Journal of International Money and Finance 54 (2015) 116–141

Contents lists available at ScienceDirect

Journal of International Money and Finance

journal homepage: www.elsevier.com/locate/jimf

Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates

Domenico Ferraro [a], Kenneth Rogoff [b], Barbara Rossi [c, *]

[a] Arizona State University, USA
[b] Harvard University, USA
[c] ICREA-UPF, Barcelona GSE, CREI, Spain

ARTICLE INFO

Article history:
Available online 17 March 2015

JEL Codes:
F31
F37
C22
C53

Keywords:
Exchange rates
Predictive ability
Out-of-sample fit

ABSTRACT

We show the existence of a very short-term relationship at the daily frequency between changes in the price of a country's major commodity export and changes in its nominal exchange rate. The relationship appears to be robust and to hold when we use contemporaneous (realized) commodity price changes in our regression. However, when we use lagged commodity price changes, the predictive ability is ephemeral, mostly appearing after instabilities have been appropriately taken into account.

1. Introduction

In this paper, we focus on whether the price of a country's major commodity export can predict movements in its nominal exchange rate in a pseudo out-of-sample forecasting exercise. The novelty of our approach is to consider data at the daily frequency to capture the contemporaneous short-run co-

* Corresponding author. Centre de Recerca en Economia Internacional (CREI), Universitat Pompeu Fabra (UPF), carrer Ramon Trias Fargas, 25-27, Mercè Rodoreda bldg., 08005 Barcelona, Spain. Tel.: +34 93 542 1655; fax: +34 93 542 2826
E-mail address: barbara.rossi@upf.edu (B. Rossi).

http://dx.doi.org/10.1016/j.jimonfin.2015.03.001
0261-5606/

movements in these variables, as well as to allow for time variation in the models' relative predictive performance.

Our main focus is on the Canadian-U.S. dollar exchange rate and oil prices, although we demonstrate that similar results hold for other commodity prices/exchange rates pairs, such as the Norwegian krone-U.S. dollar exchange rate and oil prices; the South African rand-U.S. dollar exchange rate and gold prices; the Australian-U.S. dollar and oil prices; and the Chilean peso-U.S. dollar exchange rate and copper prices. We perform two distinct exercises: out-of-sample fit and truly out-of-sample forecasts. Our results suggest that there is little systematic relation between commodity price changes and exchange rate changes at the monthly and quarterly frequencies. In contrast, the very short-term, "out-of-sample fit" relationship between commodity prices and exchange rates is rather robust: our results indicate that contemporaneous realized commodity prices are related to daily nominal exchange rates of commodity currencies, and the relationship is statistically and economically significant. On the other hand, the predictive ability of lagged realized commodity price changes is more ephemeral, and allowing for time variation in the relative performance is crucial to show that lagged commodity prices can be statistically significant predictors of exchange rates out-of-sample. It is noteworthy that the out-of-sample predictive ability result breaks down for monthly and quarterly data, suggesting that not only the predictive ability is transitory, but also that the effects of oil price changes on exchange rate changes are short-lived and that the frequency of the data is crucial to capture them.

Why is our finding of a contemporaneous, out-of-sample correlation between commodity prices and exchange rates relevant? Our results suggest that, conditional on knowing the future value of commodity prices, we can forecast exchange rates well.[1] Thus, if one had a good model to forecast oil prices, one could exploit it to forecast future exchange rates.[2] On the other hand, a limitation of our analysis is that the existence of an out-of-sample correlation is not informative regarding the economic causality in the data. For a paper that addresses the latter issue, see Fratzscher et al. (2013), who resolve the identification issue by exploiting heteroskedasticity in daily asset prices.

We conjecture that a possible mechanism leading to this result is the fact that, for a small open economy exporting commodities, the exchange rate is expected to reflect movements in commodity prices.[3] The effects of changes in commodity prices are immediately translated into changes in exchange rates and, as such, do not necessarily portend further changes, after taking into account that commodity prices have a significant unit root component. This might shed light on why our out-of-sample forecasts are significant in daily data but not at monthly or quarterly frequencies. Thus, the fundamental we investigate to predict commodity currencies, namely oil prices and commodity prices in general, suggest the terms of trade channel as a possible interpretation of our out-of-sample fit results. However, we cannot rule out the possibility that what we observe is either a portfolio rebalancing effect or a mechanism similar to the one suggested in Engel and West (2005). Hau and Rey (2004), for example, argue that the empirical patterns of international equity returns, equity portfolio flows, and exchange rates are consistent with the hypothesis that (un-hedged) global investors rebalance their portfolio in order to limit their exchange rate exposure when there are either relative equity returns or exchange rate shocks. In this paper we focus on commodities, which are yet another asset traded in international markets; as such, the portfolio rebalancing argument could be applied to commodity markets as well. This is consistent, for example, with Büyükşahin and Robe

[1] For example, Groen and Pesenti (2011) document that it is hard to predict oil prices with daily data.

[2] The flip side can also be true, however there is anecdotal evidence that the former might be more likely. For example, on January 6, the Canadian dollar fell 0.2% relative to the US dollar at 5pm; the press attributed the event to the Canadian finance minister's declarations of an expected depreciation of the Canadian dollar possibly engineered by the Central bank in the hope to help country's manufacturing (see http://www.bloomberg.com/news/2014-01-06/canadian-dollar-falls-after-flaherty-says-to-expect-depreciation.html). The oil price was virtually unchanged between January 5 and 7 (see http://research.stlouisfed.org/fred2/series/DCOILWTICO/).

[3] See Obstfeld and Rogoff (1996). The Canadian example is interesting for three reasons. First, crude oil represents a substantial component of Canada's total exports. Second, Canada has a sufficiently long history of market-based floating exchange rate. Finally, Canada is a small open economy whose size in the world oil market is relatively small to justify the assumption that it is a price-taker in that market. For the latter reason, crude oil price fluctuations might serve as an observable and essentially exogenous terms-of-trade shock for the Canadian economy.

(2014), who recently studied commodity future markets and their financialization; their empirical evidence confirms the role of speculators in driving cross-market correlations between equity returns and commodity returns.

Regarding the relationship with the existing literature, our paper is clearly related to studies using commodity prices/indices to predict exchange rates. The empirical evidence in this paper is consistent with Chen et al. (2010), who find that exchange rates predict commodity prices at the quarterly frequency and, at the same time, commodity prices do not predict exchange rates, at the same frequency.[4] In addition, Chen et al. (2010) focus on commodity price indices, which average across several commodities, not just individual commodities.[5] Other papers consider commodity prices as *in-sample* explanatory variables for *real* exchange rates (Amano and Van Norden, 1998a,b; Issa et al., 2008; Cayen et al., 2010), whereas in this paper we consider *out-of-sample* predictive ability for *nominal* exchange rates.[6] Note that the real and nominal Canadian dollar exchange rates have tracked each other closely since the beginning of the Great Moderation, so the consequences of using the nominal exchange rate instead of the real one for monthly and quarterly regressions should be quite small.

In addition, our empirical evidence of a short-term relationship between oil prices and exchange rate fluctuations somewhat parallels the very high frequency relationship people have found between unanticipated Federal Reserve interest rate changes, macroeconomic news announcements and exchange rates.[7] In our paper, instead, daily oil price changes potentially act as the observable macroeconomic news announcement. In contrast to the literature, our analysis focuses on the contemporaneous relationship between oil price "news" and exchange rates, rather than the delayed effect, and on out-of-sample fit, rather than in-sample. The broader exchange rate literature has also demonstrated that at high frequencies exchange rate fluctuations are linked to order flows (Evans and Lyons, 2002, 2005); our paper instead focuses on investigating whether there exist economic fundamentals linked to exchange rate fluctuations. While data on order flows are available at the daily frequency, they are not economic fundamentals, so we did not consider them. In addition, it is well-known that monetary fundamentals do not help forecast exchange rates out-of-sample, not even in terms of out-of-sample fit, at the monthly or quarterly frequencies (e.g. Cheung et al., 2005, among many others). Our results are stronger at the daily frequency; the latter thus constrains in the selection of alternative fundamentals/models that could be investigated for comparison. One such model is uncovered interest rate parity (UIP), which we show has no predictive power. On the other hand, we cannot consider purchasing power parity, money or output differentials, as such data are not available at the daily frequency. Regarding interest rates, it is possible that our findings depend on the fact that oil prices are a good predictor of monetary policy (which might react to eventual wealth effects, capital inflows, etc.). The relationship between oil

[4] This evidence is consistent with the idea that commodity currencies are forward-looking indicators of developments in global commodity markets.

[5] Note that our results are also consistent with Chen and Rogoff (2003), but we differ in two respects: (i) first, Chen and Rogoff (2003) conduct an in-sample analysis at the quarterly frequency. They conclude that commodity prices "do appear to have a strong and stable influence on the real exchange rates of New Zealand and Australia. For Canada, the relationship is somewhat less robust, especially to de-trending." (see p. 155). In Ferraro et al. (2015), we also conduct an in-sample analysis, which confirms Chen and Rogoff's (2003) results. However, we show that out-of-sample the results depend on the frequency. So it is the out-of-sample results that are different. At the quarterly frequency, the same frequency considered by Chen and Rogoff (2003), there seems to be no relationship between commodity prices and exchanges rates, neither in terms of out-of-sample fit nor of true predictive ability. (ii) Second, Chen and Rogoff (2003) find that, for Canada, non-oil commodities have a better in-sample predictive content than when energy is included. In this paper, we focus on oil instead. Therefore, the difference between our paper and Chen and Rogoff's (2003) is not a matter of frequency, but in-sample versus out-of-sample and the data used (non-oil commodities versus oil). Therefore, in this sense, our paper is not in contradiction with Chen and Rogoff (2003), but instead it poses a new challenge to the literature.

[6] Chen and Rogoff (2003) consider instead commodity price indices and find in-sample empirical evidence in favor of their explanatory power for real exchange rates – see Alquist et al. (2011) for a review of the literature on forecasting oil prices and Obstfeld (2002) for a discussion on the correlation between nominal exchange rates and export price indices.

[7] For example, Andersen et al. (2003), Faust et al. (2007), Kilian and Vega (2011) and Chaboud et al. (2008) have studied the consequences of macroeconomic news announcements (related to unemployment, output, etc.) on future exchange rates, oil prices or traded volume at high frequencies.

prices and exchange rates dissipates quickly over time, just as the effects of unanticipated Fed announcements on exchange rates do.

More generally, our paper is related to the large literature on predicting nominal exchange rates using macroeconomic fundamentals.[8] In particular, empirical evidence in favor of the predictive ability of macroeconomic fundamentals has been found mainly at longer horizons, although inference procedures have been called into question.[9] Our paper focuses instead on short-horizon predictive ability, for which the empirical evidence has been more controversial, and mainly successful when using Taylor rule fundamentals (Wang and Wu, 2008; Molodtsova and Papell, 2009; Molodtsova et al., 2008). In particular, Cheung et al. (2005) concluded that none of the fundamentals outperform the random walk and, in particular, found no predictive ability of traditional macroeconomic models in forecasting the Canadian-U.S. Dollar exchange rate. We show that commodity prices contain valuable information for predicting exchange rates in a few countries that are significant commodity exporter when predictive ability is measured by out-of-sample fit. Short-horizon predictive ability has never been convincingly demonstrated in the literature, especially with the high statistical significance levels that we are able to find. Our result is rather the opposite of what is commonly found in the literature: we do find predictive ability using daily data, which disappears at longer horizons. Our paper is also related to Faust et al. (2003), who pointed out that predictive ability is easier to find in real-time data: our paper focuses only on real-time data but uses an economic fundamental that is very different from the traditional ones used in their paper.

To further study the link between oil prices and exchange rates, in addition to a simple linear regression of exchange rates on oil prices (both in first differences), we consider nonlinear as well as cointegrated models (Mark, 1995). Overall, neither model provides significantly better forecasts than the simple linear commodity price model at the daily and monthly frequencies.

