When the Walk Is Not Random: Commodity Prices and Exchange Rates*

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We show that there is a distinct commodity-related driver of exchange rate movements, even at fairly high frequencies. Commodity prices predict exchange rate movements of eleven commodity-exporting countries in an in-sample panel setting for horizons up to two months. We also find evidence of systematic (pseudo) out-of-sample predictability, overturning the results of Meese and Rogoff (1983): information embedded in our country-specific commodity price indexes clearly helps to improve upon the predictive accuracy of the random walk in the majority of countries. We further show that the link between commodity prices and exchange rates is not driven by changes in global risk appetite or carry.

JEL Codes: F10, F31, G12.

1. Introduction

Recent developments in the oil market have brought the connection between commodity prices and the exchange rates of a number of countries back to the forefront of the policy debate. By affecting prospective inflows, substantial changes to the terms of trade of a given country are thought to exert a significant influence on exchange rates.

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In the short run, higher commodity prices lead to an increased supply of foreign exchange in the markets of commodity exporters, as a result of increased export revenues—causing an appreciation of the domestic currency. In the medium to long run, this effect might then be compounded by ensuing foreign direct investment, as a result of more attractive investment prospects in the local commodity sector.[1]

The above mechanisms tend to be fairly evident in the economies of commodity exporters. For such countries, price variation of key export commodities is often seen as a reasonably good *proxy* for terms-of-trade movements, as export price variation typically trumps the variation in import prices—which tends to be more dependent on more rigidly priced manufactured goods. Hence, changes in the prices of key exports may well bear a close link with exchange rate movements.[2]

In this paper we analyze the relation between commodity prices and the exchange rates of key commodity exporters in a systematic way. We base our analysis on a more timely proxy for terms of trade, which is based on granular three-digit UN Comtrade data as well as market price information of eighty-three associated proxy commodities, which were used to construct country-specific commodity export price indexes (CXPIs) at daily frequency for eleven commodity-exporting countries.[3]

The daily CXPIs allow us to analyze the relation between commodity prices and exchange rates with greater precision at different frequencies, as well as to tease out the extent to which this relation is independent of variations in global risk appetite or carry. We show how the information that is contained in these indexes clearly

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[1] Over time, increased income due to improved terms of trade also tends to raise the demand for non-tradable goods, pushing their relative prices up, causing further real exchange rate appreciation.

[2] While it is of course possible that commodity price movements also affect the exchange rates of commodity importers, the link in these cases is likely to be less clear-cut, as there may be greater symmetry in the effects of import price fluctuations on different countries.

[3] As we show in the paper, the volatility of the export indexes (expressed in U.S. dollars) is lower than that of the oil price. It is, however, typically much larger than that of the aggregate Commodity Research Bureau (CRB) commodity price index for all eleven countries. Indeed, for eight of them the standard deviation of the commodity export price indexes is more than double that of the CRB.

improves the predictive performance of exchange rate models for all eleven of the commodity exporters that we study. In addition, the indexes provide more prompt information about the direction in which equilibrium exchange rates may be moving. They could thus prove to be useful for the evaluation of central bank or sovereign wealth fund actions in foreign exchange (FX) markets.

We find that commodity prices predict exchange rate movements of commodity exporters up to two months ahead when the analysis is based on in-sample panel regressions. Out-of-sample estimations also show that simple linear predictive models based on our commodity price indexes tend to have superior predictive performance for exchange rates when compared with random-walk benchmarks. These findings hold true for the three advanced economies and eight emerging markets in our sample. They hold for bilateral variations against the U.S. dollar (USD) and the Japanese yen (JPY), as well as for the nominal effective exchange rate (NEER) variations.

The key finding that commodity price models dominate random-walk models is based on the usual approach of utilizing realized variables as predictors (so-called pseudo out-of-sample tests), as pioneered by Meese and Rogoff (1983). As we show, evidence of out-of-sample predictability using only lagged predictors is clearly weaker, possibly as a consequence of the fact that commodity prices themselves are hard to predict.

We further show that variation in commodity prices has an effect on nominal exchange rates at high frequency that goes beyond the impact of global risk appetite. Daily variations in the Chicago Board Options Exchange (CBOE) volatility index (VIX) also explain a share of the nominal exchange rate variation. But, commodity prices explain a significant part of the variation of the exchange rate that is orthogonal to risk.[4] In other words, the high-frequency relation that exists between commodity prices and exchange rates goes beyond what is driven by the simultaneous movement of investors into (out of) commodity markets and high-yielding currencies during risk-on

[4]The finding that variations in global risk and risk appetite influence currency movements—in particular, those that feature strongly as funding or investment currencies in carry trades—is in line with recent studies by Adrian, Etula, and Shin (2009), Lustig, Roussanov, and Verdelhan (2011), Menkhoff et al. (2012), Gourio, Siemer, and Verdelhan (2013), and Farhi and Gabaix (2014), among others.

(risk-off) episodes. Our results are also found to be robust to the incorporation of information on short-term government bond yields differentials.

All in all, we provide extensive evidence that there is a distinct commodity-related driver of exchange rate movements, even at relatively high frequencies. For commodity exporters, variation in exchange rates is not random, but is tightly linked to movements in commodity prices.

1.1 Relation to the Literature

Several prior studies have established a low-frequency relation between commodity export prices and real exchange rates, including the seminal papers of Chen and Rogoff (2003) and Cashin, Cespedes, and Sahay (2004). Along the same lines, MacDonald and Ricci (2004) found strong evidence of cointegration between the real value of the South African rand and real commodity export prices.[5] In contrast to this literature, our study focuses on the high-frequency relation by drawing on a very rich data set that allows us to examine the relation between daily variations in nominal variables in a systematic way for eleven major commodity-exporting countries. More specifically, we make use of much more granular data on commodity export prices and export volumes. This much broader coverage ensures that the constructed country-specific export indexes are a better *proxy* of terms-of-trade shocks, measured at high frequency. Furthermore, incorporating price information for eighty-three commodity groups allows us to investigate the link between commodity prices and exchange rates also for countries that have a more diversified base of commodity exports.

In terms of the empirical strategy and methodology, our paper is closely related to that of Ferraro, Rogoff, and Rossi (2015), which

[5]Sidek and Yussof (2009) as well as Kohlscheen (2014) report similar findings for the Malayan ringitt and the Brazilian real, respectively. Also Hambur et al. (2015) report a strong relationship between Australia's terms of trade and the real exchange rate. Equally, terms-of-trade shocks affect the Chilean peso in a very significant way, according to estimates presented in de Gregorio and Labbe (2011). These authors find that effects on the exchange rate under inflation targeting are more immediate but of smaller magnitude in the long run when compared with the pre-inflation targeting period.

focuses mostly on the relationship between oil prices and the nominal value of the Canadian dollar. We go beyond by studying a much wider array of currencies and commodity prices. By finding that a key economic variable—commodity prices—consistently helps improve upon the predictive accuracy of the random walk, we overturn the well-known negative results of Meese and Rogoff (1983) and of Cheung, Chinn, and Pascual (2005). These two papers had established that models based on macroeconomic fundamentals are unable to outperform a simple random walk.[6] We also show that these findings are not driven by changes in uncertainty and global risk appetite, as proxied for by the VIX, which generally tend to be correlated with commodity price movements.

1.2 Outline

The article proceeds as follows. Section 2 describes the construction of the country-specific commodity export price indexes (the CXPIs). Section 3 shows how the high-frequency variation in these indexes is tightly related to the nominal exchange rate movements of commodity exporters. Section 4 shows that short-term yield differentials tend to perform relatively poorly as exchange rate predictors (with the notable exceptions of Australia and Canada), while adding information on commodity prices greatly improves forecasting performance. Section 5 presents several robustness tests. We conclude by discussing some possible directions for future research.

2. Constructing Country-Specific Commodity Export Price Indexes (CXPIs)

To study the link between commodity prices and exchange rates, we construct a daily commodity export price index (CXPI) for each major commodity-exporting country based on market price data of key commodities. We were able to associate quoted prices at daily frequency with a total of eighty-three UN Comtrade three-digit

[6]While many studies claimed better long-horizon predictability for models based on monetary fundamentals, Kilian (1999) argued that these findings were mostly due to size distortions.

commodity groups. Twenty-six referred to metals, thirty-six to agricultural commodities, eleven to livestock, and ten to energy. Price information was collected from Datastream and from Bloomberg. The main original source of data is the London Metal Exchange (LME) and the Chicago Mercantile Exchange (CME), but data from a number of alternative sources were also used. Iron ore prices, for instance, were based on data from the Shanghai Metal Exchange. For oil we used the Brent reference price.

