NBER WORKING PAPER SERIES

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Working Paper 17998
http://www.nber.org/papers/w17998

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2012

We would like to thank K. Sheppard and D. Wang for providing data related to this project, as well as R. Alquist, H. Guay, 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", the 2012 American Economic Association Meetings and the Paris School of Economics for comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 17998
April 2012, Revised April 2012
JEL No. C22,C53,F31,F37

ABSTRACT

This paper investigates whether oil prices have a reliable and stable out-of-sample relationship with the Canadian/U.S dollar nominal exchange rate. Despite state-of-the-art methodologies, we find little systematic relation between oil prices and the exchange rate at the monthly and quarterly frequencies. In contrast, the main contribution is to show the existence of a very short-term relationship at the daily frequency, which is rather robust and holds no matter whether we use contemporaneous (realized) or lagged oil prices in our regression. However, in the latter case the predictive ability is ephemeral, mostly appearing after instabilities have been appropriately taken into account

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1 Introduction

In this paper, we focus on a particular commodity price, namely, oil prices, to predict the fluctuations in the U.S.-Canada's nominal exchange rates in a pseudo out-of-sample forecast experiment.[1] Our results suggest that, despite incredibly refined and clean data, we find paradoxically little systematic relation between oil prices and the exchange rate if one takes the monthly and quarterly frequencies into account. In contrast, the very short-term relationship between oil and exchange rates is rather robust. The novelty of our approach is to consider data at daily frequencies that capture the contemporaneous short-run movements in these variables, as well as to allow for time variation in the relative performance of the models. Our results indicate that contemporaneous realized oil prices do predict daily nominal exchange rates between Canada and the U.S., and their predictive ability is strongly significant. On the other hand, the predictive ability of the lagged realized oil prices is more ephemeral, and allowing for time variation in the relative performance is crucial to show that lagged commodity prices are statistically significant predictors of exchange rates out-of-sample. It is noteworthy that, although in-sample fit is stronger in monthly and quarterly data than in daily data, the out-of-sample predictive ability result breaks down for monthly or quarterly data, thus suggesting that not only the predictive ability is transitory, but also that the effects of oil price changes on exchange rates are short-lived and that the frequency of the data is crucial to capture them.

Although the main focus is on the Canadian-U.S. dollar exchange rate and oil prices, due to the availability of data and its importance in the press,[2] we demonstrate that similar

[1]Our study focuses on Canada for three reasons. The first is that crude oil represents a substantial component of Canada's total exports. The second is that 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 serve as an observable and essentially exogenous terms-of-trade shock for the Canadian economy.

[2]For example, see the Wall Street Journal ("Canadian Dollar Slumps, Weighed Down By Softer CPI, Oil Prices," January 25, 2011, at http://online.wsj.com/ article/BT-CO-20110125 -714898.html) and "Canadian Dollar Foreign Exchange Pushes Higher on Oil Prices," at http://www.foreignexchangeservice.co.uk/foreign-exchange-america/canada/01/2011/canadian-dollar-foreign-exchange-rate-pushes-higher-on-

results hold for other commodity prices/exchange rates. In particular, for the Norwegian krone-U.S. dollar exchange rate and oil prices, we find significant predictive ability of both contemporaneous and lagged oil prices. Similar results hold for the South African rand-U.S. dollar exchange rate and gold prices. For the Australian-U.S. dollar and oil prices and the Chilean peso-U.S. dollar exchange rate and copper prices, we find strong and significant predictive ability only with contemporaneous commodity prices as predictors.[3] Our result holds for in-sample daily data as well. We conjecture that the mechanism leading to this result is the fact that, for a small open economy exporting oil, the exchange rate should reflect fluctuations in oil prices (see Obstfeld and Rogoff, 1996). The effects of changes in oil prices are immediately translated into changes in exchange rates and are very short-lived. This sheds light on why our out-of-sample forecasts are significant in daily data but not at monthly or quarterly frequencies.