2. Data description

Our study considers Canada for three reasons. The first is that crude oil represents 21.4 percent of Canada's total exports over the period 1972Q1-2008Q1; more recently, in 2010–2012, crude oil represented between 12.5 and 15% of Canada's total exports, according to Statistics Canada.[10] The second is that Canada has a sufficiently long history of a market-based floating exchange rate. Finally, Canada is a small open economy whose size in the world oil market is relatively small to justify the assumption that it is a price-taker in that market. For the latter reason, crude oil price fluctuations could potentially serve as an observable and essentially exogenous terms-of-trade shock for the Canadian economy.

We use data on Canadian-U.S. dollar nominal exchange rates, oil prices, and Canadian and U.S. interest rates. The oil price series is the spot price of the West Texas Intermediate (WTI) crude oil, a type of crude oil used as a benchmark in oil pricing and the underlying commodity of the New York Mercantile Exchange's oil futures contracts, and the main benchmark for crude oil in North America. The Canadian-U.S. dollar nominal exchange rate is from Barclays Bank International (BBI). Data at daily, monthly and quarterly frequency are end-of-sample.[11] More precisely, we follow the end-of-sample data convention from Datastream: the monthly observation is the observation on the first day of the month, whereas the quarterly observation is the observation on the first day of the second month of the quarter. It is worthwhile to recall that, while the previous literature focuses on monthly and quarterly frequencies, our study switches the

[8] Since the seminal works by Meese and Rogoff (1983a,b, 1988), the literature has yet to find convincing empirical evidence that there exist standard macroeconomic fundamentals, such as interest rate differentials or income differentials, which are reliable predictors for exchange rate fluctuations. See, for example, Engel et al. (2007), Rogoff (2007) and Rogoff and Stavrakeva (2008). Predictive ability, when it exists, is unstable over time (see Rossi, 2006; Giacomini and Rossi, 2010).

[9] See Mark, 1995; Chinn and Meese, 1995; Cheung et al., 2005; and Engel et al., 2007; Kilian, 1999; Berkowitz and Giorgianni, 2001; Faust et al., 2003; Rogoff, 2007; and Rossi, 2005, 2007, among others.

[10] More details are available at http://www.statcan.gc.ca/.

[11] Note that we focus on end-of-sample data because it is harder to find predictive ability using end-of-sample data than using average-over-the-period data (see Rossi, 2013). Note that our results are therefore a lower bound on the predictive ability one may be able to find.

focus to daily data and provides a clean comparison of the results for the three frequencies. The data sample ranges from 12/14/1984 to 11/05/2010.[12] The daily data set contains 6756 observations, the monthly data set 311, and the quarterly data set 104. We acknowledge the availability of quarterly data for the Canadian-U.S. dollar nominal exchange rate since the early seventies, but we restrict our sample for the sake of comparison across frequencies. In Ferraro et al. (2015) we show that our results are robust to using data on oil prices and exchange rates from the Federal Reserve Bank of St. Louis (FRED) database.

To construct the daily Canada-U.S. interest rates differential data, we subtract the daily U.S. short-term interest rate from the daily Canadian short-term rate. The Canadian short-term interest rate is the daily overnight money market financing rate (from Bank of Canada) and the U.S. short-term rate is the daily effective Federal funds rate (from the Board of Governors of the Federal Reserve System). From the daily data, we construct the monthly and quarterly series: the monthly observation is the observation of the first day of the month and the quarterly observation is the observation of the second month of the quarter.

In addition, we consider other currencies and commodities. The Norwegian krone-U.S., South African rand-U.S. dollar and Australian Dollar-U.S. dollar nominal exchange rates are from Barclays Bank International (BBI). The Chilean peso-U.S. dollar exchange rate is from WM Reuters (WMR). Beside the oil price series described above, we use prices for copper and gold. All commodity prices and exchange rates series are obtained from Datastream.[13] The sample we consider is from 1/3/1994 to 9/16/2010.

3. Can commodity prices forecast exchange rates?

In this section, we evaluate whether commodity prices have predictive content for future exchange rates for the commodity currencies that we consider. We consider two measures of predictive ability: "out-of-sample fit" and truly "out-of-sample forecasting ability". We first show that commodity prices have significant predictive content in out-of-sample fit exercises in daily data. The predictive content, however, is much weaker at the monthly frequency and completely disappears at the quarterly frequency. We then show that, instead, the empirical evidence of out-of-sample forecasting ability is more ephemeral: lagged commodity prices can forecast future exchange rates out-of-sample only in certain sub-samples of the data.

3.1. Out-of-sample fit with realized fundamentals

We first assess the predictive ability of commodity prices using an out-of-sample fit measure. We focus on the simplest commodity price model:

$$\Delta s_t = \alpha + \beta \Delta p_t + u_t,\ t = 1, \ldots, T, \tag{1}$$

where Δs_t and Δp_t are the first difference of the logarithm of respectively the exchange rate[14] and the commodity price for that commodity currency (e.g., the Canadian-U.S. dollar exchange rate and oil prices); T is the total sample size, and u_t is an unforecastable error term. Notice that the realized right-hand-side variable is used for prediction. In the forecasting literature such "ex-post" forecasts are made when one is not interested in ex-ante prediction but in the evaluation of predictive ability of a model given a path for some un-modelled set of variables – see West (1996).[15] It is crucial to note that since the realized value of the fundamental is used, this is not an actual out-of-sample forecast exercise, rather an *"out-of-sample fit"* exercise. Important examples of the use of such a technique include Meese

[12] Starting the sample period in mid-1980s may yield a weaker relationship between the price of oil and the Canadian dollar exchange rate than starting in the mid-1990s after Canada became an net exporter of oil (see Issa et al., 2008). As we will show, our results based on the Fluctuation test reflect this. Note also that Canada's oil sector has grown in importance since 1972, but we do not examine the relationship between oil prices and the Canadian dollar before 1984 due to the lack of availability of daily data.

[13] We also investigate whether our results hold for countries which are large importers of oil, rather than exporters, by focusing on the Japanese Yen-U.S. Dollar exchange rate. Unreported results show that there is no predictive ability in that case.

[14] The value of the Canadian/U.S. exchange rate is the number of Canadian dollars per unit of U.S. dollars.

[15] This analysis captures correlations, or comovements, since it uses realized fundamentals.

and Rogoff (1983a,b) and Cheung et al. (2005), among others. Meese and Rogoff (1983a,b, 1988) demonstrated that even using realized values of the regressors, traditional fundamentals such as interest rates and monetary or output differentials would have no predictive power for exchange rates. One of the objectives of this paper is to show that the use of a different fundamental, namely, commodity prices, can lead to different results from Meese and Rogoff (1983a,b) at the daily frequency; we therefore use the same forecasting strategy. Note that such a finding does not imply that commodity prices today can forecast future exchange rates: in the next sub-section, we will assess the robustness of our results to models with lagged commodity price changes.

The reason why model (1) is evaluated on the basis of its out-of-sample fit is because we estimate the parameters of the model with rolling in-sample windows to produce a sequence of one-step-ahead pseudo out-of-sample forecasts conditional on the realized value of the commodity prices.[16] Let Δs^f_{t+1} denote the one-step-ahead pseudo out-of-sample forecast:

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

where $\widehat{\alpha}_t, \widehat{\beta}_t$ are the parameter estimates obtained from a rolling sample of observations $\{t-R+1, t-R+2, \ldots, t\}$, where R is the in-sample estimation window size. As previously discussed, the pseudo out-of-sample forecast experiment that we consider utilizes the realized value of the change in the commodity price as a predictor for the change in the exchange rate. The reason is that it is very difficult to obtain a model to forecast daily future changes in the commodity price, since they depend on political decisions and unpredictable supply shocks. If we were to use past values of commodity prices in our experiment, and the past values of commodity prices were not good forecasts of future values of commodity prices, we would end up rejecting the predictive ability of commodity prices even though the reason for the lack of predictive ability is not the absence of a relationship between exchange rates and commodity prices, but the poor forecasts that lagged price changes generate for future price changes. To avoid this problem, we condition the forecast on the realized future changes in commodity prices. It is important to note, however, that our exercise is not a simple in-sample fit exercise: we attempt to fit future exchange rates out-of-sample, which is a notably difficult enterprise. In this sense, this is an "out-of-sample fit" exercise: if the model is successful then it means that, should we have good forecasts of future daily commodity prices, we could use them to produce good forecasts of future daily exchange rates.

We compare the commodity price-based forecasts with those of the random walk, which, to date, is the toughest benchmark to beat. We consider both a random walk without drift benchmark as well as a random walk with drift benchmark given their importance in the literature.[17] We implement the Diebold and Mariano (1995) test of equal predictive ability by comparing the Mean Squared Forecast Errors (MSFEs) of the commodity price model with those of the two benchmarks. Note that even though our models are nested, we can use Diebold and Mariano (1995) for testing the null hypothesis of equal predictive ability at the estimated (rather than pseudo-true) parameter values, as demonstrated in Giacomini and White (2006) and discussed in Giacomini and Rossi (2010). We test the null hypothesis of equal predictive ability with daily, monthly and quarterly data.

We first consider the case of the Canadian-U.S. dollar and oil prices. Fig. 1A depicts the Diebold and Mariano (1995) test statistic for daily data computed with varying in-sample estimation window sizes. The size of the in-sample estimation window relative to the total sample size is reported on the x-axis.[18] When the Diebold and Mariano (1995) statistic is less than −1.96, we conclude that the commodity price model forecasts better than the random walk benchmark. Fig. 1A shows that, no matter the size of the in-sample window, the test strongly favors the model with commodity prices. This result holds for both benchmarks: the random walk without drift (solid line with circles) and with drift (solid

[16] Ferraro et al. (2015) show that our results are robust to using a recursive forecasting scheme.

[17] Meese and Rogoff (1983a,b) considered both; Mark (1995) considered a random walk with drift benchmark, and found substantial predictive ability at longer horizons; Kilian (1999) argued that the latter was mainly due to the presence of the drift in the benchmark. By considering both benchmarks, we are robust to Kilian's (1999) criticisms.

[18] Note that the procedure of reporting the test statistic for several estimation window sizes in our exercise does not introduce spurious evidence in favor of predictive ability. In fact, the predictive ability is strong for all window sizes and the results remain strongly significant even if we implemented Inoue and Rossi's (2012) test robust to data mining across window sizes.

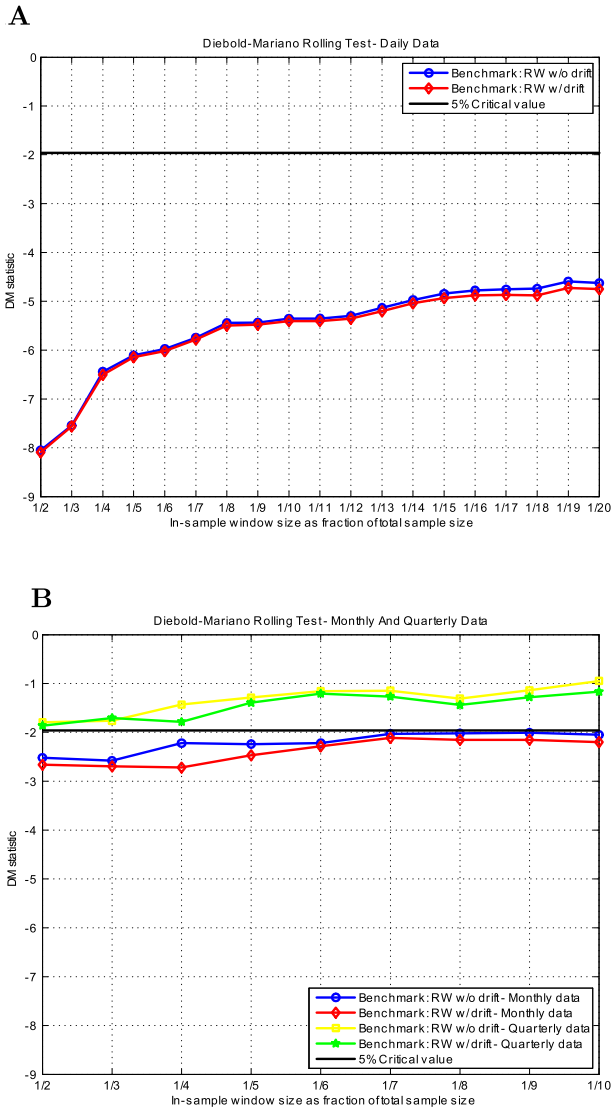


Fig. 1. A. Canadian-U.S. $ and Oil Prices. Forecastability in Daily Data. B. Canadian-U.S. $ and Oil Prices. Forecastability in Monthly and Quarterly Data. Notes: Panel A plots Diebold and Mariano's (1995) test statistic for comparing Model (1) to a random walk without drift (circles) and with drift (diamonds) in daily data, calculated for several in-sample window sizes (x-axis). The in-sample window size is reported as a fraction of the total sample size. Panel B similarly compares Model (1) to a random walk without drift (circles for monthly and squares for quarterly data) and with drift (diamonds for monthly and stars for quarterly data). The continuous line indicates the critical value of Diebold and Mariano's (1995) test statistic. Negative values indicate that Model (1) outperforms the benchmark. When the test statistic is below the continuous line Model (1) forecasts significantly better.

line with diamonds). Overall, we conclude that daily data show extremely robust results in favor of the predictive ability of the commodity price model. Note that the MSFE ratio between the model and the random walk without drift is 0.94 for R = 1/2, 0.93 for R = 1/3 and 0.91 for R = 1/5. Thus, the improvement in forecasting ability is non-negligible in economic terms.[19]

[19] The MSFE of the random walk without drift is $3.2976 \cdot 10^{-5}$ for R = 1/2, $2.6626 \cdot 10^{-5}$ for R = 1/3 and $2.3396 \cdot 10^{-5}$ for R = 1/5.