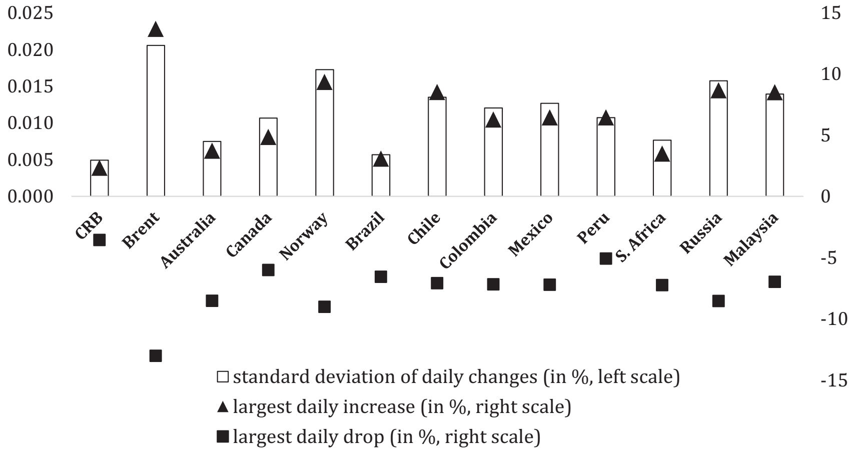
The country-specific commodity export price indexes were constructed as Laspeyres indexes. The weight of each commodity in each country basket was chosen so as to match the share of export revenues in total commodity export revenues in the respective country between 2004 and 2013.[7]

The weight of commodity groups for which good *proxy* market prices were not available was assumed to be zero. The underlying baskets of the CXPI indexes cover 98 percent of commodity exports of the countries considered in this study. The ten most important commodity segments for each country, according to their share in total export revenues, and their respective weights can be seen in table 9 in the appendix. The resulting indexes give a measure of the price of the exported commodity index in U.S. dollars. Note that this refers to nominal terms, as no correction for inflation was made. The sample period covers the time span between January 2, 2004 and February 28, 2015.

Figure 1 shows the variation of the country-specific commodity export price indexes for the eleven countries we analyze, as well as for the oil price (Brent) and the CRB commodity price index. The bars show that the Norwegian and the Russian CXPIs are clearly the most volatile indexes—which is a reflection of the very large contribution of oil in the commodity exports of these two countries. Even though the standard deviation of the Norwegian CXPI is 3.5 times larger than that of the CRB (1.73 percent versus 0.49 percent),

[7]Technically, because the basket weights are taken from an average over the entire period, the CXPI index is a Lowe index, which also belongs to the family of Laspeyres indexes. Triplett (1981) offers a more complete discussion. Strictly speaking, our index is not a pure Laspeyres index because the basket weight is not the weight measured at one specific instance of time. The value of a Lowe index tends to lie between the value given by the pure Laspeyres index and a Paasche index.

Figure 1. Variability of Commodity Export Price Indexes (CXPIs)

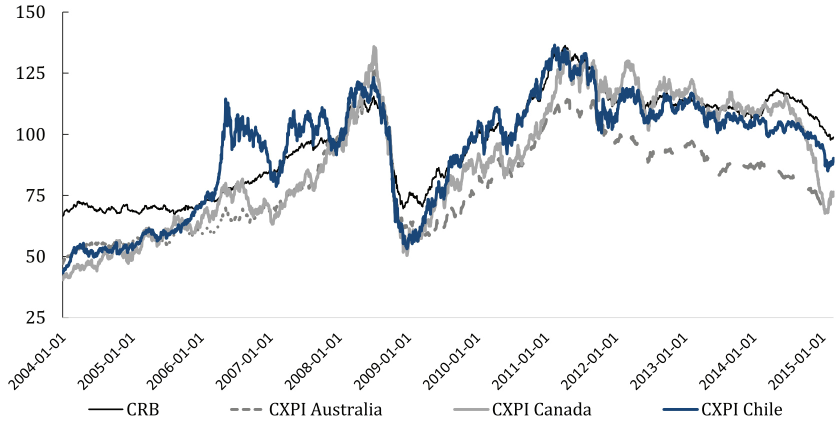


its volatility is somewhat lower than the volatility of the oil price because of diversification. On the other hand, Brazil has the least volatile index (with a standard deviation of 0.57 percent). That said, there have been episodes of basket price drops in excess of 5 percent within a day for all countries during our sample period (with one case of a drop in excess of 9 percent for the Norwegian CXPI). On the upside, Chile, Malaysia, Russia, and Norway have witnessed basket price increases above 8 percent within a single day.

Figure 2 plots the evolution of the CXPIs for each of the three selected countries, as well as for the CRB. The graph shows, for instance, how the sharp increase in commodity export prices in the second half of the 2000s in Chile predated similar movements for the Australian and Canadian indexes. The end of the sample captures the sharp oil price fall in late 2014 and the temporary partial rebound in early 2015, which is reflected in a discernible way in the evolution of the Canadian CXPI.

We compared the evolution of the Australian CXPI with the monthly index published by the Reserve Bank of Australia (RBA), which explains 75 percent of the variation in Australian exports according to Robinson and Wang (2013). At monthly frequency, the

Figure 2. Evolution of the CXPIs and the CRB



Note: Average of 2008 = 100. Own computation.

correlation of our index with that of the RBA is 0.904. While movements are broadly similar, the amplitude of the variations of the RBA index during the sample period is slightly larger than that of the corresponding CXPI, which is a reflection of the fact that the RBA index is rebased from time to time, whereas we did not rebase our daily index during our sample period.

The correlation matrix in table 1 shows that pairwise correlations vary quite substantially between countries. Commodity indexes for Colombia and Mexico, for instance, are highly correlated (0.971), again reflecting the predominance of oil in the commodity baskets of these countries. On the other hand, the cross-country correlations tend to be much lower for Chile (a large copper exporter). Of course, correlation of oil price variations with the changes in the values of the other commodity baskets creates the possibility that oil prices alone may actually predict exchange rate movements of countries that barely export any oil (see Ferraro, Rogoff, and Rossi 2015).

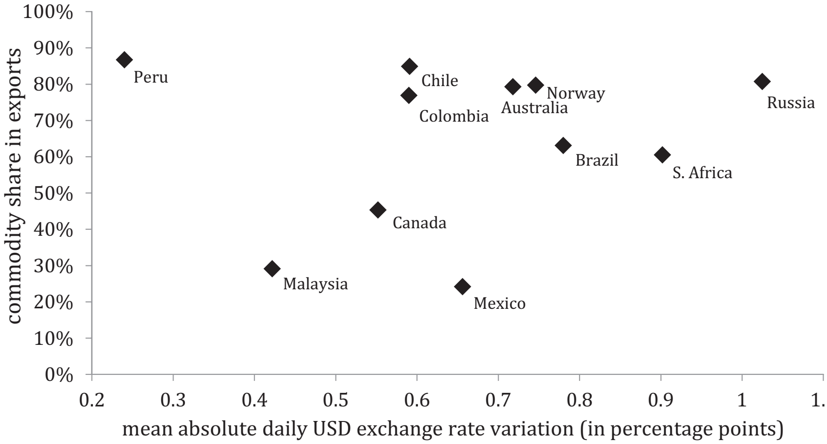
Lastly, figure 3 illustrates that the mean absolute daily exchange rate variation tends to be larger in countries in which the share of commodities in total exports is larger. An exception is Peru, possibly due to active intervention in FX markets (see Fuentes et al. 2013 and Blanchard, Adler, and Carvalho Filho 2015). This suggests

Table 1. Correlations of Commodity Price Indexes

	Australia	Canada	Norway	Brazil	Chile	Colombia	Mexico	Peru	S. Africa	Russia	Malaysia	CRB	Brent
CXPI Australia	1												
CXPI Canada	0.794	1											
CXPI Norway	0.670	0.937	1										
CXPI Brazil	0.720	0.687	0.538	1									
CXPI Chile	0.665	0.599	0.411	0.518	1								
CXPI Colombia	0.678	0.871	0.789	0.716	0.484	1							
CXPI Mexico	0.664	0.896	0.796	0.713	0.565	0.971	1						
CXPI Peru	0.763	0.730	0.543	0.607	0.919	0.631	0.698	1					
CXPI S. Africa	0.810	0.676	0.496	0.661	0.669	0.635	0.662	0.806	1				
CXPI Russia	0.691	0.964	0.969	0.618	0.453	0.894	0.903	0.587	0.552	1			
CXPI Malaysia	0.687	0.917	0.955	0.546	0.422	0.740	0.744	0.551	0.519	0.927	1		
CRB	0.491	0.475	0.329	0.477	0.517	0.425	0.473	0.543	0.507	0.375	0.367	1	
Brent	0.550	0.839	0.784	0.622	0.428	0.957	0.971	0.546	0.509	0.898	0.714	0.364	1

Note: Data at daily frequency, in log changes.

Figure 3. Commodity Share in Exports and Exchange Rate Volatility



that there could be a direct relation between commodity price and exchange rate movements. As we show in the sections that follow, this is indeed the case.

