Asymptotic dependence and exchange rate forecasting

Francisco Pinto-Avalos* Michael Bowe† Stuart Hyde‡

Abstract

In this paper, we explore 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 sample of commodity-exporting economies, we document that the forecasting ability of commodity prices lies in the asymptotic dependence relationship between these variables. We identify two main elements in the analysis. First, timing plays a key role since both the forecasting ability of commodity prices and the asymptotic dependence between these variables tend to be short-lived meaning that only contemporaneous observations can capture that relationship. On the contrary, both the asymptotic dependence and the forecasting ability of commodity prices disappear when lagged commodity prices are included in the analysis. Second, the relationship between commodity prices and exchange rate is transitory since it only appears significant at a daily frequency, while it completely vanishes when lower frequencies are included either using monthly or quarterly observations. We interpret these findings as the effect of transitory, short-lived news affecting commodity markets that conveys information to the exchange rates of commodity-exporting economies. We argue that this transmission mechanism is a central element behind the ability of commodity prices to forecast exchange rates.

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

JEL Codes: F31, F37, C22, C53.

*Corresponding author. The University of Manchester. E-mail: francisco.pintoavalos@manchester.ac.uk
†The University of Manchester. E-mail: michael.bowe@manchester.ac.uk
‡The University of Manchester. 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 log-return distributions of exchange rates and commodity prices exhibit "fatter" tails, indicating the presence of extreme values in their sample distributions. Motivated by the fact, this paper explores whether an asymptotic dependence underpins the predictive ability of commodity prices for exchange rates. We seek 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. We investigate whether any documented predictive ability of commodity prices applies to a broad sample of commodity exporting economies, and the forecast frequencies, if any, at which it exists. This analysis of the tail behaviour of exchange rates and commodity prices may be relevant in terms of policy considerations for the subset of commodity exporting economies which document a close relationship between exchange rates and commodity prices. For instance, understanding the source of shocks affecting exchange rates may provide lessons to developing countries moving from fixed-exchange to a more flexible rate regimes. In addition, emerging economies moving towards inflation targeting regimes may encounter useful implications for their policies by considering the relationship between exchange rate and commodity prices and its impact on domestic inflation.

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 full extent of the association between them. For example, Cumperayot & De Vries (2017) demonstrate that measuring the asymptotic dependence between exchange rates and classic monetary variables 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 for forecasting by examining the relationship between exchange rates and commodity prices in a tail dependence framework. To our knowledge, it is the first paper to attempt to synthesise these two literatures. We highlight the role of asymptotic dependence as the

[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.

central component of the documented ability of commodity prices to predict exchange rates. In particular, our focus is to establish the role of the additional information contained in the tails of the commodity return 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. alternatively stated, are large shocks to commodity prices transmitted to exchange rates and is it the source of any documented forecasting ability of the former for the latter? Measuring tail dependence enables us to determine the extent to which large movements in exchange rates relate to their underlying fundamentals, in this case, commodity prices. Our empirical approach is particularly relevant when variables 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 at a 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 role of commodity prices in predicting 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 to be 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. Importantly for the purpose of our study, they argue that commodity price shocks are considered exogenous shocks useful to explain the exchange rate of commodity-exporting economies. 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 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 for 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 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) document the ability of oil prices to predict exchange rates in a one-step ahead, out-of-sample forecasting 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 uncorrelated 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 commodity prices to beat a RW model in out-of-sample exercises using observations at a daily frequency. 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 predictability 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. Importantly, none of these papers investigate the source of their documented ability of commodity prices to contemporaneously forecast exchange rates, which is the motivation of the present paper.

2.2 Higher moments in exchange rate distributions

An alternative line of literature, which we contribute, analyses the role of higher moments in exchange rate distributions 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

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

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 explain exchange rates. Their results indicate that information located in the tails of the distributions of both exchange rates and monetary fundamentals contributes to explaining the relationship between them, via large shocks that drive both variables.

3 Commodity exporting economies and commodity prices

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 their economies, resulting in capital outflows and a tendency for their exchange rate 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 relevant information to the economic prospect of commodity exporting economies and ends up generating changes to the value of their currencies. This relationship is particularly noteworthy during the commodity price super-cycle occurring in 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, the large capital inflows lead to exchange rate appreciations. This logic suggests that shocks generated in commodity markets produce changes in the domestic economic expectations of commodity exporting economies. Subsequently, a change in the future outlook of the commodity sector drives capital flow movements which ultimately impacts exchange rates. The documented 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: first, commodities exports must represent a significant proportion of the total country's exports, and second, countries must have a free floating exchange rate regime. Moreover, in general, the exports of these countries are both poorly diversified and are dependant upon one or two main commodities. In addition, all countries in the sample adopt a free floating exchange rate regime.

Table 1 reports the relevant descriptive statistics for the economies we include in the sample. For each country in the sample the table shows a set of commodity related indicators during three different time periods: 2000-2005, 2006-2011, and 2012-2017. The indicators highlight the relevance of commodity exports for the economies in 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 the respective countries GDP is represented by the commodity sector. Additionally, the table also shows the main product exported by each country, which constitutes a high proportion of the commodity exports. Overall, the information exhibited in table 1 puts in perspective the relevance of commodity exports for the countries under analysis. It is worth noting that, although, oil seems to be less relevant in 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 a leptokurtic distribution. This distribution characterises by displaying higher kurtosis and a greater likelihood of observing extreme values in comparison to the normal distribution. Likewise, distributions describing exchange rate log-returns and commodity log-returns exhibit fat tails indicating a higher probability of observing extreme values. Cumperayot &

[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.

De Vries (2017) and Patton (2006) explore these properties in the case of exchange rate log-returns. Others (Buyuksahin & Robe 2014, UNCTAD 2011), following the growing degree of financialisation of commodity markets, point out that commodity log-returns also exhibit fat-tailed distributions as investors interpret them as another asset class and actively include them in investment portfolios.