Table 1
Clark and West's (2006) test statistic.

Data frequency	A. Contemporaneous Oil P. Model			B. Lagged Oil P. Model		
	Daily	Monthly	Quarterly	Daily	Monthly	Quarterly
Window size:	P-value	P-value	P-value	P-value	P-value	P-value
1/2	0.000	0.008	0.034	0.096	0.280	0.606
1/3	0.000	0.005	0.024	0.064	0.241	0.271
1/4	0.000	0.009	0.021	0.121	0.332	0.417
1/5	0.000	0.009	0.031	0.158	0.140	0.232
1/6	0.000	0.008	0.037	0.148	0.164	0.170
1/7	0.000	0.011	0.026	0.165	0.250	0.143
1/8	0.000	0.009	0.021	0.304	0.168	0.179
1/9	0.000	0.007	0.027	0.310	0.163	0.161
1/10	0.000	0.007	0.028	0.304	0.167	0.085

Notes. The table reports results based on Clark and West's (2006) test statistic for the Canadian/US Dollar exchange rate data and oil prices. Panel A reports results for the Contemporaneous Oil Price Model, Eq. (1), whereas Panel B reports results for the Lagged Oil Price Model, Eq. (2).

Fig. 1B shows Diebold-Mariano's (1995) test statistics for monthly and quarterly data, respectively. These are frequencies typically used in the literature (cfr. Cheung et al., 2005). For quarterly data, we are never able to reject the null hypothesis of equal predictive ability. For monthly data, we find empirical evidence in favor of the model with oil prices, although the significance is much lower than that of daily data. We will discuss in detail the role played by the frequency in Section 4.

We investigate the robustness of our results using the Clark and West's (2006) test statistic. Results are reported in Panel A in Table 1. It is clear that our results are extremely robust to the use of this alternative test statistic, which finds even more predictive ability than the Diebold and Mariano's (1995) test. Thus, using the alternative test by Clark and West (2006) only strengthens our results in favor of the simple oil price model, Eq. (1). Hence, our main results (based on the Diebold and Mariano (1995) statistic) can be interpreted as a conservative lower bound on the evidence of predictive ability that we find.

In what follows, we show that our results are not confined to the case of the Canadian-U.S. dollar exchange rate and oil prices. We consider the predictive ability of exchange rates of other exporting countries vis-a-vis the U.S. dollar for a few additional commodity prices. In particular, we consider: (a) the price of copper (in U.S. dollars) and the Chilean peso-U.S. dollar exchange rate; (b) the gold price (in U.S. dollars) and the South African rand-U.S. dollar exchange rate; (c) the oil price and the Norwegian krone-U.S. dollar exchange rate; and (d) the oil price and the Australian-U.S. Dollar exchange rate.

Fig. 2 shows the empirical results for forecasting the Norwegian krone-U.S. dollar exchange rate using oil prices. In this case, the data show a clear forecasting improvement over a random walk both in the model with contemporaneous regressors (Eq. (1)) at daily frequencies (Panel A) as well as in monthly data (Panel B), no matter which window size is used for estimation. The forecasting improvement is statistically significant in both cases, although the predictive ability again becomes statistically insignificant at quarterly frequencies.

Fig. 3 shows that similar results hold when considering the South African rand exchange rate and gold prices. Panel A shows that the predictive ability of contemporaneous gold prices is statistically significant in daily data, despite whether the benchmark model is a random walk with or without drift, and no matter which in-sample window size the researcher chooses. In monthly and quarterly data, instead, Panel B demonstrates that fluctuations in gold prices never improve the predictive ability over a random walk model.

Fig. 4A shows that the price of copper has a clear advantage for predicting the Chilean peso-U.S. dollar exchange rate in the model with contemporaneous regressors at daily frequencies relative to the random walk model (with or without drift), and it is strongly statistically significant. Fig. 4B demonstrates that such predictive ability becomes statistically insignificant when considering monthly and quarterly data. Results are very similar when considering the Australian-U.S. dollar and oil prices – see Fig. 5.[20]

[20] We also considered predicting the Australian/U.S. Dollar using gold prices, and the results were similar.

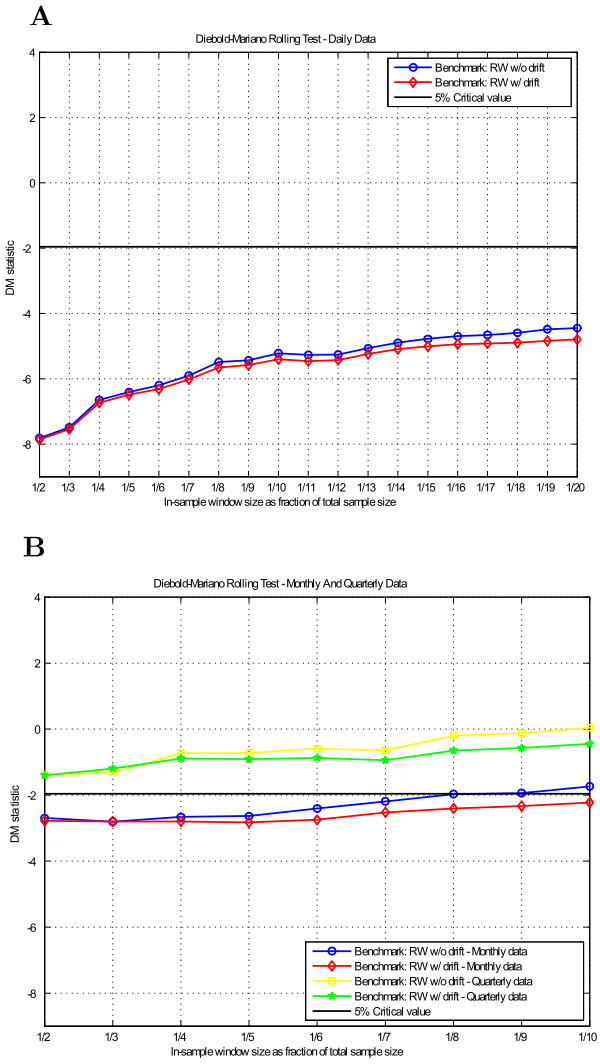


Fig. 2. A. Norw. Krone and Oil. Daily Data, Contemp. Model. B. Norw. Krone and Oil. Monthly and Quarterly Contemp. Model. Notes: Panel A reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) in daily data relative to a random walk without drift benchmark (circles) as well as relative to the random walk with drift benchmark (diamonds) calculated for several in-sample window sizes (x-axis). Similarly, Panel B reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) in monthly and quarterly data relative to a random walk without drift (circles for monthly and squares for quarterly data) and with drift (diamonds for monthly and stars for quarterly data), calculated for several in-sample window sizes (x-axis). The continuous line indicates the critical value of Diebold and Mariano's (1995) test statistic. When the estimated test statistics are below this line, Model (1) or (2) forecasts significantly better than its benchmark.

3.2. Can lagged commodity prices forecast exchange rates?

The previous sub-section focused on regressions where the realized value of commodity price changes are used to predict exchange rates contemporaneously. In reality, forecasters would not have access to realized values of commodity price changes when predicting future exchange rates. So, while the results in the previous section are important to establish the existence of a stronger link between

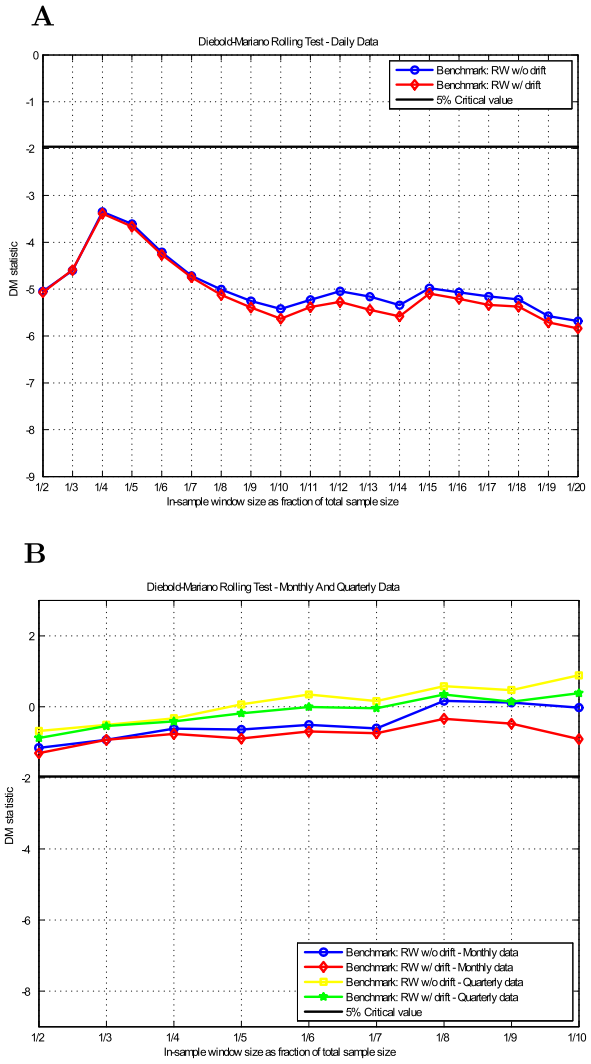


Fig. 3. A. S.A. Rand and Gold. Daily Data, Contemp. Model. B. S.A. Rand and Gold. Monthly and Quarterly Contemp. Model. Notes: Panel A reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) in daily data relative to a random walk without drift benchmark (circles) as well as relative to the random walk with drift benchmark (diamonds) calculated for several in-sample window sizes (x-axis). Similarly, Panel B reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) in monthly and quarterly data relative to a random walk without drift (circles for monthly and squares for quarterly data) and with drift (diamonds for monthly and stars for quarterly data), calculated for several in-sample window sizes (x-axis). The continuous line indicates the critical value of Diebold and Mariano's (1995) test statistic. When the estimated test statistics are below this line, Model (1) or (2) forecasts significantly better than its benchmark.

commodity prices and exchange rates in daily data (relative to monthly and quarterly data), they would not be useful for practical forecasting purposes. In this section, we consider a stricter test by studying whether lagged (rather than contemporaneous) commodity price changes have predictive content for future exchange rates. We will show that, for the Canadian-U.S. dollar and oil prices, the predictive ability depends on the estimation window size, being more favorable to the model with lagged oil prices only for large in-sample estimation window sizes. We also find that the predictive ability is now