3. Commodity Prices as Drivers of Exchange Rate Movements

3.1 In-Sample Fit: Contemporaneous Correlations

As a first step, we run some simple panel regressions to explore the contemporaneous relation between exchange rates and commodities prices for our panel of eleven commodity exporters. These first-pass regressions suggest a clear association of nominal exchange rates with daily commodity price index variations in sample for all countries. More specifically, we estimate

$$\Delta s_{i,t} = \alpha + \beta \cdot \Delta CXPI_{i,t} + \gamma_i + \theta_t + \varepsilon_{i,t}, \tag{1}$$

where $s_{i,t}$ stands for the log of the (nominal) exchange rate of country i vis-à-vis the USD on day t, $CXPI_{i,t}$ for the log of the country-specific commodity export price index on the same day,

α for the constant term, γ_i for country fixed effects, θ_t for a vector of year dummies, and $\varepsilon_{i,t}$ for the error term.[8] The choice of a first-difference approach appears natural, as we are focusing on high-frequency variations and the variables in question typically contain stochastic trends.

The exercise was based on 30,294 country-day observations. The sample period goes from January 2004 to February 2015. For Malaysia, however, the sample starts only in August 2005, after the country abandoned its peg against the USD, whereas for Russia the sample period starts only in February 2009 (i.e., after the very substantial widening of the dual currency board (Bank for International Settlements 2013).

We obtain the following panel estimation results:

$$\Delta s_{i,t} = const. - \underset{[6.19]}{0.21} \cdot \Delta CXPI_{i,t} + Fixed\ Effects,\ \mathrm{R}^2 = 0.104, \quad (2)$$

where the t-statistics in the brackets below the coefficient estimate were based on cluster-robust standard errors. The estimated coefficient indicates that a 10 percent increase in the price of the commodities that are exported by a country in our sample is associated with a 2.1 percent appreciation of the respective currency, on average.

On a country-by-country basis (not tabulated here), the information of commodity price variation alone explains more than 23 percent of the variation in the USD exchange rate in the cases of Australia and Canada, on an ex post basis. On the other hand, this explanatory power was only about 3 percent for Peru.

3.2 Predictive Regression: In-Sample

To assess whether our commodity price indexes are able to predict nominal exchange rate variations, we estimated a generalized version of equation (1):

$$\Delta s_{i,t+k} = \alpha + \beta \cdot \Delta CXPI_{i,t} + \gamma_i + \theta_{t+k} + \varepsilon_{i,t+k}, \quad (3)$$

[8] Daily variations in real terms—if they were available—would tend to follow nominal variables quite closely, as s_t and $CXPI_t$ are based on market prices which adjust rapidly to news.

Table 2. Exchange Rate Predictability (in-sample) in a Panel Setting (dependent variable: log change of bilateral exchange rate)

	Prediction Horizon in Days				
	k = 1	**k = 5**	**k = 22**	**k = 44**	**k = 66**
CXPI	−0.020***	−0.016*	−0.044***	−0.047***	−0.018
t-stat	3.51	1.89	5.19	2.65	0.88
R2 Overall	0.0032	0.0113	0.0540	0.0934	0.1228
R2 Within	0.0032	0.0111	0.0530	0.0917	0.1206
R2 Between	0.5714	0.5608	0.6062	0.6143	0.6055
Observations	30,294	30,283	30,096	29,854	29,612
Groups	11	11	11	11	11
Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the results of the panel regression $\Delta s_{i,t+k} = \alpha + \Delta CXPI_{i,t} + \gamma_i + \theta_{t+k} + \varepsilon_{i,t+k}$, where k stands for the length of the prediction horizon. t-statistics are based on clustered standard errors. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively. The estimation is based on information from January 2004 to February 2015.

where k denotes the forecasting horizon (in working days). A significant β coefficient indicates that the commodity price information that is available at day t is indeed useful for predicting the variation of the exchange rate between t and $t + k$. We estimated this panel regression for horizons of one day up to three months. Estimations were based on country fixed effects γ_i and time effects θ_{t+k} as well as clustered standard errors.[9] For a discussion of pooled panel data and their merits for studying exchange rate predictability, the reader is referred to Mark and Sul (2001, 2012).

The results that are reported in table 2 show that commodity prices are indeed significant predictors of future exchange rates for horizons of up to two months. The R^2 statistics indicate that the explanatory power in this in-sample forecasting exercise is larger for variation between countries than within.

[9] Only yearly dummy variables were used as time effects, so as to avoid having more than 2,500 daily time dummy variables.

Up to now we have imposed a common coefficient for all eleven countries of our study. Of course, coefficients may vary a great deal between countries due, for instance, to the differing weight of commodities in total export revenues or to differences in the volatility of these indexes. The exchange rate may react less to price changes in countries where price indexes are very volatile, as these changes may be perceived as having only temporary effects on export revenues.

Table 10 in the appendix reports the results country by country. Even though the much smaller sample implies greater variation in coefficients over different horizons and countries, the monthly horizon (i.e., twenty-two days) stands out as being the one in which forecasting performance is more robust across countries. Commodity prices emerge as significant in-sample predictors for ten of the eleven countries. With the notable exception of South Africa, in-sample exercises suggest that exchange rates are at least to some extent predictable.

3.3 An Out-of-Sample Forecasting Experiment

A natural question is whether exchange rates of commodity exporters are also predictable out of sample. To evaluate the out-of-sample (OOS) performance of exchange rate models, we rely on the classical pseudo-OOS prediction framework, pioneered by Meese and Rogoff (1983). To this end, we run the following regression equation based on a rolling window:

$$\Delta s_t = \widehat{\alpha}_{t-T,t-1} + \widehat{\beta}_{t-T,t-1} \cdot \Delta CXPI_{i,t} + \varepsilon_t.$$

The estimated parameters $\widehat{\alpha}_{t-T,t-1}$ and $\widehat{\beta}_{t-T,t-1}$ capture drifts and the magnitude of the exchange rate response to commodity price changes. In other words, our procedure is able to capture the long-term variations in the sensitivity of exchange rates to commodity prices that may result, for instance, from secular changes in the share of commodities in the total exports of a country or changes in FX intervention policies. The use of out-of-sample forecasts for performance evaluation also diminishes the risks associated with data mining.[10]

[10]See Cheung, Chinn, and Pascual (2005) and Inoue and Kilian (2005).

We follow the convention of the literature (Meese and Rogoff 1983; Cheung, Chinn, and Pascual 2005) in that we use a rolling window of fixed length T to estimate the parameters $\widehat{\alpha}_{t-T,t-1}$ and $\widehat{\beta}_{t-T,t-1}$, which are then used to produce an out-of-sample forecast. The window is then rolled forward one period at a time to produce the coefficient estimates for the subsequent period. This procedure has also been dubbed a pseudo out-of-sample experiment, as only contemporaneous (and not lagged) realizations of the predictors are used. Yet, even in this very basic framework it has proven very challenging for any economic models to outperform a random-walk forecast (Rossi 2013).

In our baseline specification, we use a five-year estimation window (roughly half of the sample size), which leaves an evaluation period of 1,607 working days.[11] In other words, we estimate the set of coefficients 1,607 times for each country and then evaluate the performance of the model between January 2009 and February 2015.[12]

To evaluate the predictive performance of the exchange rate models, we compare the mean square prediction error (MSPE) of the baseline model with that of a pure random walk, as well as that of a random walk with a time-varying drift (which is obtained from the estimation of the model $\Delta s_t = \alpha_{t-T,t-1} + \varepsilon_t$ for each period).

The statistical significance of the difference between the squared error losses of the models is evaluated based on a long-run estimate of its variance, following the methodology proposed by Diebold and Mariano (1995). The Diebold-Mariano (DM) test is known to be asymptotically valid also for nested models when the size of the prediction sample grows, while the length of the estimation window is held fixed (see Giacomini and White 2006).

DM test statistics for each country and benchmark are reported in table 3. A statistically significant negative DM statistic indicates that the CXPI-based model has superior forecast accuracy relative to random-walk benchmarks.

[11]Because of the shorter time series, a three-year window is used in the case of Russia.

[12]In the robustness section we reduce the length of the estimation window. As we show, this does not lead to any substantive change to our conclusions.