As an illustration, figure 1 plots the histograms of daily observations of the US dollar - Chilean peso (USDCLP) exchange rate in log-returns (left-hand side panel) and the copper price in log-returns (right-hand side panel) from Jan-2000 to July-2018. Each plot includes a theoretical normal distribution (red line) for comparison purposes. As the figures show, the empirical distributions of both 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 pair in particular both follow fat-tailed distributions. As a subsequent formal analysis reveals, this conclusion is also valid for the remainder of the exchange rates and commodity log-returns we analyse in section 5.

In this context, in standard structural asset pricing models of the exchange rate, shocks that drive fundamentals also drive the exchange rate. Cumperayot & De Vries (2017) show that except for the influence of exogenous noise, the properties of the distribution of the fundamental variables, in our case commodity prices, determine the nature of the distribution of exchange rate returns. Of particular importance for our argument is their demonstration that in a linear specification of the exchange rate relationship, if the distribution of commodity prices (fundamentals) has fat tails, then we can expect fat tails in the exchange rate distribution, and the exchange rate returns and the commodity prices to exhibit asymptotic dependence. That is, as the shocks become more extreme, in the limit the probability of large currency movements conditioned on large fundamental shocks is positive. They also show that there can still be asymptotic dependence even if the correlation coefficient is equal to 0. However, as they note, one cannot simply conclude that if the marginal distributions have fat tails, the random variables are necessarily asymptotically dependent. They provide an example of Student-t distributed random variables combined with a Gaussian copula, which are correlated but asymptotically independent. They demonstrate that it is the linearity of the model when combined with the marginal heavy tail property of the distributions which induces the asymptotic dependency between exchange rates and commodity prices and their contemporaneous shocks.

If one finds no support for asymptotic dependence between the exchange rate returns and economic fundamentals, this may be attributable to one of the following two explanations.

One possibility is that the fundamentals-based exchange rate model does not apply, so that the noise is exogenous and is unrelated to commodity prices. Alternatively, even if two random variables are (imperfectly) correlated, but follow a certain class(es) of distribution, a multivariate normal distribution, then all dependency vanishes asymptotically. Thus if we reject asymptotic dependence, there are two possible explanations. If we find that we cannot reject asymptotic dependence, this at least suggests a strong linkage between the commodity price and exchange rate returns generated via the shocks that drive both variables.

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 we now briefly described. Our candidate model is a linear 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.

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

The dependent variable corresponds to exchange rate log-returns, while the independent variable corresponds to the country-specific commodity log-returns.[4] In particular, 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 a series of forecasts for the full out-of-sample period. Following the methodology proposed by Meese & Rogoff (1983), we use perfect foresight data, meaning that we include realised values of commodity returns in the forecasting exercises. For this reason, the approach is also known as a *out-of-sample fit*, 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

[4]In this study the nominal exchange rate is initially defined as the value of one U.S. dollar in terms of the domestic currency. We conduct robustness checks using the Euro and Pound Sterling in section 5.1

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)).

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 fat-tailed 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 fat-tailed distribution.

The Hill tail index is an unbiased estimator and is also more efficient in comparison to alternative tail index indicators as pointed out by both 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, enabling us to estimate the existence of fat tails without imposing any priors.

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 arise simultaneously. In other words, it is a measure of the joint probability that large changes in two random variables happen simultaneously. Previous studies provide a variety of procedures to estimate the tail dependence between two random variables. A common approach in empirical finance focuses on modelling the entire join distribution of two or more variables using the copula methodology, capturing 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 the simultaneous occurrence of large movements in two variables, and is also an alternative standard procedure to model only the tail behaviour of two random variables.

The relevance of the asymptotic dependence analysis is due to its contribution in explaining 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 may appear to exhibit a low degree of correlation, but the relationship is driven by the information contained in the tails. For instance, this often appears to be the case for exchange rate log-returns and commodity log-returns. 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 the figure shows, most of the observations in the scatter plot tend to concentrate around the origin with no clear pattern, however, there are some extreme observations, located in the tails of the distribution, which help to explain the documented negative relationship between those variables. Importantly, this negative relationship corresponds to the relationship we would expect in the presence of an asymptotic dependence between the returns in the analysis we undertake in the following sections.

Based on this logic, in the most extreme case where the measured correlation between two variables is close to zero, the variables can still exhibit a significant 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 and, as we show later, shocks to one variable are transmitted to the other 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 any inherent relationship between the variables.

In order to test for existence of an 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, and k represents the number of observations above the threshold. Note that the threshold may differ between the two variables, meaning that each variable is compared against its own 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 and the estimated 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 simultaneously lie above a given threshold.

The advantage of this indicator results from 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 as that proposed by Poon et al. (2004). This measure allows capturing the extreme linkage between two random variables by identifying asymptotic dependence relationships and also by quantifying the degree of association. A disadvantage of this approach is that the two random variables included in the analysis must be measured in the same scale. Additionally, using Mote Carlo simulations, Fernandez

[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.

(2008) shows the Poon et al. (2004)'s measure tends to show a poor performance in detecting asymptotic dependence when the relationship between two variables is weak. 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 we implement 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 both 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. We collect all series from Bloomberg and the sample is fully available from January 2000 to July 2018. The countries under analysis and the country-specific commodity prices are shown in table 1. Initially, the nominal exchange rate is defined using the U.S. dollar as the base currency, but we also report results using the euro (EUR) and pound sterling (GBP) as an alternative specification in robustness check exercises. The set of commodities we include in the analysis are measured in U.S. dollars.

5.1 Out-of-sample forecasts

This section describes the results of the out-of-sample exercises using the basic forecasting model we introduce in equation (1).

Table 2 presents a comparison of the RMSE ratio of the commodity-based model (numerator) and the RW model (denominator) for the countries under analysis (rows) and for different forecast horizons (columns). We use two version of the RW model: without and with drift in panels A and B, respectively. The results show that in all cases and for every forecast horizon the commodity-based model forecasts better than both RW models. In addition, the Diebold-Mariano test indicates that the MSFE of the commodity-based model is significantly lower than the MSFE of the both comparator RW models at 1% level. Our results remain valid when assessing the forecasting ability of the commodity-based models using the Clark-West test as an alternative statistical measure.[6] Our findings are consistent with previous studies. 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

[6]Results are available upon request.

daily observations.