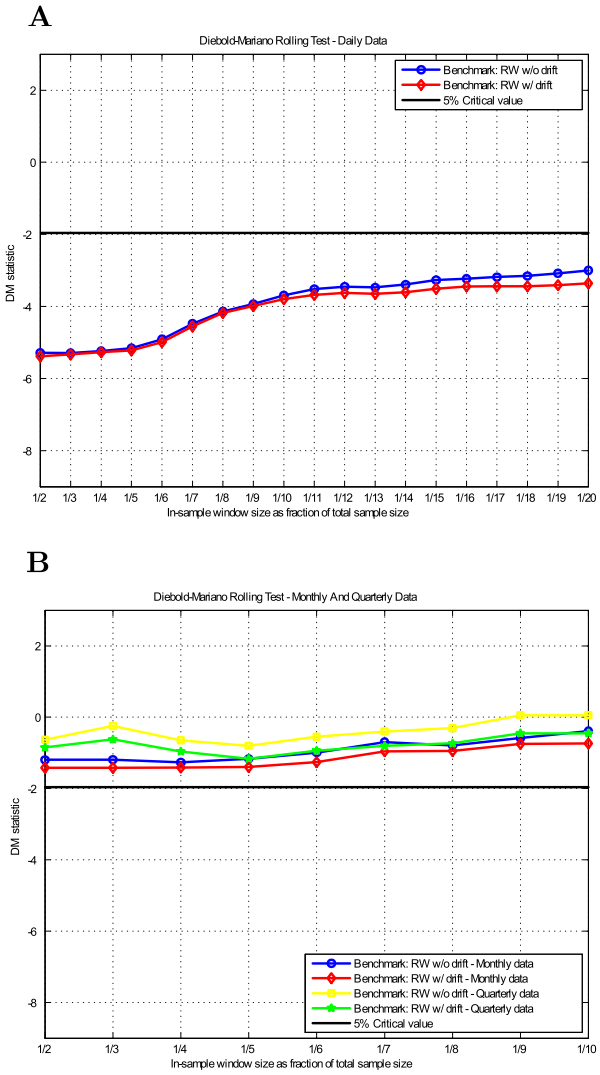


Fig. 4. A. Chilean Peso and Copper. Daily Data, Contemp. Model B. Chilean Peso and Copper. Monthly and Quarterly Contemp. Model. Notes: Panel A reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) in daily data relative to a random walk without drift benchmark (circles) as well as relative to the random walk with drift benchmark (diamonds) calculated for several in-sample window sizes (x-axis). Similarly, Panel B reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) in monthly and quarterly data relative to a random walk without drift (circles for monthly and squares for quarterly data) and with drift (diamonds for monthly and stars for quarterly data), calculated for several in-sample window sizes (x-axis). The continuous line indicates the critical value of Diebold and Mariano's (1995) test statistic. When the estimated test statistics are below this line, Model (1) or (2) forecasts significantly better than its benchmark.

more ephemeral, pointing to strong empirical evidence of time variation in the relative performance of the model with lagged oil prices relative to the random walk benchmark. However, once that time variation is taken into account, we can claim that the model with lagged oil prices forecasts significantly better than the random walk benchmark around 2006–2007 at the daily frequency. On the other hand, the same model at the monthly and quarterly frequencies never forecasts significantly better

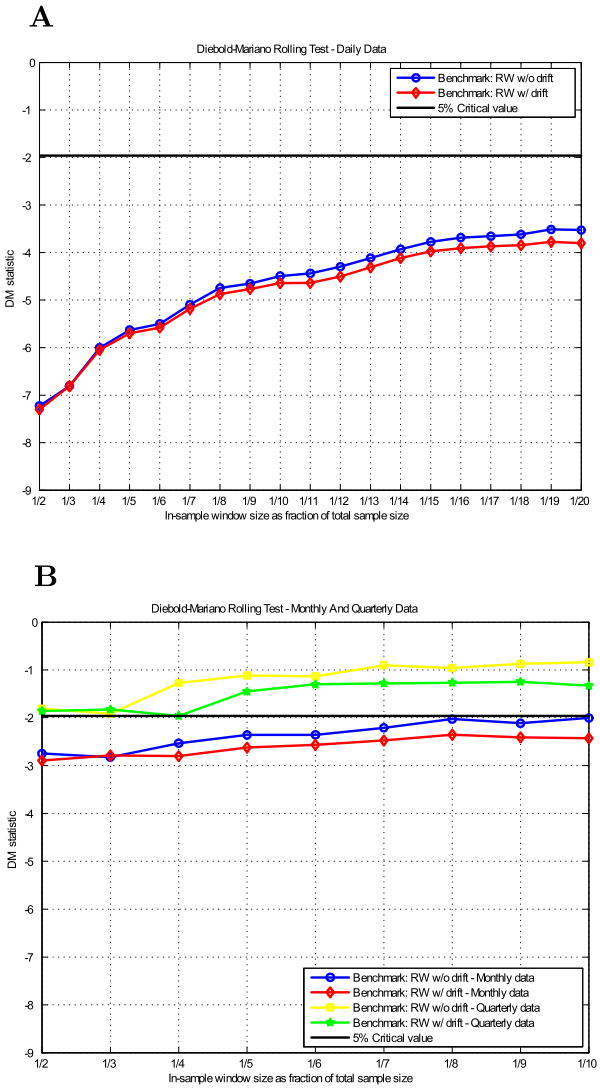


Fig. 5. A.Austr. $ and Oil. Daily Data, Contemp. Model. B. Austr. $ and Oil. Monthly and Quarterly Contemp. Model. Notes: Panel A reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) in daily data relative to a random walk without drift benchmark (circles) as well as relative to the random walk with drift benchmark (diamonds) calculated for several in-sample window sizes (x-axis). Similarly, Panel B reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) in monthly and quarterly data relative to a random walk without drift (circles for monthly and squares for quarterly data) and with drift (diamonds for monthly and stars for quarterly data), calculated for several in-sample window sizes (x-axis). The continuous line indicates the critical value of Diebold and Mariano's (1995) test statistic. When the estimated test statistics are below this line, Model (1) or (2) forecasts significantly better than its benchmark.

than the random walk. Qualitatively similar results hold for the other currencies/commodities pairs, although with some differences, which we document.

We focus on the following model with lagged oil prices:

$$\Delta s_t = \alpha + \beta \Delta p_{t-1} + u_t, \quad t = 1, \ldots, T, \tag{2}$$

where Δs_t and Δp_t, which are the first difference of the logarithm, denote the exchange rate and the commodity price, respectively; T is the total sample size; and u_t is an unforecastable error term. Notice that the lagged value of the right-hand-side variable is used for prediction in Eq. (2), whereas the realized value of the explanatory variable was used in Eq. (1). We estimate the parameters of the model with rolling in-sample windows and produce a sequence of 1-step ahead pseudo out-of-sample forecasts conditional on the lagged value of commodity prices. Let Δs^f_{t+1} denote the one-step ahead pseudo out-of-sample forecast: $\Delta s^f_{t+1} = \widehat{\alpha}_t + \widehat{\beta}_t \Delta p_t, \;\; t = R, R+1, \ldots, T-1,$ where $\widehat{\alpha}_t, \widehat{\beta}_t$ are the parameter estimates obtained from a rolling sample of observations $\{t-R+1, t-R+2, \ldots, t\}$, and R is the in-sample estimation window size. As before, we compare the oil price-based forecasts with those of the random walk by using Diebold and Mariano's (1995) test.

First, consider the Canadian-U.S. dollar and oil price case. Fig. 6A reports Diebold and Mariano's (1995) test statistic for daily data computed with varying in-sample estimation windows. The size of the in-sample estimation window relative to the total sample size is reported on the x-axis. Clearly, predictability depends on the estimation window size. Diebold and Mariano's (1995) statistic is negative for large in-sample window sizes, for which model (2) forecasts better than both the random walk, with and without drift; however, the opposite happens for small in-sample window sizes. Since the Diebold and Mariano (1995) statistic is never less than -1.96, we conclude that the oil price model never forecasts significantly better than the random walk benchmark on average over the out-of-sample forecast period.[21] Fig. 6B reports forecast comparisons for the same model, Eq. (2), at the monthly and quarterly frequencies. The model estimated at monthly and quarterly frequencies forecasts worse than the one estimated in daily data. Again, the model with monthly data does show some predictive ability for the largest window sizes, although it is not statistically significant, whereas the quarterly data model never beats the random walk. Finally, Panel B in Table 1 demonstrates the robustness of our results using the Clark and West's (2006) test statistic. It is clear that our results are extremely robust to the use of this alternative test statistic, which even finds statistically significant predictive ability for large window sizes for the daily model.

4. Why are we able to find out-of-sample fit?

The finding that commodity prices do forecast nominal exchange rates in out-of-sample fit exercises is very different from the conventional result in the literature, namely, the fact that nominal exchange rates are unpredictable. For example, Cheung et al. (2005) consider the same model in first differences for the Canadian-U.S. Dollar, among other models; in their paper, achieving a MSFE ratio lower than unity is actually considered a success: they fail to find macroeconomic predictors which achieve a MSFE ratio lower than one, let alone significance at the 5% level, among all the models and currencies they consider, including the Canadian-U.S. Dollar. It is therefore crucial to understand the reasons why we find predictability. This section explores various explanations. We will show that: (i) the predictability at daily frequencies is specific to commodity prices and does not extend to other traditional fundamentals such as interest rates; (ii) predictability in terms of out-of-sample fit is extremely reliable, in the sense that it does not depend on the sample period; (iii) the predictability is not due to a Dollar effect and it is robust to controlling for macro news shocks; (iv) in addition, we verify that the predictability is present not only out-of-sample but also in-sample. For brevity, we focus our analysis on the representative case of oil prices and the Canadian exchange rate, although we provide some discussion on how the results extend to other commodities/currencies as well.

4.1. Frequency vs. choice of fundamental: which one matters?

Our empirical results greatly differ from the existing literature in two crucial aspects: the choice of the economic fundamental (commodity prices) and the choice of the data frequency (daily data). Therefore, it is important to understand whether it is the frequency of the data or the nature of the

[21] The MSFE ratio between the model and the random walk without drift is 0.99 for most window sizes.

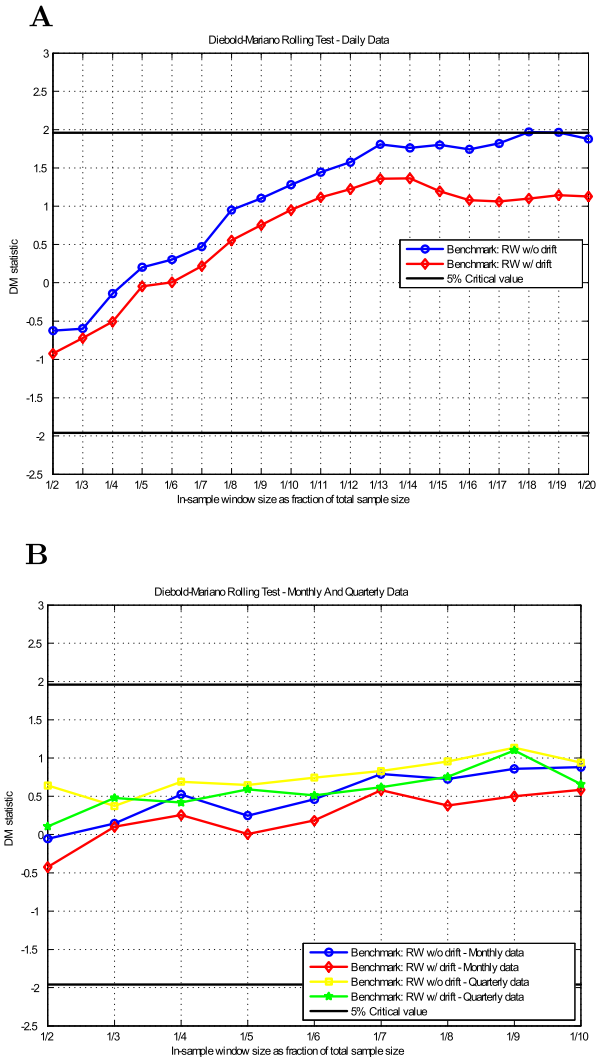


Fig. 6. A. Canadian-U.S. Dollar and Lagged Oil. Daily Data B. Canadian-U.S. Dollar and Lagged Oil. Monthly and Quarterly Data. Notes: Panel A reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (2) in daily data relative to a random walk without drift benchmark (circles) as well as relative to the random walk with drift benchmark (diamonds) calculated for several in-sample window sizes (x-axis). Panel B reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (2) relative to a random walk without drift benchmark (circles for monthly data and squares for quarterly data) as well as relative to the random walk with drift benchmark (diamonds for monthly data and stars for quarterly data) calculated for several in-sample window sizes. In both panels, the in-sample window size is reported as a fraction of the total sample size. Negative values indicate that Model (2) outperforms the benchmark. The continuous line indicates the critical value of Diebold and Mariano's (1995) test statistic. When the estimated test statistics are below the negative critical value line, Model (2) forecasts significantly better than the benchmark.