Table 3. Exchange Rate Predictability by Commodity Prices (out-of-sample analysis)

		Forecasting Performance vs. RW Benchmark					
		RW without Drift			RW with (Time-Varying) Drift		
Currency	**Observations**	**RMSE Ratio**	**DM Stat**	**p-value**	**RMSE Ratio**	**DM Stat**	**p-value**
AUD	1,607	0.858	−5.30***	0.000	0.858	−5.29***	0.000
CAD	1,607	0.850	−4.16***	0.000	0.850	−4.16***	0.000
NOK	1,607	0.908	−3.79***	0.000	0.908	−3.78***	0.000
BRL	1,607	0.936	−3.51***	0.001	0.937	−3.45***	0.001
CLP	1,607	0.918	−4.64***	0.000	0.918	−4.63***	0.000
COP	1,607	0.953	−3.83***	0.000	0.953	−3.82***	0.000
MXN	1,607	0.910	−4.29***	0.000	0.910	−4.32***	0.000
PEN	1,607	0.965	−4.12***	0.000	0.966	−4.09***	0.000
ZAR	1,607	0.905	−5.36***	0.000	0.905	−5.34***	0.000
RUB	802	0.958	−2.04**	0.041	0.960	−1.99**	0.046
MYR	1,195	0.972	−1.95*	0.052	0.972	−1.95*	0.051

Notes: The null hypothesis of the Diebold-Mariano test is that forecast accuracy is equal. Negative DM statistics indicate that the tested model has superior predictive performance when compared with the benchmark. The coefficients were estimated with a five-year rolling window, following the Meese-Rogoff approach. The RMSE ratio refers to the root mean square error of the model based on commodities divided by the RMSE of the random-walk (RW) benchmark in question. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

The results show that the information on commodity price variation clearly leads to a one-step-ahead prediction performance that beats both benchmark random-walk models. The null of equal forecast accuracy is rejected with p-values below 1 percent for ten of the eleven currencies (Australia, Canada, Norway, Brazil, Chile, Colombia, Mexico, Peru, Russia, and South Africa). The two cases where the DM statistics are less significant are those of the two countries for which the sample size is smaller (Russia and Malaysia).[13]

Note also that the countries in which the reduction in the relative RMSE ratio is larger are advanced economies (in particular, the RMSE ratio is 0.850 for Canada and 0.858 for Australia). Countries that tend to perform larger interventions in terms of the average turnover of the respective FX market show considerably lower MSE reductions.

Since in most cases the absolute value of the DM statistic is smaller in the case of the random walk with time-varying drift, this model proves to be (slightly) more difficult to beat. For this reason we adopt the random walk with drift as the benchmark to beat in the sections that follow.

3.4 OOS Predictability over Longer Horizons

Given the strong relationship between commodity price developments captured by the CXPI indexes and exchange rates, we checked whether this link is also evident at lower frequencies.[14]

The results in table 4—and plotted in the associated figure 4—show that for most cases the relation is also found to be important at lower frequencies. In most cases, lengthening the window in which price variations are measured has the effect of weakening the relation somewhat in this out-of-sample exercise. Lengthening the window could have the effect of including additional sources of shocks that end up affecting the measured relation.

[13]Overall, we find that adding a drift component to the random-walk benchmark has very minor effects on forecast accuracy, as the estimated drifts are very small and generally not statistically significant.

[14]We thank an anonymous referee for making this suggestion.

Table 4. Exchange Rate Predictability by Commodities over Longer Horizons

Currency	Observations	DM Stats [p-value] Length of Window			
		One Day	**One Week**	**One Month**	**Six Months**
AUD	1,611	−5.28***	−4.81***	−3.27***	−2.83***
		[0.000]	[0.000]	[0.001]	[0.005]
CAD	1,611	−4.16***	−4.43***	−3.62***	−3.08***
		[0.000]	[0.000]	[0.000]	[0.002]
NOK	1,611	−4.63***	−3.84***	−2.80***	−2.93***
		[0.000]	[0.000]	[0.005]	[0.003]
BRL	1,611	−3.45***	−3.06***	−2.62***	−2.65***
		[0.001]	[0.002]	[0.009]	[0.008]
CLP	1,611	−4.63***	−3.75***	−2.72***	−4.98***
		[0.000]	[0.000]	[0.007]	[0.000]
COP	1,611	−3.81***	−3.17***	−1.55	−1.37
		[0.000]	[0.002]	[0.121]	[0.168]
MXN	1,611	−4.32***	−3.51***	−2.53**	−2.48**
		[0.000]	[0.000]	[0.011]	[0.013]
PEN	1,611	−4.08***	−2.50**	−1.76*	−2.01**
		[0.000]	[0.012]	[0.077]	[0.044]
ZAR	1,611	−5.34***	−4.12***	−2.18**	−3.55***
		[0.000]	[0.000]	[0.029]	[0.000]
RUB	806	−1.99**	−1.90*	−1.54	−1.53
		[0.046]	[0.057]	[0.123]	[0.126]
MYR	1,199	−1.95*	−2.15**	−1.52	−1.42
		[0.051]	[0.031]	[0.127]	[0.154]

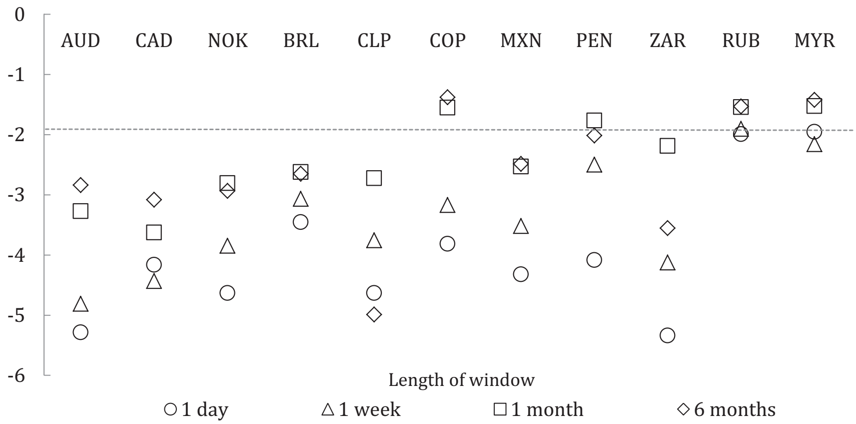
Notes: The null hypothesis of the Diebold-Mariano test is that forecast accuracy is equal. The benchmark that is used as a reference is the random-walk model with a time-varying drift. Negative DM statistics indicate that the tested model has superior predictive performance when compared with the benchmark. The coefficients were estimated with a five-year rolling window, following the Meese-Rogoff approach. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

3.5 OOS Predictability with Alternative Commodity Prices

As we have already pointed out above, the correlation of oil price variations with changes in the values of the other commodity baskets creates the possibility that oil prices alone may actually predict exchange rate movements of countries that barely export any oil (Ferraro, Rogoff, and Rossi 2015).

Indeed, the results shown in the third column of table 5 show that daily Brent price variations predict the exchange rates of many

Figure 4. Exchange Rate Predictability by Commodities: DM Test Statistics



of the countries in question in a way that is superior to the random walk at the 5 percent confidence level at daily frequency. Overall, however, the performance of the CXPI model is superior at daily frequency in all these cases, with the exception of the Russian ruble. Contrary to the case of the CXPI models, however, this relation disappears completely once the frequency is lowered to six months.

Similar results obtain for the CRB commodity price index. Again, the performance of the CXPI is superior, even though the CRB clearly does convey information that is relevant for exchange rate prediction at daily frequency.

3.6 OOS Predictability with Lagged Commodity Prices

An important consideration is that the out-of-sample exercises above are based on the well-established Meese and Rogoff (1983) benchmark of utilizing realized economic variables which are not known ex ante. This implies that the relations that were found are not necessarily useful for true forecasting or for making profitable investment bets, as the Meese and Rogoff methodology is based on information which is only available ex post.

Table 5. Exchange Rate Predictability by Oil Prices and the CRB Index (out-of sample analysis)

		DM Stats [p-value]			
		Model Based on Brent Price		Model Based on CRB	
Currency	Observations	One Day	Six Months	One Month	Six Months
AUD	1,611	−2.86*** [0.004]	−1.28 [0.200]	−2.83*** [0.005]	−0.38 [0.698]
CAD	1,611	−3.25*** [0.001]	−0.74 [0.462]	−2.81*** [0.005]	0.98 [0.329]
NOK	1,611	−3.69*** [0.000]	−1.32 [0.185]	−3.32*** [0.001]	1.11 [0.267]
BRL	1,611	−2.52** [0.012]	−0.76 [0.449]	−2.29** [0.022]	0.13 [0.896]
CLP	1,611	−2.99*** [0.003]	−0.29 [0.770]	−2.65*** [0.008]	0.97 [0.331]
COP	1,611	−2.70*** [0.007]	−0.02 [0.986]	−1.75 [0.079]	1.46 [0.143]
MXN	1,611	−2.83*** [0.005]	−0.23 [0.821]	−2.99*** [0.003]	0.67 [0.501]
PEN	1,611	−1.86* [0.062]	0.72 [0.473]	−1.04 [0.296]	2.52 [0.988]
ZAR	1,611	−3.25*** [0.001]	−1.25 [0.208]	−3.28*** [0.001]	−1.18 [0.235]
RUB	806	−2.15** [0.031]	−1.35 [0.177]	−1.99** [0.046]	0.88 [0.377]
MYR	1,199	−0.47 [0.639]	0.42 [0.672]	−1.21 [0.225]	−0.74 [0.457]

Notes: The null hypothesis of the Diebold-Mariano test is that forecast accuracy is equal. The benchmark that is used as a reference is the random-walk model with a time-varying drift. Negative DM statistics indicate that the tested model has superior predictive performance when compared with the benchmark, while positive values indicate that the random-walk benchmark is superior. The coefficients were estimated with a five-year rolling window, following the Meese-Rogoff approach. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

While forecasting actual exchange rate movements is clearly beyond the scope of this paper, we reestimated the model using only information on lagged commodity prices. Results of this exercise are shown in table 11 in the appendix. Forecasts that use exclusively lags of CXPIs beat the random-walk benchmarks in only a few countries (at the 10 percent level), with Chile standing out as the case with the greatest success. This result is in line with earlier findings in the literature, which have concluded that success in forecasting future exchange rate movements is often only detectable in certain instances and sample periods (Rossi 2013).[15,16]

3.7 A Reverse Link: Do Exchange Rates Predict CXPIs?

As our commodity price indexes are country specific, there could also be a reverse link—going from exchange rates to commodity prices measured in U.S. dollars. One rationale is that by increasing production costs, an appreciation of the currency of a commodity exporter might push up the U.S. dollar prices of the commodities produced in these exporters.