In addition, our results are robust to the inclusion of what the literature terms unobservable global factors affecting financial returns. Related studies maintain the VIX index gauges those unobservable global factors by capturing global risk appetite.[7] They argue that changes in global risk appetite affect investors' decisions which end up by affecting exchange rate and commodity returns. For instance, Adrian et al. (2009) and Kohlscheen et al. (2017) emphasise the role of global risk appetite, captured by the VIX index, in forecasting exchange rates. Others, in the context of carry trade strategies, discuss how exchange rate movements may be linked to global risk factors such as the VIX index (Gourio et al. 2013) and equity market volatility (Lustig et al. 2011). Importantly, as the VIX index is variable that is available at a daily frequency, we are able to capture the short-lived effect of risk aversion over the relationship between exchange rate and commodity returns. In order to test for the potential effect of this factor we replicate the previous out-of-sample exercise using exchange rate returns which are orthogonal to the change in the VIX index. The results in table 2 panel C reveal that, even after controlling for the potential effect of a global common factor, the conclusion remains the same and we hold that commodity returns forecast better than a random walk model without drift for all the countries in the sample.

Furthermore, we implement the out-of-sample forecasting exercises of table 2 panel A using an alternative definition of the base currency. Panels D and E in table 2 report the results using the euro (EUR) and the pound sterling (GBP) as the currency base, respectively. From the results, we conclude that the findings generally confirm that the forecasting ability of commodity-based models is still significant even using alternative base currencies. Some minor exceptions appear both in the case of Peru whether the base currency is GBP or EUR, where the relevant ratio remains below 1 but is insignificant, and also in the case of South Africa using EUR as the base currency where the statistical significance falls to the 10% level. Overall, the results of this robustness exercise show that the forecasting ability of commodity prices is not limited to using dollar as a base currency, suggesting the predictive power goes beyond a mere dollar effect.

5.2 Lagged commodity prices

This section undertakes *truly* out-of-sample exercise using lagged commodity prices rather than contemporaneous prices. In this process we replace equation (1) with equation (5).

[7] The VIX is an index computed by the Chicago Board Options Exchange (CBOE) that estimates the implied market volatility obtained from option prices traded on the S&P 500.

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

We estimate equation (5) using an observation 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 then produce h-steps ahead forecasts. We then roll forward the window one observation, re-estimate equation (5) over the window 05/01/2000 to 13/04/2009 and generate a new series of h-step ahead forecasts. We repeat this process up to $T - h$ to produce a series of forecasts for the full out-of-sample period.

Table 3 depicts the results comparing the commodity-based models with a RW without drift and with drift in panels A and B, respectively. As the results in panel A 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 3 panel B 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 closely relates to the findings of Ferraro et al. (2015) and Kohlscheen et al. (2017). First, they similarly highlight that lagged commodity prices exhibit a lower forecasting ability in comparison to contemporaneous values when the benchmark is the driftless RW. Second, as in our study, they demonstrate that there is still some evidence suggesting commodity-based models continue to forecast better than the RW with drift.

5.3 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 involves a harder task in finding forecasting ability in comparison to computing a monthly or quarterly average from daily observations.

Table 4 presents the results comparing the model with contemporaneous commodity prices of equation (1) at monthly frequency against the RW model as a benchmark. As we observe in panel A, where the benchmark corresponds to the driftless RW model, 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 (Panel B). 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). Table 4 panels C and D 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, we also replicate the previous forecast exercises using quarterly observations and we reach the same following 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 and RW with drift. 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 or a RW with drift.[8]

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

[8]Results are available upon request.

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.

5.4 Fat-tailed distributions of log-returns

We now proceed to investigate the main focus of this paper, the role of the asymptotic dependence in explaining the performance of commodity prices in forecasting exchange rates. Initially we seek to determine if the distributions of log-returns of commodity prices and exchange rates both exhibit a fat-tailed shape. This is a necessary but not sufficient condition to analyse what is underpinning the documented ability of commodity prices to predict exchange rates.

Table 5 panel A reports the results of the Hill tail index we define in equation (2) for both the lower and upper log-returns tails, representing the most negative and positive log returns, respectively. Confidence intervals at the 99% level are also included in parenthesis. As shown, in all cases and also for both upper and lower tails, the indicator is positive and statistically different from zero indicating that the distribution of log-returns of each variable follows a fat-tailed distribution.

A more conservative evaluation of fat-tailed distributions is also undertaken using the Dekkers et al. (1989) index. Table 5 panel B presents the results of the $\widehat{\gamma}$ tail index estimator in equation (3). As the table shows, in general the majority most currencies and commodity prices exhibit heavily-tailed distributions at least in one of the tails. Overall, despite the occurrence some exemptions and acknowledging its relative inefficiency compared to the Hill tail index, we interpret the $\widehat{\gamma}$ tail index estimator as supporting the presence of heavy tails in both the log-returns commodity and exchange rate distributions, allowing us to conclude that there is relevant information in the tails of the distribution which can be examined further by carrying out an asymptotic dependence analysis.

5.5 Asymptotic dependence

In this section we introduce the results of our selected asymptotic dependence measure, following de Haan & Ferreira (2007). Before analysing the results, it is relevant to consider a taxonomy of the important cases we wish to discuss. As noted in section 4, the ADI measures the asymptotic dependence between a pair of random variables. Given the nature of our study, there are four cases we need to analyse corresponding to different relevant combinations of the two distributional tails of each of the random variables under analysis. In particular, as we compute the ADI using the log-returns of nominal exchange rates and commodity prices, the following four cases are the ones in which we focus:

- **Case 1**: An increase in country-specific commodity price (upper tail of commodity log-return distribution) and a nominal exchange rate appreciation (lower tail of exchange rate log-return distribution).

- **Case 2**: A reduction in country-specific commodity price (lower tail of commodity log-return distribution) and a nominal exchange rate depreciation (upper tail of exchange rate log-return distribution).