fundamental that drives our results. Section 2 showed that the frequency of the data does play a role; to sort out how important the choice of the fundamental is, we consider a model with traditional fundamentals, i.e. interest rate, output and money differentials (Meese and Rogoff, 1983a,b, 1988, and Engel et al., 2007). Since output and money data are not available at the daily frequency, we focus on the interest rate model:

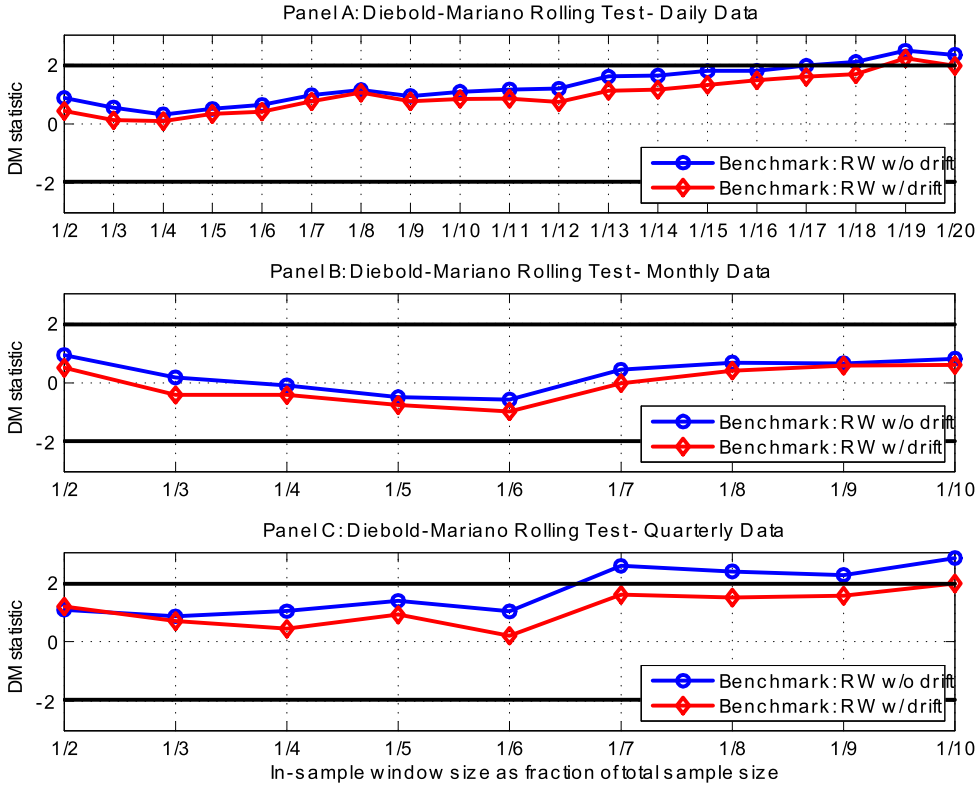


Fig. 7. Canadian-U.S. Dollar and the Interest Rate Model. Notes: The figure reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (3) relative to a random walk without drift benchmark (circles) as well as relative to the random walk with drift benchmark (diamonds) calculated for several in-sample window sizes (x-axis), respectively for daily data (Panel A), monthly data (Panel B) and quarterly data (Panel C). The in-sample window size is reported as a fraction of the total sample size. Negative values indicate that Model (3) outperforms the benchmark. The continuous line indicates the critical value of Diebold and Mariano's (1995) test statistic. When the estimated test statistics are below the negative critical value line, Model (3) forecasts significantly better than the benchmark.

$$\Delta s_t = \alpha + \beta i_t + \mu_t \tag{3}$$

where i_t is the interest rate differential between Canada and the U.S., Δs_t is the first difference of the logarithm of the Canadian-U.S. dollar exchange rate, and μ_t is an unforecastable error term. Fig. 7 reports the results. Panel A shows that the interest rate model never forecasts better than the random walk benchmark; Panels B and C show that similar results hold at the monthly and quarterly frequencies. We conclude that the reason why we are able to find predictive ability is also due the new fundamental that we consider (the oil price), and not only the frequency of the data. The predictive ability is also not present in the model with lagged fundamentals (Eq. (2)) if we use interest rates differentials:

$$\Delta s_t = \alpha + \beta i_{t-1} + \varepsilon_t. \tag{4}$$

Fig. 8 shows the model's forecasts never beat the random walk's forecasts, no matter what the estimation window size is.

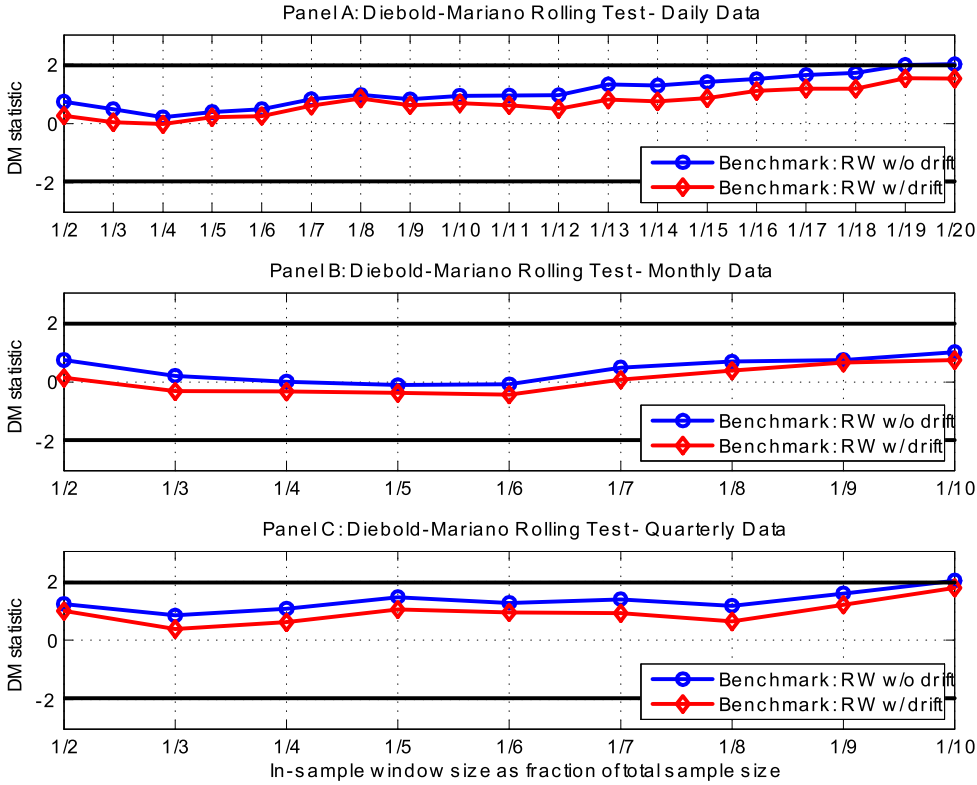


Fig. 8. Canadian-U.S. Dollar and the Lagged Interest Rate Model. Notes: The figure reports Giacomini and Rossi's (2010) Fluctuation test statistic for comparing forecasts of Model (4) relative to a random walk without drift benchmark (circles) as well as relative to the random walk with drift benchmark (diamonds). Negative values indicate that Model (4) outperforms the benchmark. The continuous line indicates the critical value of the Fluctuation test statistic. When the estimated test statistic is below the negative critical value line, Model (4) forecasts significantly better than the benchmark.

4.2. Frequency vs. length of the sample: which one matters?

To check whether the improved out-of-sample predictive ability in daily data is due to the higher frequency or the larger number of observations, we make them comparable by selecting the number of in-sample observations for daily data equal to the number of in-sample observations for monthly and quarterly data. Table 2 reports results for the representative Canadian-U.S. dollar exchange rate and oil prices case. Diebold and Mariano's (1995) test statistics against a random walk without drift is highly significant in daily data: it equals −4.1829, which implies a p-value of zero; for monthly data, instead, the statistic is −2.5201, with a p-value of 0.011 (Panel A). Thus, predictive ability is much stronger in daily than in monthly data.[22] Panel B compares daily and quarterly frequencies; the test statistics is still significant in daily data: it equals −2.11, with a p-value of 0.03, while in quarterly data the statistic is −1.79, and it is not significant. Thus, the evidence in favor of predictive ability is present only in daily data and not at the quarterly frequency. In summary, even when the number of in-sample observations is the same, the daily oil price model outperforms the monthly and quarterly oil price model out-of-

[22] In fact, at the 5% significance level the predictive ability is evident at both frequencies, but at the 1% level it is evident only in daily data.

Table 2
Frequency versus number of observations.

	RW w/o drift	RW w/drift		RW w/o drift	RW w/drift
Panel A. Comparing daily and monthly data			Panel B. Comparing daily and quarterly data		
Daily	−4.1829	−4.3710	Daily	−2.1160	−2.7254
	(0.0000)	(0.0000)		(0.0343)	(0.0064)
Monthly	−2.5201	−2.6630	Quarterly	−1.7967	−1.8654
	(0.011)	(0.007)		(0.0724)	(0.0621)

Notes. The table reports the Diebold and Mariano's (1995) test statistics (p-values in parentheses) calculated with the same number of observations in both daily and monthly data (Panel A), and in daily and quarterly data (Panel B). The benchmarks are the random walk without drift and the random walk with drift (columns labeled "RW w/o drift" and "RW w drift").

sample. We conclude that the reason of the forecasting success in daily data is the frequency of the data, rather than the length of sample.[23]

4.3. Oil prices and macro news announcements

We compare the predictive power of oil prices with that of other predictors which have been found to be important in explaining exchange rate fluctuations at high frequencies. Andersen et al. (2003) and Faust et al. (2007) demonstrate that macroeconomic news announcements do predict future exchange rates at the daily frequency.[24] They consider "macroeconomic news announcement shock", i.e. the difference between expected and realized macroeconomic fundamentals in the International Money Market Services real-time database, and show that macroeconomic news announcements produce significant jumps in future exchange rates. To investigate whether oil prices are a better predictor for exchange rate changes than macroeconomic news announcements, we consider the following model for the Canadian-U.S. dollar exchange rate:

$$\Delta s_t = \alpha + \beta \Delta p_t + \sum_{k=1}^{K} \gamma_k S_{k,t} + u_t, \quad \text{for } t = 1, \ldots, T, \tag{5}$$

where $S_{k,t}$ is the $k-th$ macroeconomic news announcement shock announced at time t. In contrast to the previous literature, we include oil price changes among the regressors. The macroeconomic announcements include the unemployment rate, consumer price index, leading indicators change in non-farm payrolls and industrial production, among others.[25] Table 3 reports the performance of the models with macroeconomic news relative to the random walk without or with drift (labeled "Random Walk w/o drift" and "Random Walk w/drift", respectively) for several window sizes. Panel A report results for the model with macroeconomic news, Eq. (5), whereas panel B report results for the model with only oil prices, Eq. (1). The model with oil prices forecasts better (relative to a random walk) than a model that includes both oil prices and macroeconomic fundamentals. Unreported results show that the model with only macroeconomic news (that is, a model that does not include oil prices) performs much worse than the model with macroeconomic news and oil prices that we consider: while it is hard to beat a random walk, the model that includes oil prices gets closer to the random walk benchmark than the model that does not include it.[26]

4.4. Is the predictive ability due to a dollar effect?

Since the price of oil in international markets is quoted in U.S. Dollars, and our representative analysis focuses on the U.S. Dollar-Canadian Dollar exchange rate, one might expect a correlation due to

[23] It is still possible that, in longer sample sizes, results might be significant for monthly and quarterly data as well; however, our analysis suggests that the results in daily data would be even stronger than those in monthly and quarterly data.
[24] We consider daily data and not 5-min data due to concerns of micro-structure noise.
[25] See Ferraro et al. (2015) for details on the type of announcements that we consider.
[26] The previous literature used 5-min data whereas we use daily data; thus, our results should not be interpreted as invalidating the former, but only indicating that, at the daily frequency, the predictability of oil prices remains after controlling for "news".