To further study the link between oil prices and exchange rates, in addition to a simple regression of exchange rates on oil prices, we consider the asymmetric model by Kilian and Vigfusson (2009) as well as a threshold model where the oil price has asymmetric effects on the nominal exchange rate. Both the asymmetric and threshold model do not provide significantly better forecasts than the simple benchmark model. This result seems to suggest that, as in Kilian and Vigfusson (2009), asymmetries are not too relevant.

Our empirical results are noteworthy and provide clear evidence of a short-term relationship between oil prices and exchange rate fluctuations, somewhat parallel to the very high frequency relationship people have found between unanticipated Federal Reserve interest rate, macroeconomic announcements and exchange rates. For example, Andersen et al. (2003) have shown that macroeconomic news announcements are associated with jumps in exchange rates at high frequencies. Faust, Rogers, Wang and Wright (2007) study the response of the U.S. dollar and the term structure of interest rates to macro news announcements in high frequency data. When comparing our results to theirs, we show that including

oil-prices.html.

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

macroeconomic news announcements in addition to oil prices does not improve forecasts of the Canadian-U.S. dollar exchange rate fluctuations. Our results are also related to Kilian and Vega (2008) and Chaboud, Chernenko and Wright (2008). The former show that macroeconomic news announcements do not contemporaneously predict oil prices at either daily or monthly frequencies, whereas we show that oil prices do predict exchange rates. The latter examine the high frequency relationship between macro news announcements and trading volumes in foreign exchange markets, whereas we focus on the relationship between oil price changes and nominal exchange rates in daily data.

Our paper is clearly also related to the literature on using commodity prices/indices (in particular, oil prices) to predict exchange rates. In particular, in a very recent paper Chen, Rogoff and Rossi (2010) find that exchange rates of commodity currencies predict primary commodity prices both in-sample and out-of-sample; however, the out-of-sample predictive ability in the reverse direction (namely, the ability of the commodity price index to predict nominal exchange rates) is not strong at the quarterly frequency that they consider. Other papers have considered oil prices or more general commodity prices as exchange rate determinants, but mostly as *in-sample* explanatory variables for *real* exchange rates, whereas in this paper we consider *out-of-sample* predictive ability for *nominal* exchange rates. Amano and Van Norden (1995, 1998a,b), Issa, Lafrance and Murray (2008) and Cayen et al. (2010) consider the in-sample relationship between real oil prices and the real exchange rate; 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[4] – see Alquist, Kilian and Vigfusson (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.

More generally, our paper is related to the large literature on predicting nominal exchange

[4]Note that our paper significantly extends the scope of Chen and Rogoff (2003) by showing that oil prices have significant predictive ability in forecasting *nominal* exchange rates *out-of-sample.* Chen and Rogoff (2003) find a stronger in-sample correlation when using a non-energy price index, but their data are not available at daily frequencies.

rates using macroeconomic fundamentals.[5] In particular, empirical evidence in favor of the predictive ability of macroeconomic fundamentals has been found mainly at longer horizons (see Mark, 1995; Chinn and Meese, 1995; Cheung, Chinn and Pascual, 2005, and Engel, Mark and West, 2007), although inference procedures have been called into question (see Kilian, 1999; Berkowitz and Giorgianni, 2001; Rogoff, 2007; and Rossi, 2005, 2007). There is, however, some empirical evidence that models with Taylor rule fundamentals may have some predictive ability (Wang and Wu, 2008, Molodtsova and Papell, 2009; and Molodtsova, Nikolsko-Rzhevskyy and Papell, 2008). See also Faust, Rogers and Wright (2003), Kilian and Taylor (2003) and Engel, Mark and West (2007) for additional empirical evidence on predictive ability at longer horizons. Our paper focuses instead on short-horizon predictive ability, for which the empirical evidence in favor of the economic models has been more controversial. In particular, Cheung, Chinn and Pascual (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 oil prices contain valuable information for predicting exchange rates out-of-sample in a country that is a significant oil exporter. 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, Rogers and Wright (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 fundamentals used in their paper (such as output, prices, money supply and the current account).