- **Case 3**: A reduction in country-specific commodity price (lower tail of commodity log-return distribution) and a nominal exchange rate appreciation (lower tail of exchange rate log-return distribution).

- **Case 4**: An increase in country-specific commodity price (upper tail of commodity log-return distribution) and a nominal exchange rate depreciation (upper tail of exchange rate log-return distribution) .

Table 6 panel A reports the results of the ADI measures using daily contemporaneous commodity prices and exchange rate returns for the period Jan-2000 to Jul-2018. We compute confidence bands using bootstrap procedures over 5000 resampling iterations. As the table shows, the asymptotic dependence index is positive and statistically significant for all countries in cases 1 and 2, with a minor exception in the case of Peru case 1. In contrast, for cases 3 and 4, the index both reduces in magnitude and becomes statistically insignificant in all countries.

Overall, the results are in line with the conjectured relationship between commodity prices and exchange rates. As we discuss in section 3, commodity price shocks generate changes in commodity exporting economies which transmit through to impact exchange rates. In particular, a sharp decrease (increase) in the price of the major country-specific commodity export is associated with a deterioration (improvement) in the economic outlook of that commodity exporting economy. As a result of this sudden deterioration (improvement) in economic confidence, a sharp depreciation (appreciation) of the nominal exchange rate occurs.

Following this logic, the asymptotic dependence only makes sense when the variables are related as in cases 1 (exchange rate appreciation concomitant with an increase in commodity prices) and case 2 (exchange rate depreciation and a reduction in the commodity's price). Moreover, this expected negative relationship between the variables receives empirical support in the data as we illustrate in section 3.1. Importantly, cases 3 and 4 report low values for ADI and show no statistical significance for the majority of the countries.

Our asymptotic dependence measure appears 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 6 panel B shows, cases 1 and 2 are statistically significant even after controlling for the effect of global risk appetite, captured by the VIX index. This suggests that the asymptotic dependence measure goes beyond a mere risk factor that may move both exchange rates and commodity returns. As expected, the ADI measure in cases 3 and 4 are close to zero or statistically insignificant for all countries.

Second, due to the nature of time-series of log-returs, there is a possibility that heteroskedasticity in log-returns biases the result of the asymptotic dependence analysis. To identify if this is an issue, we estimate our ADI measure using standardised residuals for both commodity and exchange rate returns, thereby controlling for possible heteroskedasticity effect. In order to compute the standardised residuals, we model the univariate conditional variance for each commodity and exchange rate log-return using an ARCH(1) model. As table 6 panel C reveals, the ADI results after we control for heteroskedasticity remain the same, cases 1 and 2 are statistically significant indicating the presence of an asymptotic dependence relationship, while the measure for cases 3 and 4 are much lower, either close to zero, or statistically insignificant.[9]

Third, as we initially measure commodity prices and exchange rates in U.S. dollars, it is important to establish that the asymptotic relationship between the variables does not simply reflect a dollar effect. Table 6 panels D and E present the ADI defining the exchange rate using Euros and Pound Sterling as a currency base, respectively. Our results show the asymptotic dependence between exchange rates and commodity returns remains generally significant in cases 1 and 2, while cases 3 and 4 are again close to zero or statistically insignificant.

[9]Following the ARCH(1) model estimation, the Engle's Lagrange multiplier test for standardised residuals reveals there is no left over heteroskedasticity effect after modelling the conditional variance with that model, therefore, the strategy is suitable to get rid of this potential issue. Results of the Engle's test are available upon request.

We interpret our findings as the effect of news and its ability to convey information from one market to another. As it is widely reported, in general, news exerts a significant impact on asset return volatility. Consequently, episodes characterised by the frequent arrival of news are associated with changes in asset prices and periods of high return volatility. Several studies maintain the same logic also applies to commodity markets (Caporale et al. 2017; Frankel & Hardouvelis 1985; Roache & Rossi 2010), documenting that the arrival of news significantly impacts commodity price volatility. According to these studies, it is the news affecting commodity markets which represents the key driver of large fluctuations in commodity prices. The resulting large fluctuations in commodity prices translate into leptokurtic commodity log-return distributions where the extreme observations generate fat tails in the log-returns distributions.

In particular, the interpretation of the asymptotic dependence measure is based on the effect of 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. Following the earlier discussion in section 3 concerning the transmission channel of external shocks into the domestic economy, the large swings in commodity prices, which are driven commodity market news, convey information relevant to the economic prospects of commodity exporting economies by changing investor perceptions. One channel through which this sentiment quickly manifest is changes in the value of the domestic currency. Our proposed measure of tail dependence allows us to quantify how the extreme values of exchange rate log-returns relate to extreme values of commodity log-returns. Consequently, the measured relationship between the tails of the relevant return distributions provides us with some idea of the extent to which the arrival of news relating to commodity markets is transmitted into exchange rates. This point of view is also consistent with Ferraro et al. (2015) who also interpret commodity price shocks as the mechanism conveying information about macroeconomic news that may affect exchange rates. The results we document in this study provide support for this previously investigated conjecture.

As a further illustration of the above mechanism we provide an example using copper prices and the Chilean exchange rate. In the particular case of the copper market, China's copper demand is considered an important driver of the international copper price accounting for roughly the half of the global copper imports.[10] As Bailliu et al. (2019) argue, the sustained expansion during last decades of the housing market and infrastructure investment in China, both being highly intense sectors in copper consumption, underpins the country's

[10] According to the United Nations Comtrade database (https://comtrade.un.org/), China's copper demand corresponds to 49.4% of the world copper imports in 2018, followed by Japan (14.3%) and South Korea (6.6%).