Table 3
Macroeconomic news versus oil prices.

Window size:	1/2	1/3	1/4	1/5
Panel A. Model with macroeconomic news and oil prices, Eq. (5)				
Random walk w/o drift	−2.1446	−1.1072	−0.3511	0.4657
Random walk w/drift	−2.2030	−1.1578	−0.3764	0.4245
Panel B. Model with oil prices only, Eq. (1)				
Window size:	1/2	1/3	1/4	1/5
Random walk w/o drift	−3.9819	−3.3144	−3.1826	−2.9482
Random walk w/drift	−4.0661	−3.3882	−3.2154	−2.9930

Notes. The table reports the MSFE of the models with macroeconomic news relative to the MSFE of a random walk without or with drift (labeled "Random Walk w/o drift" and "Random Walk w/drift", respectively). Panel A reports results for the model with macroeconomic news and oil prices, Eq. (5), whereas Panel B reports results for the model with oil price only, Eq. (1). We report results for four window sizes equal to either half, a third, a fourth or a fifth of the total sample size.

the common U.S. Dollar denomination. It is important to assess whether the daily predictive power holds up to a cross-exchange rate that does not involve the U.S. Dollar.[27] We collected data on the Canadian Dollar-British Pound exchange rate from WM Reuters. Table 4 shows that our results are robust.[28]

4.5. Instabilities in forecast performance

The existing literature on the effects of oil price shocks on the economy points to the existence of instabilities over time; in particular, Maier and DePratto (2008) have noticed in-sample parameter instabilities in the relationship between the Canadian exchange rate and commodity prices. In order to evaluate whether potential instabilities may affect the forecast performance of the oil price model, we report the results of the Fluctuation test proposed by Giacomini and Rossi (2010). The latter suggests to report rolling averages of (standardized) MSFE differences over time to assess whether the predictive ability changes over time. The in-sample estimation window is one-half of the total sample size and the out-of-sample period equals five hundred days. Fig. 9A shows the Fluctuation test for daily data in the Canadian-U.S. dollar and oil prices case. The figure plots the relative performance (measured by Diebold and Mariano's (1995) statistics) for the oil price model (Eq. (1)) against the random walk without drift (solid line with circles) and with drift (solid line with diamonds), together with the 5% critical values (solid lines). Since the values of the statistic are below the (negative) critical value, we conclude that the oil price model forecasts better in some periods, in particular after 2005. This finding is consistent with the fact that, starting in the mid-1990s, Canada has become a net exporter of oil (Issa et al., 2008). Fig. 9B,C show that at the monthly and quarterly frequencies we do not detect significant predictive ability improvements of the oil price model over the random walk.[29] Results are similar for the other commodities/exchange rates.

When considering the predictive ability of lagged oil prices for the Canadian-U.S. dollar exchange rate, again, once we allow the relative performance of the models to be time-varying, the most interesting empirical results appear. Fig. 10 reports results based on the Fluctuation test implemented with both Clark and West's (2006) and Diebold and Mariano's (1995) statistics (lines with diamonds and circles, respectively).[30] Panel A shows that there is significant evidence in favor of the model with lagged prices in daily data, especially with the Clark and West (2006) test, around 2007, against the random walk without drift. Panels B and C show, instead, that there was never statistically significant

[27] We thank M. Chinn for raising this issue.
[28] The predictive ability, however, depends on the window size, and seems to disappear for very small window sizes, perhaps due to the short sample of the Canadian Dollar/British Pound.
[29] The Fluctuation test focuses on rolling windows over the out-of-sample portion of the data, which is more appropriate than expanding windows in the presence of instabilities (Rossi, 2013).
[30] Note that in Fig. 3 the Fluctuation test was implemented using Diebold and Mariano (1995); the Fluctuation test with Clark and West (2006) would only find even stronger evidence in favor of predictive ability.

Table 4
Oil prices and the Canadian Dollar-British Pound.

Window size:	RW w/o drift	RW w/drift
1/2	−2.326 (0.020)	−2.304 (0.021)
1/3	−2.141 (0.032)	−2.191 (0.028)

Notes. The table reports the Diebold and Mariano's (1995) test statistic (and p-values in parenthesis) for model (1) for various values of the window size as a fraction of the total sample size (labeled "Window"), where the exchange rate is the Canadian dollar- British pound.

empirical evidence in favor of the model for monthly and quarterly data. Ferraro et al. (2015) show that the predictive ability disappears in the model with lagged fundamentals (Eq. (2)) also for the Norwegian krone-U.S. dollar exchange rate and oil prices, as well as for the South African rand exchange rate and gold prices, the Chilean peso-U.S. dollar and copper prices, and the Australian U.S. dollar and oil prices under the assumption that the relative performance of the models is constant over the entire out-of-sample span of the data. However, for some currencies/commodities, the model with lagged regressors does forecast significantly better than the random walk benchmark when we allow the models' forecasting performance to change over time. For example, in the Norwegian krone and the South African rand case with, respectively, oil and gold prices fundamentals, the fundamental statistically improves forecasts of exchange rates no matter if the oil price is a contemporaneous regressor or a lagged regressor when we allow for time variation in the relative forecasting performance of the

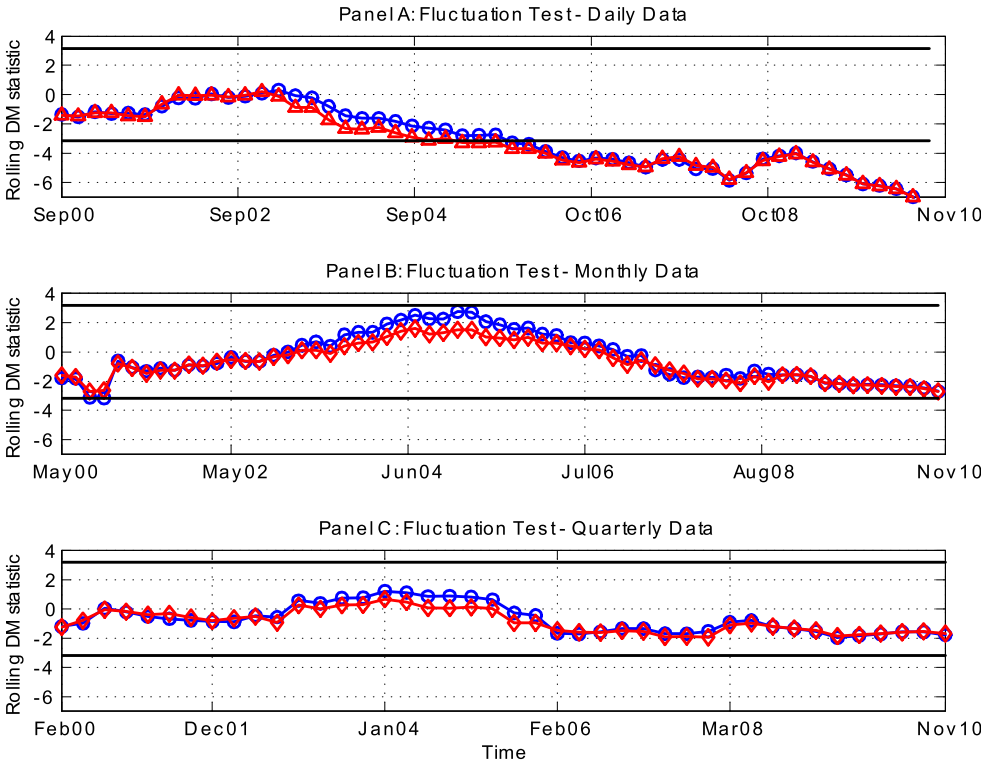


Fig. 9. Fluctuation Test. Canadian-U.S. Dollar and Oil P. Model. Notes: The figure reports Giacomini and Rossi's (2010) Fluctuation test statistic for comparing forecasts of Model (1) relative to a random walk without drift benchmark (circles) as well as relative to the random walk with drift benchmark (diamonds) for daily data (Panel A), monthly data (Panel B) and quarterly data (panel C). Negative values indicate that Model (1) outperforms the benchmark. The continuous line indicates the critical value of the Fluctuation test statistic. When the estimated test statistic is below the negative critical value line, Model (1) forecasts significantly better than the benchmark.

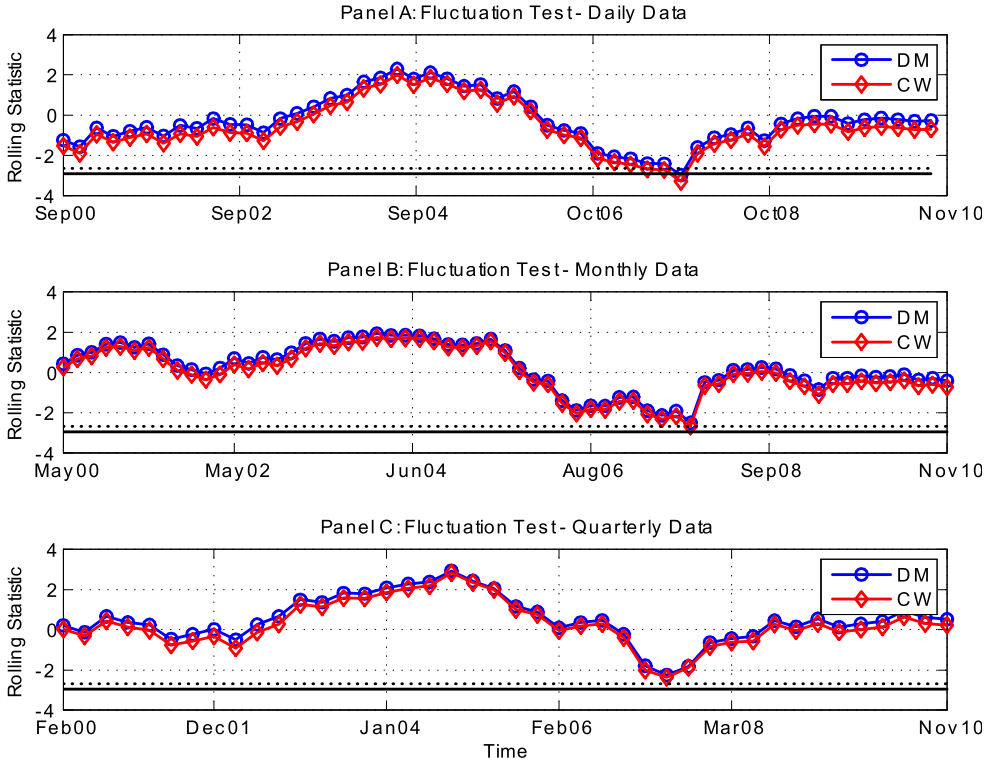


Fig. 10. Fluctuation Test. Canadian-U.S. Dollar and Lagged Oil P. Model. Notes: The figure reports Giacomini and Rossi's (2010) Fluctuation test statistic implemented with Clark and West's (2006) statistic for comparing forecasts of Model (2) relative to a random walk without drift benchmark (diamonds) as well as Giacomini and Rossi's (2010) Fluctuation test statistic implemented with the Diebold and Mariano (1995) and Giacomini and White (2006) statistic for comparing forecasts of Model (2) relative to a random walk without drift benchmark (circles). Negative values indicate that Model (2) outperforms the benchmark. The dashed and continuous lines denote, respectively, the one-sided 5% and 10%-level critical values of the Fluctuation test statistic. When the estimated test statistic is below the negative critical value line, Model (2) forecasts significantly better than the benchmark.

models. The predictive ability is present only for the contemporaneous regression model for the other countries/commodity prices.[31]

4.6. *In-sample fit and Clark and West's (2006) out-of-sample test analysis*

To better link our results with the large literature on the in-sample fit of exchange rates and commodity prices (e.g. Chen and Rogoff, 2003; Amano and van Norden, 1998a,b, Issa et al., 2008; Cayen et al., 2010),[32] we estimate the oil price model, Eq. (1), over the entire sample period with daily, monthly and quarterly data. Table 5A shows that the constant α is never statistically significant; the coefficient on the growth rate of the oil price, β, instead, is statistically significant at any standard level of significance, and for all frequencies. The in-sample fit of the model (measured by the R^2) improves when considering quarterly data relative to monthly and, especially, daily data. Comparing these results with those in the previous section, interestingly, it is clear that the superior in-sample fit at

[31] Note that the weight of oil on the Canadian commodity price index is between 20 and 25% (source: IMF), for Norway is about 20% (source: Statistics Norway), whereas for Australia it is only 4% (source: RBA statistics).

