreciation (∇S) and increase in comm. price (ΔP_{comm}). **Case 2**: NER depreciation (ΔS) and reduction in comm. price. (∇P_{comm}) **Case 3**: ∇S and ∇P_{comm}. **Case 4**: ΔS and ΔP_{comm}.

Table 28: ADI using lagged commodity returns at different frequencies

	Daily				Monthly				Quarterly			
	C1	C2	C3	C4	C1	C2	C3	C4	C1	C2	C3	C4
Brazil	0.06	0.07	0.14	--	--	--	--	--	--	--	--	--
Canada	0.06	0.07	0.05	--	--	--	--	--	--	--	--	--
Chile	--	0.10	0.06	0.06	--	--	--	--	--	--	--	--
Colombia	--	0.07	0.06	0.06	--	--	--	--	--	--	--	--
Mexico	0.07	0.04	0.11	0.06	--	--	--	--	--	--	--	--
Norway	0.05	0.10	0.04	--	--	--	--	--	--	--	--	--
Peru	0.06	0.06	--	0.05	0.40	--	--	--	--	--	--	--
Russia	0.09	0.05	0.04	0.04	--	--	--	--	--	--	--	--
S. Africa	0.05	--	0.07	0.05	--	--	--	--	--	--	--	--

Note: Asymptotic dependence index computed at different frequencies using log-returns from Jan-2000 to July-2018. "−−" indicates no statistical significance at 5%. **Case 1**: NER appreciation (∇S) and increase in comm. price (ΔP_{comm}). **Case 2**: NER depreciation (ΔS) and reduction in comm. price. (∇P_{comm}) **Case 3**: ∇S and ∇P_{comm}. **Case 4**: ΔS and ΔP_{comm}.

Appendices

A World's top oil producers

Table A.1: World's top oil producers

	2000	2005	2010	2015	2016
United States	9,058	8,327	9,691	15,139	14,829
Saudi Arabia	9,476	11,496	10,908	12,072	12,387
Russia	6,724	9,511	10,290	11,040	11,250
China	3,389	3,871	4,572	5,146	4,863
Canada	2,753	3,096	3,442	4,511	4,594
Iraq	2,582	1,889	2,398	4,039	4,443
Iran	3,765	4,239	4,243	3,485	4,364
United Arab Emirates	2,572	2,845	2,815	3,673	3,765
Brazil	**1,534**	**2,038**	**2,723**	**3,183**	**3,240**
Kuwait	2,201	2,672	2,449	2,880	2,991

Note: Data in thousand barrels per day are on a calendar day basis.
Source: U.S. Energy Information Administration (EIA).