copper demand. Kruger et al. (2016) estimate that the Chinese housing market development accounts for 85% of the copper price increase during the 2000's decade. Moreover, the economic activity in that country is closely related to the global copper market. Kolerus et al. (2016) estimate that a 1% increase in China's industrial production generates an increase in global metal prices (iron, copper, nickel, lead, and tin) between 5% and 7% over a one-year horizon. Importantly for our purpose, they empirically estimate that the impact of China's industrial activity news on global metal commodity prices is comparable in magnitude to the effect of U.S. industrial production announcements. This evidence suggests news about the current economic situation in China tends to impact the global price of copper. Figure 3 plots the value of the asymptotic dependence indicator for case 2 of a large fall 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) occurs in China. We define the negative economic news episodes based on the Citigroup China Economic Surprise Index obtained from Bloomberg. As figure 3 indicates, during episodes of negative economic news in China, we observe an increase in our asymptotic dependence measure, signalling that negative news in China relates with a decrease in copper price, which, in turn, are correlated with large depreciations of the Chilean nominal exchange rate. This pattern is consistent with the view that some aspects of the negative news affecting the copper market are also transmitted to the Chilean exchange rate, via the copper price.[11]

We now examine the effect of information availability on our asymptotic dependence measure. Table 7 panel A 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 the indicator is not statistically different to zero for the majority of the cases. We obtain similar results for cases 3 and 4 where in most of the cases the indicator is statistically insignificant. All in all, the asymptotic dependence between nominal exchange rates and lagged commodity prices at daily frequency, if any, is rather than weak specially compared with the cases 1 and 2 of ADI using contemporaneous commodity prices. We obtain the same conclusion when replicating the exercise controlling by the effect of VIX (table 7 panel B) and heteroskedasticity in returns (table 7 panel C).

We also analyse the effect of data frequency on the relationship between exchange rates and commodity prices. Table 8 panel A presents a comparison of the the asymptotic depen-

[11]Naturally, although China is an important global agent influencing demand in the copper market, there is not a perfect correlation between events in figure 3 and our asymptotic dependence measure, as news about economic activity in China only represents a fraction of the potential shocks affecting the copper market, and other major elements also play a role in explaining changes in the international copper price.

dence measure between exchange rates and contemporaneous commodity prices computed at daily, monthly and quarterly frequency. As we previously document, the asymptotic dependence measure is statistically significant at daily frequency only for cases 1 and 2, while cases 3 and 4 are statistically insignificant. However, when computing our measure at a monthly frequency all evidence of asymptotic dependence vanishes, being Chile in case 2 is the only exception. Likewise, when we replicate the exercise using quarterly frequency, the our measure shows no statistical significance at all in the whole sample. The results we obtain using lower frequencies contrast 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. Similarly, when using lagged commodity prices at low frequency data to estimate our asymptotic dependence measure we obtain similar results. As table 8 panel B shows, that the asymptotic dependence evidence complete disappears at every frequencies under analysis, daily, monthly and quarterly, and for all countries in the sample.

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.[12] 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 an omitted factor drives our results.[13] In the same vein, demonstrating causality between variables goes beyond the scope of this research.[14] 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.

[12]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 observations). Conversely, Kilian & Vega (2011) show that U.S. macroeconomic news measured at a monthly frequency show no impact on oil prices.

[13]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.

[14]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

In this study, we analyse the non-linear relationship between commodity and exchange rate returns. We capture this relationship using an asymptotic dependence measure which appear robust to a number of alternative specifications. We show that the non-linear relationship between the variables is a key element that underpins the documented ability of commodity returns to forecast exchange rate returns. We find that both the asymptotic dependence between exchange rate and commodity returns and the forecasting ability of commodity returns are short-lived and transitory. Consequently, only contemporaneous information at a daily frequency can capture the non-linear relationship and the forecasting ability of commodity returns. On the contrary, at lower frequencies or using lagged commodity prices, we observe no asymptotic dependence between the variables and we note no forecasting ability of commodity prices. Our findings are consistent with related studies (Ferraro et al. 2015; Kohlscheen et al. 2017) which document similar results in terms of the forecasting ability of commodity returns, although, without offering a discussion of the mechanism behind the forecasting exercises. We argue that a central transmission mechanism behind the forecasting ability of commodity prices lies in the information transmitted from commodity price shocks to exchange rates which we capture using our asymptotic dependence measure. We interpret our findings as the effect of short-lived, transitory commodity price shocks conveying information to commodity-exporting economies by generating changes in the economic outlook of these economies which, ultimately, affect their domestic currencies.

Bibliography

Adrian, T., Etula, E. & Shin, H. S. (2009), 'Risk appetite and exchange Rates', **1**(361).

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.

Bailliu, J., Bilgin, D., Mo, K., Niquidet, K. & Sawatzky, B. (2019), 'Global Commodity Markets and Rebalancing in China: The Case of Copper', *Bank of Canada Discussion Papers* (2019-3).

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.

Gourio, F., Siemer, M. & Verdelhan, A. (2013), 'International risk cycles', *Journal of International Economics* **89**(2), 471 – 484.

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 (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.

Kolerus, C., N'Diaye, P. M. & Saborowski, C. (2016), 'China's Footprint in Global Commodity Markets', *International Monetary Fund* (16/06).

Kruger, M., Mo, K. & Sawatzky, B. (2016), 'The Evolution of the Chinese Housing Market and Its Impact on Base Metal Prices', (16-7).

Lustig, H., Roussanov, N. & Verdelhan, A. (2011), 'Common Risk Factors in Currency Markets', *Review of Financial Studies* **24**(11), 3731–3777.
URL: *https://ideas.repec.org/a/oup/rfinst/v24yi11p3731-3777.html*

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.

Prokopczuk, M., Stancu, A. & Symeonidis, L. (2019), 'The economic drivers of commodity market volatility', *Journal of International Money and Finance* **98**(C), 1–13.

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.