[32] The in-sample literature mainly focused on real exchange rates, whereas we focus on the nominal rate; however, results should be similar given their high correlation.

Table 5
In-sample fit of the linear model with oil prices.

	Daily		Monthly		Quarterly	
Panel A. Model with oil prices						
R^2	0.03		0.09		0.21	
A	−0.000	(−0.69)	−0.000	(−0.59)	−0.002	(−0.552)
B	−0.03	(−7.14)	−0.059	(−3.18)	−0.085	(−2.95)
Panel B. Model with interest rates						
R^2	0.00001		0.0014		0.0008	
A	−0.00001	(−0.25)	−0.0007	(−0.36)	−0.0007	(−0.13)
B	0.00002	(0.09)	0.0004	(0.54)	−0.0004	(−0.25)

Notes. The model in Panel A is Eq. (1) and the model in Panel B is Eq. (3); HAC robust t−statistics reported in parentheses (with a bandwidth equal to $4(0.01T)^{1/4}$).

monthly, and especially quarterly, frequencies does not translate into superior out-of-sample forecasting performance.[33] We conclude that the frequency of the data does not matter for in-sample analysis, at least when we evaluate the oil price model over the full sample.

4.7. The importance of timing

The contemporaneous out-of-sample fit relationship between commodity prices and exchange rates almost disappears when considering monthly or quarterly data. A possible reason why such relationship is much weaker at low frequencies is that oil price shocks are very short-lived; it is therefore essential that researchers focus on daily frequencies (or higher) to capture the relationship: spikes in oil prices and exchange rates would be much harder to identify in monthly or quarterly data, as they would be washed out in small samples. We use a small Monte Carlo example to show that, if exogenous commodity price spikes are generated randomly according to a Poisson distribution calibrated such that the spikes are very rare events, and exchange rates are a contemporaneous function of them, one may find out-of-sample predictability in daily but not monthly or quarterly data. In particular, we generate exchange rates equal to the Poisson process plus a random standard normal distribution. Thus, there is predictive ability in the data we create, although it is rare. When $\lambda = 0.05$, across 1000 simulations, the percentage of times a researcher would be able to identify predictive ability using the Diebold and Mariano (1995) test based on daily data is 100%, whereas the percentage is only 10% in end of sample monthly data. When $\lambda = 0.02$, the percentage based on daily data is 97%, whereas it becomes 2% in monthly data. This example shows that a researcher would find much less predictive ability in monthly than in daily data, even if the predictability is there.

It is important to note that our empirical results do not prove that oil price shocks cause changes in exchange rates, only that they are correlated in the out-of-sample fit exercise we investigate; for example, we cannot rule out that there is a third, unobserved factor, which drives both. However, the objective of this Monte Carlo exercise is to show that, even if, in reality, oil price changes cause changes in exchange rates, it is quite possible that such relationship is more visible at the daily frequency than at the monthly or quarterly frequencies when such shocks are rare and transitory, and revert back to the mean quickly. At the same time, if one believes that oil price changes are exogenous (and, for a small open economy like Canada, this is certainly a possibility) then one could interpret changes in oil prices as terms-of-trade shocks to which exchange rates react.

4.8. The importance of the fundamental

To shed more light on the possible mechanisms behind our results, Fig. 11 plots Diebold and Mariano's (1995) test statistic for comparing Model (1) to a random walk without drift in daily data, for several countries (in different panels) and several commodities, not necessarily the commodities that those countries export heavily.[34] The top panel reports results for the Canadian dollar, the middle

[33] Table 1B reports in-sample estimates of the interest rate model, Eq. (3). The interest rate is never significant at any frequency.
[34] Again, the test statistic is depicted as a function of the in-sample window size, reported as a fraction of the total sample size.

panel reports results for the Norwegian krone and the bottom panel reports results for the South African rand, all relative to the U.S. dollar. In each panel, the line with circles refers to the model with the oil price, the line with diamonds refers to gold prices and the line with squares refers to copper prices. For Canada and Norway, both oil and gold prices are useful fundamentals in terms of out-of-sample fit; copper is never useful. For South Africa, only gold prices are useful. The case of South Africa is consistent with the terms of trade explanation, but for Norway and Canada results are mixed. In fact, oil represents 21% of Canadian exports, while gold and copper represent only 2%; similarly in the case of Norway, whose significant exports include primarily oil. Overall, we cannot exclude a terms of trade explanation, but neither re-balancing motives nor the possibility that the exchange rate and the fundamental are driven by common unobserved shocks.

5. Other models' specifications

One could consider other econometric specifications, such as non-linear and cointegrated models. First, regarding cointegrated models, note that, typically, imposing cointegration is important at lower frequencies; therefore we expect them not to be important in our analysis on high frequency data. To investigate whether this is the case, consider the cointegration model (Mark, 1995):

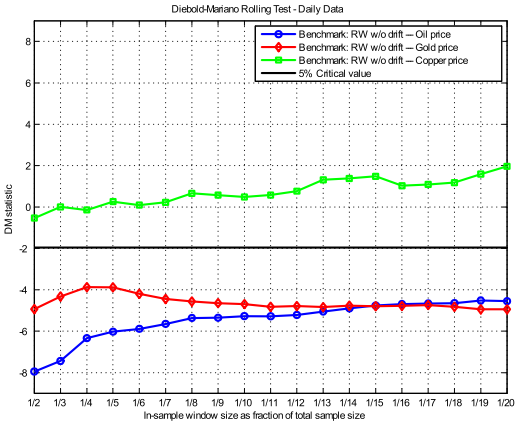
$$\Delta s_t = \alpha + \beta(p_{t-1} - s_{t-1}) + u_t, \quad t = 1, \ldots, T. \tag{6}$$

The empirical results, reported in Fig. 12, confirm our intuition. Panel A in the figure plots Diebold and Mariano's (1995) test statistic for comparing Model (6) to a random walk without drift (circles) and with drift (diamonds) in daily data, calculated for several in-sample window sizes (x-axis). Panels B and C, respectively, compare Model (6) to a random walk without drift in monthly and quarterly data (circles denote the random walk without drift benchmark case and diamonds denote the random walk with drift benchmark case). Negative values indicate that Model (6) forecasts better than the benchmark, i.e. when the test statistic is below the continuous line, Model (6) forecasts significantly better than the benchmark. Clearly, the figure shows that the cointegrated model never performs better than the benchmark. Second, regarding non-linearities, the recent debate on whether oil price changes have asymmetric effects on the economy motivates us to consider such models in our forecasting experiment (e.g. Kilian and Vigfusson, 2011; Herrera et al., 2010). We consider both a model with asymmetries, as in Kilian and Vigfusson (2011), where the exchange rate response is asymmetric in oil price increases and decreases, and a threshold model in which “large” changes in oil prices have additional predictive power for the nominal exchange rate. Our goal is to compare the forecasting ability of the nonlinear models with the linear model in Eq. (1). Unreported results show that, for the representative case of the Canadian-U.S. dollar exchange rate and oil prices, although both the model with asymmetries and the model with threshold effects are not rejected in-sample, their forecasting ability is worse than that of the linear model, Eq. (1) – see Ferraro et al. (2015) for details.

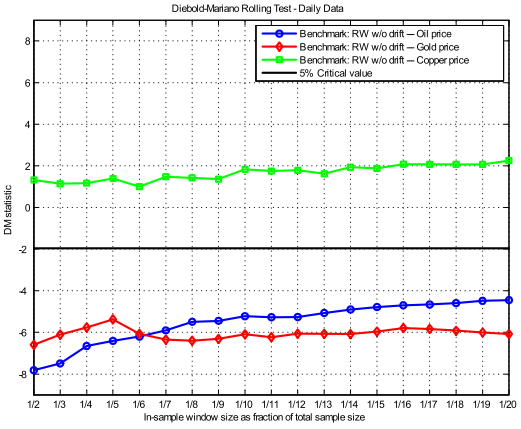
6. Conclusions

Our empirical results suggest that commodity prices can predict commodity currencies' exchange rates at a daily frequency, in the sense of having a stable “out-of-sample fit” relationship. However, the predictive ability is not evident at quarterly and monthly frequencies. When using contemporaneous realized daily commodity price changes to predict exchange rate changes, the predictive power of commodity prices is robust to the choice of the in-sample window size, and it does not depend on the sample period under consideration. When using the lagged commodity prices to predict exchange rates, the predictive ability is more ephemeral and appears only for some commodities and only in daily data after allowing the relative forecasting performance to be time-varying. Both the out-of-sample and in-sample analyses suggest that the frequency of the data is important to detect the predictive ability of commodity prices, as the out-of-sample predictive ability breaks down when considering monthly and quarterly data. We find that non-linearities and cointegration do not significantly improve upon the simple linear commodity price model.