Indeed, there is the possibility of emergence of feedback loops between countries that produce the same type of commodities. An appreciation of the Brazilian real, for instance, could increase the costs of iron ore production, increasing the international price of this commodity. This in turn may well exert upward pressure on the value of the Australian dollar, which then pushes the price of iron ore further up, leading to a new round of appreciation of the Brazilian real and amplifying initial shocks. Mechanisms of this kind are explored in greater detail in Clements and Fry (2008).

To test for the possibility of this reverse link, we estimated the inverse model

$$\Delta CXPI_{i,t+k} = \alpha + \beta \cdot \Delta s_{i,t} + \gamma_i + \theta_{t+k} + \varepsilon_{i,t+k}, \qquad (4)$$

using the panel approach that was outlined in the previous section.

Contrary to what is the case for the direct link, any indication of a reverse link disappears as soon as the six (or twelve) months after the collapse of Lehman Brothers are excluded from the analysis (table 6).

[15] It is commonly accepted that forecasting exchange rates in the time-series dimension is very hard, especially at shorter horizons. Engel and West (2005) show that the weak predictive relation between exchange rates and economic fundamentals can be reconciled within a standard present-value model when discount factors are close to unity and fundamentals are non-stationary.

[16] More success in predicting actual exchange rates has been obtained in the microstructure literature (Evans and Lyons 2005; Rime, Sarno, and Sojli 2010; and Menkhoff et al. 2016).

Table 6. The Reverse Link: Commodity Price Predictability by Exchange Rates (dependent variable: log change of commodity prices)

	Prediction Horizon in Days				
	k = 1	**k = 5**	**k = 22**	**k = 44**	**k = 66**
Bilateral Exchange Rate	−0.017	−0.005	−0.030	−0.037	−0.077
t-stat	1.41	0.46	0.71	0.94	0.75
R2 Overall	0.0066	0.0228	0.0912	0.1700	0.1802
R2 Within	0.0065	0.0226	0.0907	0.1690	0.1794
R2 Between	0.5762	0.5413	0.5957	0.6280	0.5290
Observations	28,941	28,897	28,710	28,468	28,226
Groups	11	11	11	11	11
Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the results of the fixed effects regression $\Delta CXPI_{i,t+k} = \alpha + \Delta s_{i,t} + \gamma_i + \theta_{t+k} + \varepsilon_{i,t+k}$, where k stands for the length of the prediction horizon. t-statistics are based on clustered standard errors. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively. The estimation is based on information from January 2004 to February 2015, except for observations of the six months after the collapse of Lehman Brothers.

4. Commodity Prices vs. Carry

To check for the robustness of the results of the previous section, we also compared the performance of forecasting models based on commodities with that of models based on interest rate differentials vis-à-vis the United States (known as "carry"). The literature on the forward premium puzzle (Fama 1984) has generally established that interest rate differentials have predictive power for exchange rates, yet in a manner that is inconsistent with uncovered interest parity (UIP).[17]

Our carry indicator is based on the difference between the one-year government bonds yield for the country in question and the United States. These data were obtained from Datastream. Overall,

[17]Verdelhan (2015) also presents evidence that carry is an important driver of variation in bilateral exchange rates. Akram and Mumtaz (2016) on the other hand show that, in the case of Norway, the correlations between money market rates and nominal exchange rates have fallen towards zero.

the results in table 7 show that the pure yield differential models only outperform the random-walk benchmarks in the cases of the Australian and Canadian dollar. When the information of the CXPIs is added to the yield differential model, the expanded model beats the random-walk benchmarks in nine cases at the 5 percent confidence level (and in ten cases at the 10 percent level).

What is clear is that for many commodity exporters, information of commodity prices appears to be more important than that of government bond yields. The DM statistics when commodity prices are used as predictors are systematically below those obtained when relying on carry—also in the cases of Australia and Canada.[18] In the latter two cases, however, the model that combines information of both factors tends to be the superior one.

5. Robustness

We performed a number of robustness checks, which largely confirmed the conclusions drawn above. In the following, we summarize a few main take-aways.

5.1 Changes in Uncertainty and Global Risk Appetite

At least in principle, there could be the possibility that the relations that were highlighted in the previous sections are mainly due to changes in global risk appetite. These may cause global investors to move into or out of commodity markets and foreign exposures in a synchronized way, with consequent effects on exchange rates. Daily variation in risk perceptions can be proxied by the CBOE VIX, as in Adrian, Etula, and Shin (2009), McCauley (2012), or Bock and Carvalho Filho (2015).[19] The latter studies suggest that the VIX is indeed a good indicator to flag risk-off episodes in global financial markets.

[18] Note that this does not mean that trading strategies based on interest differentials (so-called carry trades) are unprofitable. See Hassan and Mano (2014) for evidence that the informational content of carry is mostly cross-sectional rather than in the time-series dimension.

[19] As discussed in Bekaert, Hoerova, and Lo Duca (2013), the VIX can be thought of as a measure of stock market uncertainty and the reward investors require for taking on risk.

Table 7. Exchange Rate Predictability: Carry vs. Commodities

Currency	Observations	Carry Model			Carry + CXPI Model		
		RMSE Ratio	DM Stat	p-value	RMSE Ratio	DM Stat	p-value
AUD	1,607	0.951	−4.66***	0.000	0.819	−6.15***	0.000
CAD	1,607	0.992	−2.85***	0.004	0.841	−4.42***	0.000
NOK	1,607	1.000	0.23	0.817	0.908	−3.80***	0.000
BRL	1,607	1.036	2.62	0.009	0.958	−2.66***	0.008
CLP	1,607	1.000	0.74	0.460	0.918	−4.69***	0.000
COP	1,607	1.009	1.64	0.100	0.961	−3.31***	0.001
MXN	1,607	0.998	−0.72	0.474	0.909	−4.29***	0.000
PEN	1,607	1.003	0.90	0.368	0.961	−3.42***	0.001
ZAR	1,607	1.023	0.61	0.544	0.919	−2.20**	0.028
RUB	802	0.808	−1.12	0.261	0.776	−1.25	0.210
MYR	1,195	1.000	1.702	0.089	0.972	−1.90*	0.057

Notes: The null hypothesis of the Diebold-Mariano test is that forecast accuracy is equal. The benchmark that is used as a reference is the random-walk model with a time-varying drift. Negative DM statistics indicate that the tested model has superior predictive performance when compared with the benchmark, while positive values indicate that the random-walk benchmark is superior. The coefficients were estimated with a five-year rolling window, following the Meese-Rogoff approach. The RMSE ratio refers to the RMSE of the model based on commodities divided by the RMSE of the RW benchmark in question. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

To ensure that the relation which we found above is not just a side effect of variations in global risk (appetite), we checked whether commodity price variations are able to explain the component of exchange rate variation that is orthogonal to changes in the VIX. The results in table 8 show that in all eleven cases that were listed before, daily variations in the commodity price index indeed explain the exchange rate movements that are unrelated to changes in the VIX. The explanatory power attains its maximum in the cases of Australia and Canada, but is economically and statistically significant at 1 percent in all eleven cases.

5.2 Changing the Base Currency

Results in the previous sections were based on bilateral USD exchange rates. Table 12 in the appendix shows that results weaken only marginally when the nominal exchange rate vis-à-vis the JPY is used instead.[20] This can be explained by the fact that most commodities are actually priced in U.S. dollars. A change in the value of the U.S. dollar—the invoicing currency—tends to lead to some change in the final USD price of commodities. Indeed, periods of U.S. dollar weakness tend to be associated with higher oil prices (see Akram 2009). Nevertheless, linear JPY exchange rate models based on commodities still outperform the random-walk benchmark for nine of the eleven currencies at the 5 percent significance level.