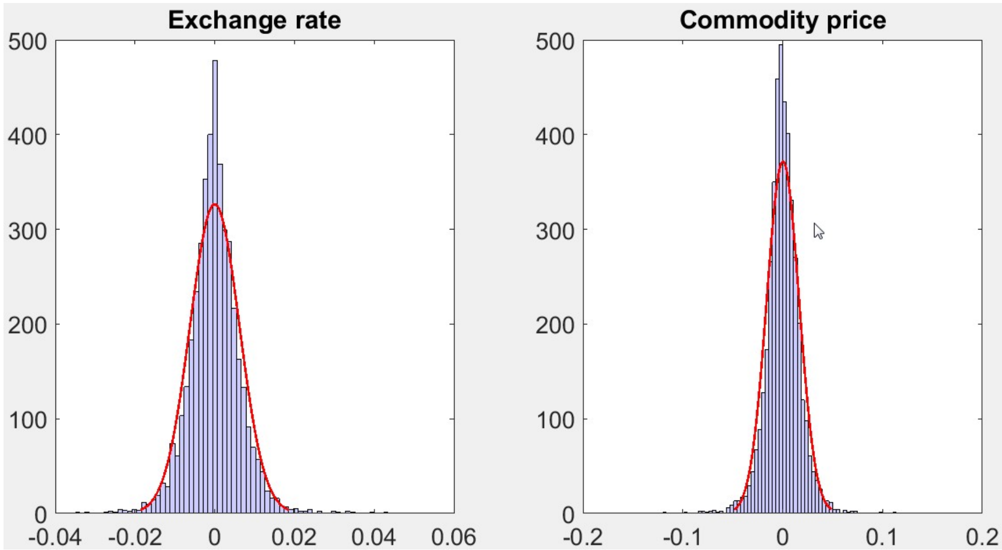
Skiadopoulos, G. (2013), 'Advances in the commodity futures literature: A review', *The Journal of Derivatives* **20**(3), 85–96.

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**.

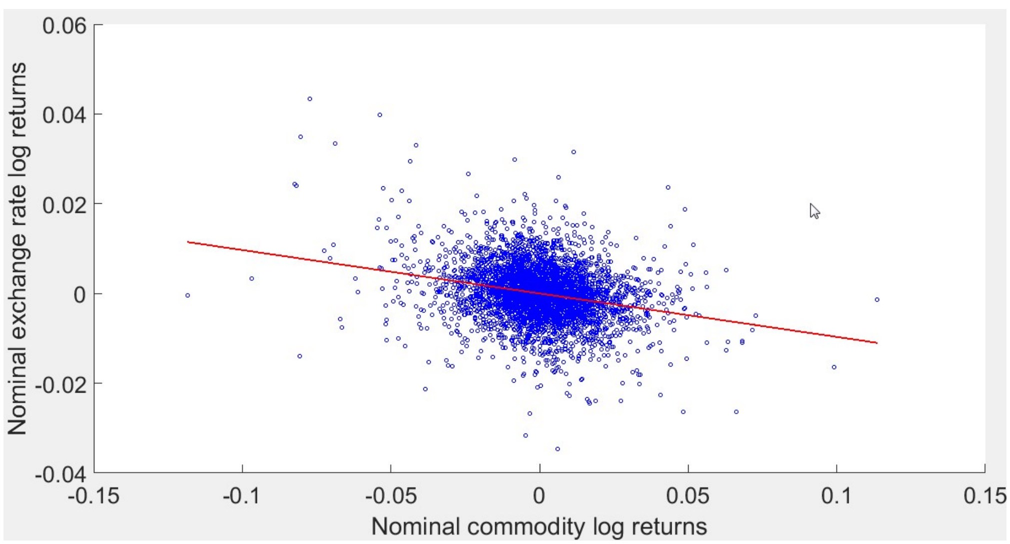
Yang, L. & Hamori, S. (2014), 'Gold prices and exchange rates: a time-varying copula analysis', *Applied Financial Economics* **24**(1), 41–50.

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.



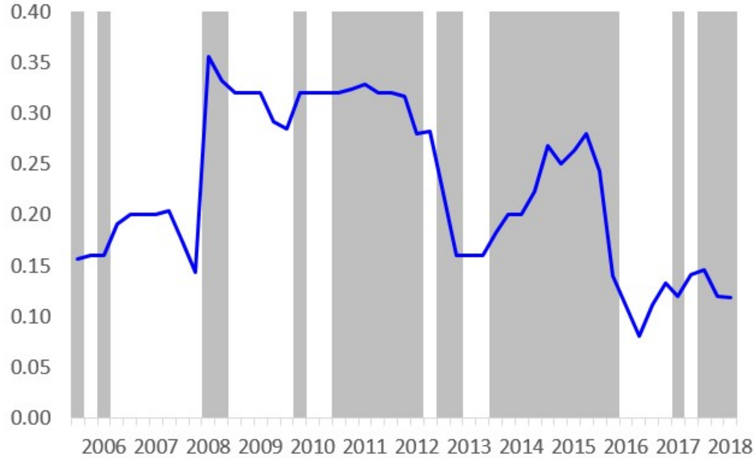
Estimation sample corresponds to daily data from 01/Jan/2000 to 18/Jul/2018.

Figure 1: Daily log-returns for the Chilean peso and copper price



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

Figure 2: Daily log-returns for the Chilean peso and copper price



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 the 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: Panel A

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 2: Panel B

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 2: Panel C

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 2: Panel D

Contemporaneous commodity prices vs. RW model without drift, using Euro (EUR) 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 2: Panel E

Contemporaneous commodity prices vs. RW model without drift, using Pound Sterling (GBP) 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 3: Panel A

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 3: Panel B

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 4: Panel A

Monthly frequency: 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 4: Panel B

Monthly frequency: 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 4: Panel C

Monthly frequency: 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 4: Panel D

Monthly frequency: 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 5: Panel A

Hill index estimator

	Lower tail	Upper tail
Brazil	0.30 (0.25;0.35)	0.33 (0.27;0.38)
Canada	0.27 (0.23;0.31)	0.26 (0.22;0.30)
Chile	0.25 (0.21;0.29)	0.29 (0.25;0.34)
Colombia	0.32 (0.27;0.37)	0.34 (0.28;0.39)
Mexico	0.32 (0.27;0.37)	0.38 (0.32;0.44)
Peru	0.33 (0.28;0.38)	0.40 (0.34;0.46)
Norway	0.27 (0.23;0.31)	0.25 (0.21;0.29)
Russia	0.38 (0.32;0.44)	0.40 (0.33;0.46)
S. Africa	0.25 (0.21;0.29)	0.30 (0.25;0.34)
Copper	0.32 (0.27;0.37)	0.25 (0.21;0.29)
Gold	0.31 (0.26;0.35)	0.32 (0.27;0.37)
WTI	0.30 (0.25;0.35)	0.31 (0.26;0.35)