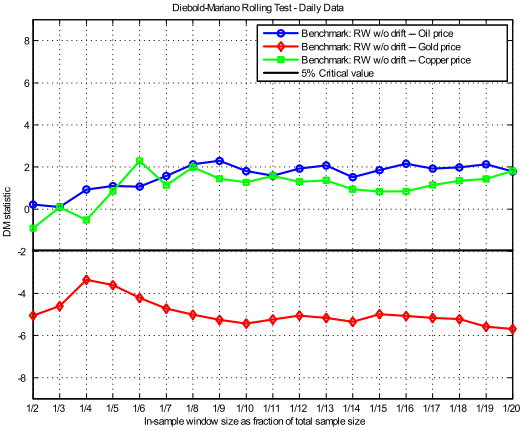
The Canadian dollar



The Norwegian krone



The South African rand



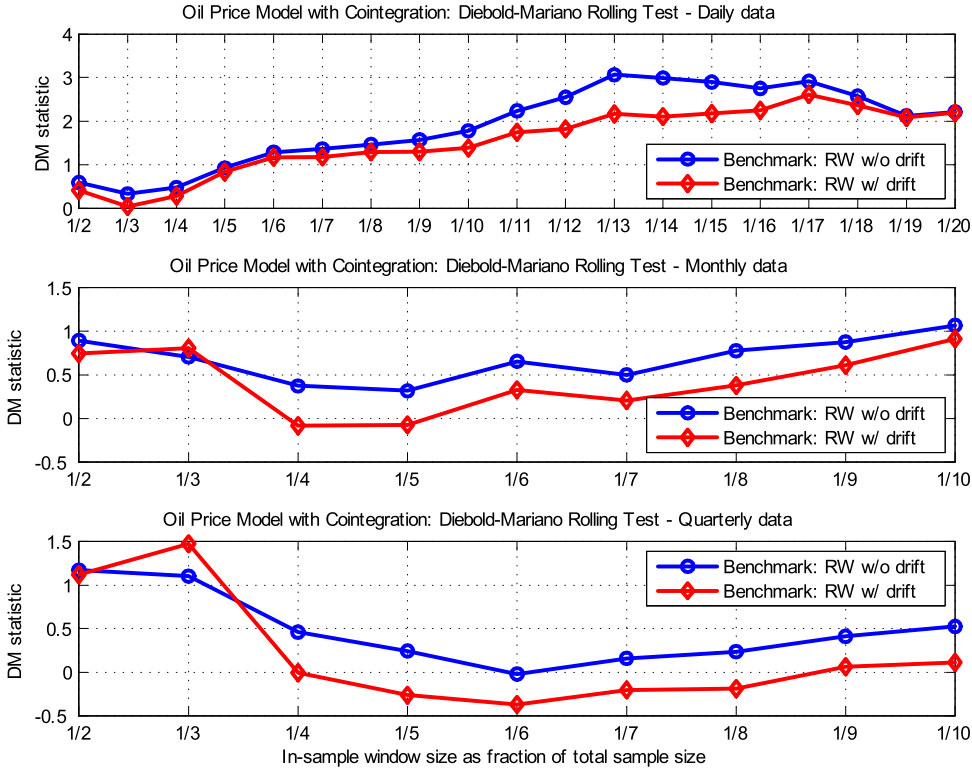


Fig. 12. Cointegrated Models. Notes: The figure plots Diebold and Mariano's (1995) test statistic for comparing Model (6) to a random walk without drift (circles) and with drift (diamonds) in daily data, calculated for several in-sample window sizes (x-axis). Negative values indicate that Model (6) forecasts better than the benchmark: when the test statistic is below the continuous line, Model (6) forecasts significantly better than the benchmark.

Our results suggest that the most likely explanations for why the existing literature has been unable to find evidence of predictive power in commodity prices are that researchers have focused on low frequencies where the short-lived effects of commodity prices wash away and that the predictive ability in commodity prices is very transitory. At the same time, our results also raise interesting questions. For example, does the Canadian-U.S. dollar exchange rate respond to demand or supply shocks to oil prices? It would be interesting to investigate this question by following the approach in Kilian (2009). However, Kilian's (2009) decomposition requires a measure of aggregate demand shock, which is not available at the daily frequency. It would also be interesting to consider predictive ability at various horizons by adjusting the current exchange rate for recent changes in oil price over a longer period (e.g. a week). We leave these issues for future research.

Fig. 11. Predictability for Several Fundamentals and Countries. Notes: The figure plots Diebold and Mariano's (1995) test statistic for comparing Model (1) to a random walk without drift in daily data, calculated for several in-sample window sizes (x-axis). The in-sample window size is reported as a fraction of the total sample size. The top panel reports results for the Canadian dollar, the middle panel reports results for the Norwegian krone and the bottom panel reports results for the South African rand, all relative to the U.S. dollar. The continuous line indicates the critical value of Diebold and Mariano's (1995) test statistic. Negative values indicate that Model (1) outperforms the benchmark. When the test statistic is below the continuous line Model (1) forecasts significantly better. In each panel, the line with circles refers to the model with the oil price fundamentals, the line with diamonds refers to gold prices and the line with squares refers to copper prices.

Acknowledgments

We thank K. Sheppard and D. Wang for providing data, R. Alquist, H. Guay, L. Guerrieri, A. Herrera, M. Chinn, L. Kilian, M. Obstfeld, J. Wright and participants at the 2011 Bank of Canada-ECB conference on "Exchange Rates and Macroeconomic Adjustment", 2012 AEA Meetings, 2012 "Exchange Rates" Conference (Duke U.), 2012 NBER Meeting on Commodity Markets (Stanford), the "Monetary Policy and Commodity Prices" Conference (ECB and Norges Bank), MAF conference, 2013 SNDE Conference, Graduate Institute of International and Development Studies in Geneva, Carlos III, and Paris School of Economics for comments.

References

Alquist, R., Kilian, L., Vigfusson, R.J., 2011. Forecasting the price of oil. In: Elliott, G., Timmermann, A. (Eds.), Handbook of Economic Forecasting, vol. 2. Elsevier.
Amano, R., Van Norden, S., 1998a. Exchange rates and oil prices. Rev. Int. Econ. 6 (4), 683–694.
Amano, R., Van Norden, S., 1998b. Oil prices and the rise and fall of the U.S. real exchange rate. J. Int. Money Finance.
Andersen, T., Bollerslev, T., Diebold, F.X., Vega, C., 2003. Micro effects of macro announcements: real-time price discovery in foreign exchange. Am. Econ. Rev. 93, 38–62.
Berkowitz, J., Giorgianni, L., 2001. Long-horizon exchange rate predictability? Rev. Econ. Stat. 83, 81–91.
Büyükşahin, B., Robe, M.A., 2014. Speculators, commodities and cross-market linkages. J. Int. Money Finance 42.
Cayen, J.P., Coletti, D., Lalonde, R., Maier, P., 2010. What Drives Exchange Rates? New Evidence from a Panel of U.S. Dollar Exchange Rates. Bank of Canada W.P., pp. 2010–2015
Chaboud, A., Chernenko, S., Wright, J., 2008. Trading activity and macroeconomic announcements in high-frequency exchange rate data. J. Eur. Econ. Assoc. 6, 589–596.
Chen, Y., Rogoff, K.S., 2003. Commodity currencies. J. Int. Econ. 60, 133–169.
Chen, Y., Rogoff, K.S., Rossi, B., 2010. Can exchange rates forecast commodity prices? Q. J. Econ. forthcoming.
Chinn, M.D., Meese, R.A., 1995. Banking on currency forecasts: how predictable is change in money? J. Int. Econ. 38, 161–178.
Cheung, Y.W., Chinn, M.D., Pascual, A.G., 2005. Empirical exchange rate models of the nineties: are any fit to survive? J. Int. Money Finance 24, 1150–1175.
Clark, T., West, K.D., 2006. Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. J. Econ. 135, 155–186.
Diebold, F.X., Mariano, R., 1995. Comparing predictive accuracy. J. Bus. Econ. Stat. 13, 253–263.
Engel, C., West, K.D., 2005. Exchange rates and fundamentals. J. Polit. Econ. 113 (3), 485–517.
Engel, C., Mark, N., West, K.D., 2007. Exchange rate models are not as bad as you think. In: Acemoglu, D., Rogoff, K.S., Woodford, M. (Eds.), NBER Macroeconomics Annual. MIT Press.
Evans, M.D., Lyons, R., 2002. Order flow and exchange rate dynamics. J. Polit. Econ. 110 (1), 170–180.
Evans, M.D., Lyons, R., 2005. Meese-Rogoff Redux: micro-based exchange rate forecasting. Am. Econ. Rev. Pap. Proc. 95, 405–414.
Faust, J., Rogers, J.H., Wright, J.H., 2003. Exchange rate forecasting: the errors we've really made. J. Int. Econ. 60 (1), 35–59.
Faust, J., Rogers, J.H., Wang, S.-Y.B., Wright, J.H., 2007. The high-frequency response of exchange rates and interest rates to macroeconomic announcements. J. Monet. Econ. 54, 1051–1068.
Ferraro, D., Rogoff, K., Rossi, B., 2015. Can Oil Prices Forecast Exchange Rates?. BGSE WP at. http://www.econ.upf.edu/~brossi/OilAndExchangeRates.pdf.
Fratzscher, M., Schneider, D., Van Robays, I., 2013. Oil Prices, Exchange Rates and Asset Prices. CESifo W.P 4264, Munich.
Giacomini, R., White, H., 2006. Tests of conditional predictive ability. Econometrica 74 (6), 1545–1578.
Giacomini, R., Rossi, B., 2010. Forecast comparisons in unstable environments. J. Appl. Econ. 25 (4), 595–620.
Groen, J.J.J., Pesenti, P.A., 2011. Commodity prices commodity currencies and global economic developments. In: Commodity Prices and Markets, East Asia Seminar on Economics, vol. 20, pp. 15–42.
Hau, H., Rey, H., 2004. Can portfolio rebalancing explain the dynamics of equity returns, equity flows, and exchange rates? Am. Econ. Rev. 94 (2), 126–133.
Herrera, A.M., Lagalo, L.G., Wada, T., 2010. Oil price shocks and industrial production: is the relationship linear? mimeo, Wayne State U.
Inoue, A., Rossi, B., 2012. Out-of-sample forecast tests robust to the window size choice. J. Bus. Econ. Stat. 30 (3), 432–453.
Issa, R., Lafrance, R., Murray, J., 2008. The turning black tide: energy prices and the Canadian Dollar. Can. J. Econ. 41 (3), 737–759.
Kilian, L., 1999. Exchange rates and monetary fundamentals: what do we learn from long-horizon regressions? J. Appl. Econ. 14, 491–510.
Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. Am. Econ. Rev. 99 (3), 1053–1069.
Kilian, L., Vega, C., 2011. Do energy prices respond to U.S. macroeconomic news? A test of the hypothesis of predetermined energy prices. Rev. Econ. Stat. 93 (2), 660–671.
Kilian, L., Vigfusson, R., 2011. Are the responses of the U.S. economy asymmetric in energy price increases and decreases? Quant. Econ. 2 (3), 419–453.
Maier, P., DePratto, B., 2008. The Canadian Dollar and Commodity Prices: has the Relationship Changed Over Time? Bank of Canada D.P, pp. 08–15.
Mark, N.C., 1995. Exchange rates and fundamentals: evidence on long-horizon prediction. Am. Econ. Rev. 85, 201–218.
Meese, R., Rogoff, K.S., 1983a. "Exchange rate models of the seventies. Do they fit out of sample? J. Int. Econ. 14, 3–24.

Meese, R., Rogoff, K.S., 1983b. "The out of sample failure of empirical exchange rate models. In: Frankel, J. (Ed.), Exchange Rates and International Macroeconomics. University of Chicago Press.
Meese, R., Rogoff, K.S., 1988. Was it real? The exchange rate-interest differential relation over the modern floating rate period. J. Finance 43, 923–948.
Molodtsova, T., Papell, D.H., 2009. Out-of-sample exchange rate predictability with Taylor rule fundamentals. J. Int. Econ. 77 (2), 167–180.
Molodtsova, T., Nikolsko-Rzhevskyy, A., Papell, D.H., 2008. Taylor rules with real-time data: a tale of two countries and one exchange rate. J. Monet. Econ. 55, S63–S79.
Obstfeld, M., 2002. Exchange rates and adjustment: perspectives from the new open-economy macroeconomics. Monet. Econ. Stud. 23–46.
Obstfeld, M., Rogoff, K.S., 1996. Foundations of International Macroeconomics. MIT Press.
Rogoff, K.S., 2007. Comment to: exchange rate models are not as bad as you think. In: Acemoglu, D., Rogoff, K.S., Woodford, M. (Eds.), NBER Macroeconomics Annual. MIT Press, Cambridge, MA.
Rogoff, K.S., Stavrakeva, V., 2008. The Continuing Puzzle of Short-horizon Exchange Rate Forecasting. NBER W.P. 14071.
Rossi, B., 2005. Testing long-horizon predictive ability with high persistence, and the Meese-Rogoff Puzzle. Int. Econ. Rev. 46 (1), 61–92.
Rossi, B., 2006. Are exchange rates really random walks. Macroecon. Dyn. 10 (1), 20–38.
Rossi, B., 2007. Comment to: exchange rate models are not as bad as you think. In: Acemoglu, D., Rogoff, K.S., Woodford, M. (Eds.), NBER Macroeconomics Annual. MIT Press.
Rossi, B., 2013. Exchange rate predictability. J. Econ. Lit. 51 (4), 1063–1119.
Wang, J., Wu, J., 2008. The Taylor Rule and Forecast Intervals for Exchange Rates. Federal Reserve Bank of Dallas W.P. 22.
West, K., 1996. Asymptotic inference about predictive ability. Econometrica 64, 1067–1084.