The paper is organized as follows. Section 2 describes the data. Section 3 shows our main

[5]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, Mark, Engel and West (2007), Rogoff (2007) and Rogoff and Stavrakeva (2008). Predictive ability, when it exists, is unstable over time (see Rossi, 2006, and Giacomini and Rossi, 2010).

empirical results for the contemporaneous oil price model, and Section 4 reports results for the lagged oil price model. Section 5 extends the analysis to other commodity prices and currencies, and Section 6 presents the empirical results for more general oil price models that allow for asymmetries and threshold effects. Section 7 concludes.

2 Data Description

Our study focuses on Canada for three reasons. The first is that crude oil represents 21.4 percent of Canada's total exports over the period 1972Q1-2008Q1. 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 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 crude oil. West Texas Intermediate (WTI) is 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. 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.[6] 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 focus to daily data and provides a clean comparison of the results for

[6] Note that we focus on end-of-sample data because we are interested in relating our work to the previous literature, according to which it is harder to find predictive ability using end-of-sample data than using average-over-the-period data. Since the puzzle in the literature is lack of predictive ability, we do not consider the latter. Note that our results are therefore a lower bound on the predictive ability one may be able to find.

the three frequencies. The data sample ranges from 12/14/1984 to 11/05/2010. 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.

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 and the U.S. short-term rate is the daily effective Federal funds rate. The series of the daily Canadian overnight money market financing rate is from the Bank of Canada, whereas the series of the Federal funds rate is 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.

We also extend our analysis to other currencies and commodities. The original series for 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 series for 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.[7]

3 Can Oil Prices Forecast Exchange Rate Movements?

In this section, we analyze the relationship between oil prices and exchange rates by evaluating whether oil prices have predictive content for future exchange rates. We first show that oil prices have significant predictive content in out-of-sample forecasts in daily data. The predictive content, however, is much weaker at monthly frequencies and completely

[7] 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.

disappears at quarterly frequencies.

The finding that oil prices do forecast nominal exchange rates overturns an important conventional result in the literature, namely, the fact that nominal exchange rates are unpredictable. It is therefore crucial to understand the reasons why we find predictability. We will show that: (i) predictability is very short-lived: it appears at daily frequencies but is much weaker at monthly frequencies and non-existent at quarterly frequencies; (ii) the predictability at daily frequencies is specific to oil prices and does not extend to other traditional fundamentals such as interest rates; (iii) predictability is extremely reliable, in the sense that it does not depend on the sample period; (iv) the predictability is not due to a Dollar effect and it is robust to controlling for macro news shocks; (v) in addition, we verify that the predictability is present not only out-of-sample but also in-sample. While this section focuses on the contemporaneous predictive content of oil prices, based on realized oil prices as predictors in the out-of-sample forecasting exercise, the next section verifies the robustness of the results to actual ex-ante predictive content by using lagged oil prices as predictors.

3.1 Out-of-Sample Forecasts with Realized Fundamentals

We first assess the out-of-sample predictive ability of oil prices. We focus on the simplest oil price model:[8]

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

where Δs_t and Δp_t are the first difference of the logarithm of respectively the Canadian-U.S. dollar exchange rate[9] and the oil price, 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

[8]Note that one could consider other econometric specifications, such as cointegrated models. Note that the gains of cointegrated models typically are important at lower frequencies; therefore we do not consider them, being the focus of this paper on high frequency data.

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

un-modelled set of variables – see West (1996).[10] Important examples of the use of such a technique include Meese and Rogoff (1983a,b) and Cheung, Chinn and Pascual (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. Another example of the use of such technique is Andersen et al. (2003), who used realized macroeconomic announcements to predict exchange rates. One of the objectives of this paper is to show that the use of a different fundamental, namely, oil prices, can overturn the Meese and Rogoff's (1983a,b) finding at the daily frequencies, and link our paper to the literature on macroeconomic news announcements; we therefore use the same forecasting strategy. In a later section, we will assess the robustness of our results to models with lagged oil prices.