Notes: Note: Confidence Intervals at 99% 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 5: Panel B

Tail index estimator of Dekkers et al. (1989)

	Lower tail	Upper tail
Brazil	0.18 (0.02;0.34)	0.23 (0.07;0.39)
Canada	0.22 (0.06;0.38)	0.05 (−0.11;0.20)
Chile	0.11 (−0.05;0.27)	0.24 (0.08;0.41)
Colombia	0.20 (0.04;0.36)	0.11 (−0.05;0.27)
Mexico	0.15 (−0.01;0.30)	0.34 (0.18;0.51)
Peru	0.20 (0.04;0.36)	0.30 (0.13;0.46)
Norway	0.30 (0.14;0.46)	0.07 (−0.09;0.22)
Russia	0.21 (0.05;0.37)	0.29 (0.13;0.45)
S. Africa	0.04 (−0.11;0.19)	0.29 (0.13;0.45)
Copper	0.06 (−0.10;0.22)	0.16 (0.00;0.33)
Gold	0.14 (−0.02;0.29)	0.23 (0.08;0.39)
WTI	0.16 (0.00;0.32)	0.16 (0.00;0.32)

Notes: Confidence Intervals at 99% 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 6: Panel A

ADI using contemporaneous commodity returns

	Case 1	Case 2	Case 3	Case 4
Brazil	0.11 (0.03;0.19)	0.15 (0.06;0.23)	0.05 (0.00;0.10)	0.03 (−0.01;0.07)
Canada	0.22 (0.12;0.32)	0.16 (0.07;0.25)	0.02 (−0.01;0.05)	0.00 (−0.01;0.02)
Chile	0.10 (0.02;0.18)	0.19 (0.09;0.28)	0.03 (−0.01;0.07)	0.03 (−0.01;0.07)
Colombia	0.20 (0.09;0.29)	0.21 (0.11;0.32)	0.01 (−0.01;0.04)	0.01 (−0.01;0.04)
Mexico	0.15 (0.06;0.24)	0.17 (0.08;0.26)	0.01 (−0.01;0.03)	0.01 (−0.01;0.04)
Norway	0.18 (0.08;0.27)	0.19 (0.09;0.28)	0.03 (−0.01;0.07)	0.01 (−0.01;0.03)
Peru	0.06 (0.00;0.11)	0.10 (0.02;0.18)	0.06 (0.00;0.11)	0.05 (0.00;0.10)
Russia	0.21 (0.11;0.32)	0.17 (0.08;0.26)	0.01 (−0.01;0.04)	0.01 (−0.01;0.03)
S. Africa	0.09 (0.02;0.16)	0.13 (0.05;0.21)	0.06 (0.00;0.11)	0.06 (0.00;0.12)

Note: Confidence Intervals in parenthesis at 99% 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 6: Panel B

ADI using contemporaneous commodity returns and exchange rates orthogonal to VIX

	Case 1	Case 2	Case 3	Case 4
Brazil	0.10 (0.02;0.18)	0.14 (0.05;0.22)	0.04 (−0.01;0.09)	0.04 (−0.01;0.08)
Canada	0.21 (0.11;0.31)	0.12 (0.03;0.20)	0.03 (−0.01;0.07)	0.02 (−0.01;0.05)
Chile	0.12 (0.04;0.20)	0.18 (0.08;0.27)	0.03 (−0.01;0.07)	0.03 (−0.01;0.07)
Colombia	0.16 (0.07;0.25)	0.16 (0.06;0.25)	0.02 (−0.01;0.05)	0.01 (−0.01;0.03)
Mexico	0.12 (0.04;0.19)	0.10 (0.02;0.17)	0.07 (0.00;0.14)	0.03 (−0.01;0.07)
Norway	0.15 (0.06;0.24)	0.14 (0.06;0.23)	0.04 (0.00;0.08)	0.01 (−0.01;0.03)
Peru	0.06 (0.00;0.13)	0.09 (0.02;0.16)	0.05 (0.00;0.10)	0.06 (0.00;0.11)
Russia	0.22 (0.12;0.32)	0.17 (0.08;0.26)	0.01 (−0.01;0.03)	0.01 (−0.01;0.03)
S. Africa	0.09 (0.02;0.16)	0.12 (0.04;0.19)	0.05 (0.00;0.10)	0.03 (0.00;0.08)

Note: Confidence Intervals in parenthesis at 99% 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 6: Panel C

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

	Case 1	Case 2	Case 3	Case 4
Brazil	0.12 (0.03;0.20)	0.07 (0.00;0.14)	0.02 (−0.01;0.05)	0.02 (−0.01;0.05)
Canada	0.14 (0.05;0.23)	0.15 (0.06;0.23)	0.01 (−0.01;0.03)	0.00 (0.00;0.01)
Chile	0.09 (0.02;0.17)	0.15 (0.06;0.24)	0.05 (0.00;0.10)	0.01 (−0.01;0.03)
Colombia	0.15 (0.06;0.23)	0.19 (0.09;0.28)	0.00 (−0.01;0.02)	0.01 (−0.01;0.04)
Mexico	0.11 (0.02;0.19)	0.13 (0.04;0.21)	0.00 (0.00;0.00)	0.04 (0.00;0.08)
Norway	0.15 (0.06;0.24)	0.13 (0.05;0.22)	0.02 (−0.01;0.05)	0.01 (−0.01;0.03)
Peru	0.06 (0.00;0.13)	0.10 (0.02;0.17)	0.04 (0.00;0.08)	0.01 (−0.01;0.03)
Russia	0.13 (0.05;0.22)	0.15 (0.06;0.24)	0.01 (−0.01;0.03)	0.01 (−0.01;0.03)
S. Africa	0.09 (0.02;0.16)	0.12 (0.04;0.19)	0.03 (−0.01;0.08)	0.05 (0.00;0.10)