The last column of the table shows that very similar results are also obtained when daily exchange rate variations are measured in terms of an effective nominal exchange rate. Here the effective nominal exchange rates were computed against a basket of the five major global currencies (the U.S. dollar, the euro, the Japanese yen, the British pound, and the Chinese yuan). The weight of each currency in the country-specific basket was based on the total trade relation of the country in question with the United States, Japan, the twelve first members of the euro area, the United Kingdom, and China.

[20]The JPY is the global currency that is least correlated with the USD during our sample period.

Table 8. Global-Risk-Adjusted Exchange Rates and Commodity Prices

	Australia	**Canada**	**Norway**	**Brazil**	**Chile**	**Colombia**	**Mexico**	**Peru**	**S. Africa**	**Russia**	**Malaysia**
*First-Stage Regression (D.V.: 100*Log Diff of Exchange Rate)*											
VIX	0.130***	0.088***	0.088***	0.158***	0.100***	0.088***	0.120***	0.028***	0.152***	0.165***	0.026***
	(7.24)	(7.45)	(6.12)	(8.46)	(8.36)	(7.75)	(7.99)	(6.36)	(8.46)	(6.37)	(5.24)
R2	0.0673	0.0597	0.0368	0.0896	0.0695	0.0482	0.1011	0.0285	0.0655	0.0725	0.0166
Second-Stage Regression (D.V.: Residual of First-Stage Regression)											
CXPI	−0.518***	−0.257***	−0.167***	−0.440***	−0.154***	−0.131***	−0.163***	−0.039***	−0.493***	−0.221***	−0.061***
	(11.46)	(17.56)	(14.49)	(9.94)	(13.03)	(9.64)	(12.64)	(5.43)	(12.20)	(11.94)	(10.07)
R2	0.1967	0.1928	0.1301	0.0768	0.0999	0.0515	0.1042	0.0207	0.1330	0.0896	0.0461
Obs.	2,912	2,912	2,912	2,912	2,912	2,912	2,912	2,912	2,912	1,584	2,499

Notes: This table shows regression of the residual of the first-stage regression on the log change of the commodity price index at daily frequency. The sample period is January 2004 to February 2015. Constants are not shown, as they were not significant in any case. t-statistics based on Newey-West standard errors are reported in parentheses. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

5.3 Clark and West Tests

So far we have reported the outcome of Diebold and Mariano tests, which is appropriate given the setup of our out-of-sample exercise (Giacomini and White 2006). Clark and West (2007), however, point out that, for nested models, the mean square prediction errors should be adjusted to account for the possibility that less parsimonious models might introduce noise by estimating a parameter whose value might actually be zero in the population. The statistic proposed by Clark and West properly takes this possibility of model degeneration into account. The adjusted MSPE is

$$\frac{\Sigma\left(y_{t+\tau}-\widehat{y}_{1t,t+\tau}\right)^2-\left[\Sigma\left(y_{t+\tau}-\widehat{y}_{2t,t+\tau}\right)^2-\Sigma\left(\widehat{y}_{1t,t+\tau}-\widehat{y}_{2t,t+\tau}\right)^2\right]}{N},$$

where $\widehat{y}_{1t,t+\tau}$ is the predicted value of the parsimonious model, $\widehat{y}_{2t,t+\tau}$ is the predicted value of the model that nests the parsimonious specification, $y_{t+\tau}$ is the actual outcome, and N is the number of predictions. The last term on the numerator represents the adjustment to the estimated variance of the nesting model.

Table 13 in the appendix shows that the use of the Clark and West statistic tends to strengthen the results of the previous sections. In all cases the p-values of the null of equal forecast accuracy diminishes relative to the one obtained from the Diebold and Mariano comparison of MSPEs.

5.4 Shorter Estimation Windows

Finally, to be sure that our results are not driven by our particular selection of the window length, we also replicated the estimation of the previous section using a different window length. The original five-year choice had been made so that the estimation window was roughly half the sample size of eleven years. Table 14 shows that our conclusions are not changed in any material way if we use a three-year window instead. We find that the commodity price model outperforms the random-walk models at the 5 percent significance level for all eleven countries.

6. Conclusion

This paper shows evidence of a distinct commodity-related driver in currency movements. The link between commodity prices and exchange rates is economically and statistically significant even at high frequency. Further, the commodity price–exchange rate nexus is largely unaffected when changes in uncertainty and global risk appetite are taken into account: models incorporating commodity prices explain the component of exchange rate variations that is purely orthogonal to changes in risk and risk appetite. They also tend to deliver better predictive accuracy than standard models based on interest rate differentials (carry).

Our intention in this paper was not to provide daily forecasts of movements in actual exchange rates. Following the usual practice of the literature, we utilized realized variables in the exchange rate prediction. Based on this standard setting, we show that even high-frequency movements of the exchange rates of commodity exporters have a strong relationship with the market value of their exports.

Our finding of a distinct commodity-related driver of exchange rates suggests that currency movements are not purely random. There is a factor related to commodities that helps explain movements in exchange rates which goes beyond the information embedded in carry, global uncertainty, and risk appetite.

Finally, the connection between export commodity prices and the exchange rates of resource rich countries raises a number of more fundamental questions. For instance, several commodity exporters intervene in their FX markets with some regularity. It would be interesting to establish the degree to which these interventions are affected by commodity price developments or take these into account. Still other countries seek some degree of stabilization via operations of sovereign wealth or oil funds. To the extent that these operations shift inflows intertemporally and generate expectations of future inflows, they may well have an effect on the exchange rate and possibly other macroeconomic variables. Identifying such effects could be an additional interesting avenue for future research.

Appendix

Table 9. Shares of Commodity Groups in Exports (2004–13)

	Commodity Exports/Total Exports	Share in Commodity Exports	Description of Group
Australia	0.793	0.227	Iron ore, concentrates
		0.212	Coal, not agglomerated
		0.076	Gold, non-monetary excl. ores
		0.054	Petroleum oils, crude
		0.053	Natural gas
		0.033	Aluminum ore, conctr., etc.
		0.029	Bovine meat
		0.028	Aluminum
		0.028	Wheat, meslin, unmilled
		0.026	Copper ores, concentrates
Brazil	0.631	0.172	Iron ore, concentrates
		0.103	Petroleum oils, crude
		0.100	Oilseed (sft. fix veg. oil)
		0.074	Sugars, molasses, honey
		0.058	Other meat, meat offal
		0.042	Coffee, coffee substitute
		0.041	Animal feed stuff
		0.033	Petroleum products
		0.032	Pulp and waste paper
		0.032	Bovine meat
Canada	0.453	0.271	Petroleum oils, crude
		0.107	Naural gas
		0.076	Petroleum products
		0.054	Gold, non-monetary excl. ores
		0.042	Aluminum
		0.037	Wood, simply worked
		0.035	Pulp and waste paper
		0.026	Wheat, meslin, unmilled
		0.025	Coal, not agglomerated
		0.023	Oilseed (sft. fix veg. oil)
Chile	0.849	0.402	Copper
		0.229	Copper ores, concentrates
		0.066	Fruit, nuts excl. oil nuts
		0.049	Fish, fresh, chilled, frozen

(*continued*)

Table 9. (Continued)

	Commodity Exports/Total Exports	Share in Commodity Exports	Description of Group
		0.040	Pulp and waste paper
		0.034	Ore, concentr. base metals
		0.017	Wood in chips, particles
		0.017	Petroleum products
		0.017	Gold, non-monetary excl. ores
		0.015	Iron ore, concentrates
Colombia	0.769	0.429	Petroleum oils, crude
		0.162	Coal, not agglomerated
		0.094	Petroleum products
		0.067	Coffee, coffee substitute
		0.055	Gold, non-monetary excl. ores
		0.038	Crude veg. materials, nes
		0.031	Pig iron, spiegeleisn, etc.
		0.025	Fruit, nuts excl. oil nuts
		0.012	Sugars, molasses, honey
		0.011	Coke, semi-coke, ret. carbn.
Malaysia	0.291	0.206	Natural gas
		0.205	Fixed veg. fat, oils, other
		0.175	Petroleum oils, crude
		0.160	Petroleum products
		0.025	Copper
		0.020	Wood simply worked
		0.017	Petroleum Gases, nes
		0.015	Cocoa
		0.015	Aluminum
		0.011	Wood rough, rough squared
Mexico	0.242	0.532	Petroleum oils, crude
		0.065	Petroleum products
		0.058	Vegetables
		0.055	Gold, non-monetary excl. ores
		0.032	Silver, platinum, etc.
		0.030	Fruit, nuts excl. oil nuts
		0.019	Coffee
		0.016	Ore, concentr. base metals
		0.016	Ingots etc. iron or steel
		0.013	Non-ferrous waste, scrap

(*continued*)

Table 9. (Continued)

	Commodity Exports/Total Exports	Share in Commodity Exports	Description of Group
Norway	0.797	0.475	Petroleum oils, crude
		0.267	Natural gas
		0.059	Petroleum products
		0.056	Fish, fresh, chilled, frozen
		0.042	Aluminum
		0.026	Liquified propane, butane
		0.017	Nickel
		0.008	Fish, dried, salted, smoked
		0.006	Pig iron, spiegeleisn, etc.
		0.004	Petroleum gases, nes
Peru	0.867	0.229	Gold, non-monetary excl. ores
		0.183	Copper ores, concentrates
		0.108	Ore, conctr. base metals
		0.101	Copper
		0.077	Petroleum products
		0.055	Animal feed stuff
		0.026	Coffee, coffee substitute
		0.018	Iron ore, concentrates
		0.017	Fruit, nuts excl. oil nuts
		0.017	Petroleum oils, crude
Russia	0.807	0.407	Petroleum oils, crude
		0.212	Petroleum products
		0.164	Natural gas
		0.025	Coal, not agglomerated
		0.022	Ingots etc. iron or steel
		0.022	Aluminum
		0.016	Nickel
		0.014	Flat-rolled iron etc.
		0.014	Copper
		0.012	Pig iron, spiegeleisn, etc.
South Africa	0.605	0.192	Silver, platinum, etc.
		0.110	Coal, not agglomerated
		0.096	Iron ore, concentrates
		0.092	Pig iron, spiegeleisn, etc.
		0.067	Gold, non-monetary excl. ores
		0.063	Ore, concentr. base metals
		0.047	Petroleum products
		0.043	Aluminum
		0.042	Fruit, nuts excl. oil nuts
		0.023	Flat-rolled, alloy steel

Note: Compiled based on three-digit UN Comtrade data.

Table 10. Exchange Rate Predictability by Commodities by Country

	Prediction Horizon in Days					
	k = 0	**k = 1**	**k = 5**	**k = 22**	**k = 44**	**k = 66**
AUD						
CXPI	−0.579***	−0.044	−0.091**	−0.074***	−0.026	0.002
t-stat	12.12	1.30	2.20	3.07	1.43	0.18
R2	0.2286	0.0013	0.0068	0.0083	0.0012	0.0000
CAD						
CXPI	−0.287***	−0.019	−0.014	−0.057***	−0.089***	−0.071***
t-stat	18.96	1.33	0.83	4.22	7.51	8.53
R2	0.2248	0.0010	0.0006	0.0136	0.0399	0.0275
NOK						
CXPI	−0.180***	−0.018*	0.001	−0.074***	−0.060***	−0.025**
t-stat	15.31	1.78	0.14	8.89	5.40	2.51
R2	0.1446	0.0015	0.0000	0.0326	0.0196	0.0034
BRL						
CXPI	−0.545***	−0.060	−0.074	−0.244***	−0.261***	−0.154***
t-stat	11.86	1.25	1.55	8.54	11.69	9.17
R2	0.1073	0.0013	0.0027	0.0503	0.0718	0.0267
CLP						
CXPI	−0.190***	−0.027**	−0.058***	−0.027**	0.027**	0.074***
t-stat	14.66	2.23	3.93	2.23	2.56	9.21
R2	0.1405	0.0029	0.0105	0.0026	0.0034	0.0263
COP						
CXPI	−0.152***	−0.025*	0.000	−0.046***	−0.099***	−0.094***
t-stat	10.43	1.74	0.02	3.71	7.45	9.76
R2	0.0657	0.0017	0.0000	0.0071	0.0329	0.0310
MXN						
CXPI	−0.195***	0.002	−0.032**	−0.076***	−0.143***	−0.121***
t-stat	13.70	0.15	2.04	6.90	13.00	13.97
R2	0.1336	0.0000	0.0039	0.0274	0.1054	0.0807
PEN						
CPXI	−0.050***	−0.004	−0.016**	−0.058***	−0.076***	−0.065***
t-stat	6.64	0.55	2.05	9.89	16.44	16.08
R2	0.0319	0.0002	0.0029	0.0445	0.0796	0.0610
ZAR						
CXPI	−0.558***	0.036	−0.015	−0.033	−0.034	0.014
t-stat	13.75	1.08	0.38	1.22	1.50	1.16
R2	0.1592	0.0007	0.0001	0.0012	0.0016	0.0004
RUB						
CXPI	−0.277***	−0.075***	−0.050*	−0.170***	−0.315***	−0.348***
t-stat	14.44	3.52	1.87	7.23	10.28	9.55
R2	0.1293	0.0097	0.0044	0.0569	0.1202	0.1165
MYR						
CXPI	−0.067***	−0.028***	−0.005	−0.041***	−0.041***	−0.039***
t-stat	10.88	5.15	0.89	7.89	7.62	9.66
R2	0.0549	0.0096	0.0003	0.0240	0.0245	0.0257

Notes: This table shows the results of the OLS regression $\Delta s_{t+k} = \alpha + \Delta \mathrm{CXPI}_t + \varepsilon_{t+k}$, where k stands for the length of the prediction horizon. Constants are not tabulated. t-statistics, which are reported below the coefficients, are based on Newey-West standard errors. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively. The estimation is based on information from the full sample period (i.e., January 2004–February 2015), except for Russia and Malaysia, where the sample period starts in February 2009 and August 2005, respectively.

Table 11. Exchange Rate Predictability with Lagged Commodity Prices (out-of-sample analysis)

		Forecasting Performace vs. RW Benchmark							
		Prediction of Exchange Rate vs. USD				Prediction of Exchange Rate vs. JPY			
		RW without Drift		RW with Drift		RW without Drift		RW with Drift	
Currency	**Obs.**	**DM Stat**	**p-value**	**DM Stat**	**p-value**	**DM Stat**	**p-value**	**DM Stat**	**p-value**
AUD	1,607	−0.01	0.994	−0.07	0.944	1.24	0.212	0.69	0.486
CAD	1,607	−0.10	0.922	−0.07	0.937	1.31	0.190	1.22	0.221
NOK	1,607	2.35**	0.019	2.58***	0.010	2.58***	0.010	2.27**	0.023
BRL	1,607	−1.66*	0.095	−1.12	0.248	0.08	0.938	−0.12	0.902
CLP	1,607	−2.13**	0.034	−2.37**	0.018	−2.78***	0.005	−2.70***	0.007
COP	1,607	−1.62	0.105	−1.62	0.104	−1.58	0.113	−1.68*	0.092
MXN	1,607	1.62	0.105	1.20	0.231	1.23	0.218	0.66	0.505
PEN	1,607	−1.01	0.311	−0.46	0.643	0.14	0.893	−0.51	0.608
ZAR	1,607	0.36	0.722	−0.23	0.818	−0.87	0.384	−0.91	0.359
RUB	802	0.21	0.836	0.08	0.933	−1.69*	0.091	−1.80*	0.071
MYR	1,195	−1.71*	0.087	−1.84*	0.065	−2.05**	0.040	−2.20**	0.028

Notes: The null hypothesis of the Diebold-Mariano test is that forecast accuracy is equal. Negative DM statistics indicate that the tested model has superior predictive performance when compared with the benchmark. The coefficients were estimated with a five-year rolling window. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

Table 12. Exchange Rate Predictability by Commodities for Alternative Base Currencies

Currency	Observations	Diebold-Mariano Statistics [p-value]	
		vs. JPY	vs. NEER
AUD	1,611	−4.09*** [0.000]	−5.23*** [0.000]
CAD	1,611	−3.09*** [0.002]	−4.16*** [0.000]
NOK	1,611	−3.16*** [0.002]	−3.82*** [0.000]
BRL	1,611	−2.70*** [0.007]	−3.43*** [0.006]
CLP	1,611	−4.24*** [0.000]	−4.62*** [0.000]
COP	1,611	−2.51** [0.012]	−3.80*** [0.001]
MXN	1,611	−3.14*** [0.002]	−4.32*** [0.000]
PEN	1,611	0.11 [0.909]	−3.97*** [0.000]
ZAR	1,611	−3.92*** [0.000]	−5.30*** [0.000]
RUB	806	−2.06** [0.039]	−2.00** [0.045]
MYR	1,199	−0.95 [0.340]	−1.89* [0.058]

Notes: The null hypothesis of the Diebold-Mariano test is that forecast accuracy is equal. The benchmark that is used as a reference is the random-walk model with a time-varying drift. Negative DM statistics indicate that the tested model has superior predictive performance when compared with the benchmark, while positive values indicate that the random-walk benchmark is superior. The coefficients were estimated with a five-year rolling window, following the Meese-Rogoff approach. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

Table 13. Exchange Rate Predictability by CXPI Model—Clark and West Statistics

Currency	Observations	RW with (Time-Varying) Drift		
		RMSE Ratio	CW Stat	p-value
AUD	1,611	0.913	11.77***	0.000
CAD	1,611	0.918	11.72***	0.000
NOK	1,611	0.920	12.90***	0.000
BRL	1,611	0.952	9.83***	0.000
CLP	1,611	0.952	9.53***	0.000
COP	1,611	0.965	8.63***	0.000
MXN	1,611	0.942	10.35***	0.000
PEN	1,611	1.002	2.35**	0.019
ZAR	1,611	0.938	9.74***	0.000
RUB	806	0.964	6.08***	0.000
MYR	1,199	0.991	4.63***	0.000