Note: Confidence Intervals in parenthesis at 99% level and obtained by bootstrap using 5000 resampling 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 *ARCH(1)* where the conditional variance is modelled as $\sigma_t^2 = \omega + \alpha u_{t-1}^2$. 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 6: Panel D

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 (0.03;0.19)	0.10 (0.02;0.18)	0.06 (0.00;0.11)	0.04 (0.00;0.08)
Canada	0.16 (0.07;0.25)	0.10 (0.02;0.17)	0.01 (−0.01;0.03)	0.01 (−0.01;0.04)
Chile	0.05 (0.00;0.11)	0.07 (0.00;0.13)	0.06 (0.00;0.12)	0.06 (0.00;0.12)
Colombia	0.11 (0.03;0.18)	0.15 (0.06;0.24)	0.04 (−0.01;0.08)	0.03 (−0.01;0.07)
Mexico	0.11 (0.03;0.18)	0.12 (0.03;0.20)	0.04 (−0.01;0.09)	0.06 (0.00;0.12)
Norway	0.19 (0.09;0.28)	0.20 (0.10;0.29)	0.03 (−0.01;0.07)	0.01 (−0.01;0.03)
Peru	0.05 (0.00;0.10)	0.02 (−0.01;0.05)	0.07 (0.00;0.13)	0.08 (0.01;0.14)
Russia	0.18 (0.08;0.28)	0.15 (0.06;0.24)	0.02 (−0.01;0.05)	0.04 (0.00;0.08)
S. Africa	0.05 (0.00;0.10)	0.10 (0.03;0.17)	0.06 (0.00;0.12)	0.07 (0.00;0.13)

Note: Confidence Intervals in parenthesis at 99% level and obtained by bootstrap using 5000 resampling 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 6: Panel E

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 (0.02;0.17)	0.12 (0.04;0.19)	0.05 (0.00;0.11)	0.03 (−0.01;0.07)
Canada	0.13 (0.04;0.20)	0.13 (0.04;0.20)	0.06 (0.00;0.12)	0.01 (−0.01;0.04)
Chile	0.08 (0.01;0.14)	0.10 (0.02;0.17)	0.08 (0.01;0.14)	0.04 (0.00;0.09)
Colombia	0.09 (0.01;0.16)	0.15 (0.06;0.24)	0.06 (0.00;0.12)	0.01 (−0.01;0.03)
Mexico	0.06 (0.00;0.13)	0.12 (0.03;0.20)	0.07 (0.00;0.13)	0.03 (−0.01;0.07)
Norway	0.07 (0.01;0.13)	0.13 (0.04;0.20)	0.05 (0.00;0.11)	0.03 (−0.01;0.07)
Peru	0.03 (−0.01;0.07)	0.04 (0.00;0.08)	0.12 (0.04;0.20)	0.06 (0.00;0.12)
Russia	0.16 (0.07;0.25)	0.14 (0.05;0.23)	0.08 (0.00;0.14)	0.03 (−0.01;0.07)
S. Africa	0.05 (0.00;0.11)	0.08 (0.01;0.14)	0.06 (0.00;0.11)	0.05 (0.00;0.10)

Note: Confidence Intervals in parenthesis at 99% 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 7: Panel A

ADI using lagged commodity returns

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

Note: Confidence Intervals in parenthesis at 99% 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 7: Panel B

ADI using lagged commodity returns and exchange rates orthogonal to VIX

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

Note: Confidence Intervals in parenthesis at 99% 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 7: Panel C

ADI using lagged commodity returns and controlling for heteroskedasticity in log-returns

	Case 1	Case 2	Case 3	Case 4
Brazil	0.05 (0.00;0.10)	0.05 (0.00;0.10)	0.08 (0.01;0.15)	0.02 (−0.01;0.05)
Canada	0.03 (−0.01;0.07)	0.02 (−0.01;0.05)	0.02 (−0.01;0.05)	0.01 (−0.01;0.03)
Chile	0.03 (−0.01;0.07)	0.08 (0.01;0.15)	0.06 (0.00;0.11)	0.03 (−0.01;0.07)
Colombia	0.03 (−0.02;0.08)	0.03 (−0.01;0.07)	0.03 (−0.01;0.07)	0.04 (0.00;0.08)
Mexico	0.04 (−0.01;0.08)	0.03 (−0.01;0.07)	0.04 (0.00;0.10)	0.07 (0.01;0.13)
Norway	0.04 (−0.01;0.08)	0.05 (0.00;0.11)	0.04 (0.00;0.10)	0.04 (0.00;0.08)
Peru	0.05 (0.00;0.10)	0.03 (−0.01;0.07)	0.04 (−0.01;0.09)	0.04 (−0.01;0.08)
Russia	0.04 (−0.01;0.08)	0.03 (−0.01;0.07)	0.02 (−0.01;0.05)	0.02 (−0.01;0.05)
S. Africa	0.06 (0.00;0.11)	0.04 (0.00;0.09)	0.03 (−0.01;0.08)	0.03 (−0.01;0.08)

Note: Confidence Intervals in parenthesis at 99% 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 *ARCH(1)* where the conditional variance is modelled as $\sigma_t^2 = \omega + \alpha u_{t-1}^2$. 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 8: Panel A

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	--	--	--	--	--	--	--	--	--	--
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	--	--	--	--	--	--	--	--	--	--
Peru	--	0.10	--	--	--	--	--	--	--	--	--	--
Russia	0.21	0.17	--	--	--	--	--	--	--	--	--	--
S. Africa	0.09	0.13	--	--	--	--	--	--	--	--	--	--

Note: Asymptotic dependence index computed at different frequencies using log-returns from Jan-2000 to July-2018. "−−" indicates no statistical significance at 1%. **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 8: Panel B

ADI using lagged commodity returns at different frequencies

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

Note: Asymptotic dependence index computed at different frequencies using log-returns from Jan-2000 to July-2018. "−−" indicates no statistical significance at 1%. **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).