Notes: The null hypothesis of the Clark West (2007) test is that forecast accuracy is equal. Coefficients were estimated with a five-year rolling window, following the Meese-Rogoff approach. Significant statistics indicate that the tested model has superior predictive performance when compared with the benchmark. The RMSE ratio refers to the RMSE of the model based on commodities divided by the RMSE of the random walk with time-varying drift benchmark. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

Table 14. Exchange Rate Predictability by CXPI Model Based on Estimation with Three-Year Rolling Windows

		Forecasting Performance vs. RW Benchmark					
		RW without Drift			RW with (Time-Varying) Drift		
Currency	Observations	RMSE Ratio	DM Stat	p-value	RMSE Ratio	DM Stat	p-value
AUD	1,607	0.856	−4.97***	0.000	0.856	−4.97***	0.000
CAD	1,607	0.831	−4.36***	0.000	0.831	−4.36***	0.000
NOK	1,607	0.891	−3.84***	0.000	0.891	−3.85***	0.000
BRL	1,607	0.937	−3.13***	0.002	0.937	−3.11***	0.002
CLP	1,607	0.919	−4.34***	0.000	0.918	−4.34***	0.000
COP	1,607	0.949	−3.84***	0.000	0.949	−3.82***	0.000
MXN	1,607	0.899	−4.05***	0.000	0.898	−4.09***	0.000
PEN	1,607	0.963	−3.74***	0.000	0.964	−3.68***	0.000
ZAR	1,607	0.907	−5.22***	0.000	0.906	−5.16***	0.000
RUB	802	0.958	−2.04**	0.041	0.960	−1.99**	0.046
MYR	1,607	0.964	−2.58***	0.010	0.964	−2.59***	0.009

Notes: The null hypothesis of the Diebold-Mariano test is that forecast accuracy is equal. Negative DM statistics indicate that the tested model has superior predictive performance when compared with the benchmark. The coefficients were estimated with a three-year rolling window, following the Meese-Rogoff approach. The RMSE ratio refers to the RMSE of the model based on commodities divided by the RMSE of the RW benchmark in question. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively.

References

Adrian, T., E. Etula, and H. S. Shin. 2009. "Risk Appetite and Exchange Rates." Staff Report No. 361, Federal Reserve Bank of New York.

Akram, Q. F. 2009. "Commodity Prices, Interest Rates and the Dollar." *Energy Economics* 31 (6): 838–51.

Akram, Q. F., and H. Mumtaz. 2016. "The Role of Oil Prices and Monetary Policy in the Norwegian Economy since the 1980s." Working Paper No. 1/2016, Norges Bank.

Bank for International Settlements. 2013. "The History of the Bank of Russia's Exchange Rate Policy." *BIS Papers* 73 (October): 293–99.

Bekaert, G., M. Hoerova, and M. Lo Duca. 2013. "Risk, Uncertainty, and Monetary Policy." *Journal of Monetary Economics* 60 (7): 771–88.

Blanchard, O., G. Adler, and I. Carvalho Filho. 2015. "Can Foreign Exchange Intervention Stem Exchange Rate Pressures from Global Capital Flow Shocks?" NBER Working Paper No. 21427.

Bock, R., and I. Carvalho Filho. 2015. "The Behavior of Currencies during Risk-off Episodes." *Journal of International Money and Finance* 53: 218–34.

Cashin, P., L. F. Cespedes, and R. Sahay. 2004. "Commodity Currencies and the Real Exchange Rate." *Journal of Development Economics* 75 (1): 239–68.

Chen, Y., and K. Rogoff. 2003. "Commodity Currencies." *Journal of International Economics* 60 (1): 133–60.

Cheung, Y. W., M. D. Chinn, and A. G. Pascual. 2005. "Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive?" *Journal of International Money and Finance* 24 (7): 1150–75.

Clark, T., and K. West. 2007. "Approximately Normal Tests for Equal Predictive Accuracy in Nested Models." *Journal of Econometrics* 138 (1): 291–311.

Clements, K. W., and R. Fry. 2008. "Commodity Currencies and Currency Commodities." *Resources Policy* 33 (2): 55–73.

de Gregorio, J., and F. Labbe. 2011. "Copper, the Real Exchange Rate and Macroeconomic Fluctuations in Chile." Working Paper No. 640, Central Bank of Chile.

Diebold, F. X., and R. Mariano. 1995. "Comparing Predictive Accuracy." *Journal of Business and Economic Statistics* 13 (3): 253–63.

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

Evans, M. D., and R. Lyons. 2005. "Meese-Rogoff Redux: Micro-based Exchange-Rate Forecasting." *American Economic Review: Papers and Proceedings* 95 (2): 405–14.

Fama, E. F. 1984. "Forward and Spot Exchange Rates." *Journal of Monetary Economics* 14 (3): 319–38.

Farhi, E., and X. Gabaix. 2014. "Rare Disasters and Exchange Rates." Mimeo, New York University.

Ferraro, D., K. Rogoff, and B. Rossi. 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: 116–41.

Fuentes, M., P. Pincheira, J. M. Julio, H. Rincon, S. G. Verdu, M. Zerecero, M. Vega, E. Lahura, and R. Moreno. 2013. "The Effects of Intraday Foreign Exchange Market Operations in Latin America: Results for Chile, Colombia, Mexico and Peru." BIS Working Paper No. 462.

Giacomini, R., and H. White. 2006. "Tests of Conditional Predictive Ability." *Econometrica* 74 (6): 1545–78.

Gourio, F., M. Siemer, and A. Verdelhan. 2013. "International Risk Cycles." *Journal of International Economics* 89 (2): 471–84.

Hambur, J., L. Cockerell, C. Potter, P. Smith, and M. Wright. 2015. "Modelling the Australian Dollar." RBA Research Discussion Paper No. 2015-12.

Hassan, T., and R. C. Mano. 2014. "Forward and Spot Exchange Rates in a Multi-currency World." NBER Working Paper No. 20294.

Inoue, A., and L. Kilian. 2005. "In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use?" *Econometric Reviews* 23 (4): 371–402.

Kilian, L. 1999. "Exchange Rates and Monetary Fundamentals: What Do We Learn from Long-Horizon Regressions?" *Journal of Applied Econometrics* 14 (5): 491–510.

Kohlscheen, E. 2014. "Long-Run Determinants of the Brazilian Real: A Closer Look at Commodities." *International Journal of Finance and Economics* 19 (4): 239–50.

Lustig, H., N. Roussanov, and A. Verdelhan. 2011. "Common Risk Factors in Currency Markets." *Review of Financial Studies* 24 (11): 3731–77.

MacDonald, R., and L. Ricci. 2004. "Estimation of the Equilibrium Real Exchange Rate for South Africa." *South African Journal of Economics* 72 (2): 282–304.

Mark, N. C., and D. Sul. 2001. "Nominal Exchange Rates and Monetary Fundamentals: Evidence from a Small Post-Bretton Woods Panel." *Journal of International Economics* 53 (1): 29–52.

———. 2012. "When Are Pooled Panel-Data Regression Forecasts of Exchange Rates More Accurate than the Time-Series Regression Forecasts?" In *Handbook of Exchange Rates,* ed. J. James, I. W. Marsh, and L. Sarno, 265–82 (chapter 9). John Wiley & Sons.

McCauley, R. N. 2012. "Risk-on/Risk-off, Capital Flows, Leverage and Safe Assets." BIS Working Paper No. 382.

Meese, R., and K. S. Rogoff. 1983. "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?" *Journal of International Economics* 14 (1–2): 3–24.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf. 2012. "Carry Trades and Global Foreign Exchange Volatility." *Journal of Finance* 67 (2): 681–718.

———. 2016. "Information Flows in Foreign Exchange Markets: Dissecting Customer Order Flow." Working Paper.

Rime, D., L. Sarno, and E. Sojli. 2010. "Exchange Rates, Order Flow and Macroeconomic Information." *Journal of International Economics* 80 (1): 72–88.

Robinson, T., and H. Wang. 2013. "Changes to the RBA Index of Commodity Prices." *RBA Bulletin* (March): 23–28.

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

Sidek, N. Z. M., and M. B. Yussof. 2009. "An Empirical Analysis of the Malayan Ringitt Equilibrium Exchange Rate and Misalignment." *Global Economy and Finance Journal* 2 (2): 104–26.

Triplett, J. 1981. "Reconciling the CPI and the PCE Deflator." *Monthly Labor Review* (September): 3–15.

Verdelhan, A. 2015. "The Share of Systematic Risk in Bilateral Exchange Rates." Mimeo, Massachussetts Institute of Technology.