We estimate the parameters of the model with rolling in-sample windows and produce a sequence of one-step-ahead pseudo out-of-sample forecasts conditional on the realized value of the commodity prices.[11] Let Δs^f_{t+1} denote the one-step-ahead pseudo out-of-sample forecast:

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

where $\widehat{\alpha}_t, \widehat{\beta}_t$ are the parameter estimates obtained from a rolling sample of observations $\{t-R+1, t-R+2, ..., t\}$, 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 oil 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 future changes in the oil price, since they depend on political decisions and unpredictable supply shocks. If we were to use past values of oil prices in our experiment, and the past values of oil prices were not good forecasts of future values of oil prices, we would end up rejecting the predictive ability of oil prices even though the reason for the lack of predictive ability is not the absence of a relationship between exchange rates and oil 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 oil prices. It is important to note, however, that our exercise

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

[11] Table A.1 in the Appendix shows that our results are robust to using a recursive forecasting scheme.

is not a simple in-sample fit exercise: we attempt to fit future exchange rates out-of-sample, which is a notably difficult enterprise.

We compare the oil 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: Meese and Rogoff (1983a,b) considered both; in a very important paper, 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.

We implement the Diebold and Mariano (1995) test of equal predictive ability by comparing the Mean Squared Forecast Errors (MSFEs) of the oil price model with those of the two benchmarks. Note that even though our models are nested, we can use the Diebold and Mariano (1995) test 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). As we show at the end of this section, using the alternative test by Clark and West (2006) would only strengthen our results in favor of the economic models.[12] Hence, our results can be interpreted as a conservative lower bound on the evidence of predictive ability that we find.

We test the null hypothesis of equal predictive ability with daily, monthly and quarterly data. Figure 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. When the Diebold and Mariano (1995) statistic is less than -1.96, we conclude that the oil price model forecasts better than the random walk benchmark. Figure 1 shows that, no matter the size of the in-sample window, the test strongly favors the model with oil prices. This result holds for both benchmarks: the random walk without drift (solid line with circles) and with drift (solid line with diamonds). Overall, we conclude that daily data show extremely robust results in

[12] Clark and West (2006) test the null hypothesis of equal predictive ability at the pseudo-true parameter values.

favor of the predictive ability of the oil price model.[13]

Our results show striking predictive ability relative to that reported in the literature. In particular, let's compare our results with those in Cheung, Chinn and Pascual (2005), who 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 significant at the 5% level, among all the models and currencies they consider, including the Canadian-U.S. Dollar! Why are we able to achieve such a remarkable success? The following sub-sections explore various explanations to answer this important question.

3.2 Why Are We Able to Find Predictive Ability?

Our empirical results greatly differ from the existing literature in two crucial aspects. First, we consider an economic fundamental for nominal exchange rates that is very different from those commonly considered in the literature, namely, oil prices. Second, we focus on a different data frequency, daily rather than monthly or quarterly. Therefore, it is important to understand whether it is the frequency of the data or the nature of the fundamental that drives our results.

In a first experiment we consider the model with oil prices but at the monthly and quarterly frequencies. Figure 1B shows Diebold-Mariano's (1995) test statistics for monthly and quarterly data, respectively. 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. Since previous research focused only on either monthly or quarterly data, this may explain why the existing literature never noticed the out-of-sample predictive ability in oil prices.

In a second experiment we consider a model with traditional fundamentals. Traditional fundamentals include interest rate, output and money differentials (see Meese and Rogoff,

[13] 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. 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.

1983a,b, 1988, and Engel, Mark and West, 2007). Since output and money data are not available at the daily frequency, we focus on interest rate differentials. That is, we consider the interest rate model:

$$\Delta s_t = \alpha + \beta \Delta i_t + \mu_t \tag{2}$$

where Δi_t are the first difference of the interest rate differential between Canada and the U.S., and μ_t is an unforecastable error term.

Figure 2 reports the results. Panel A in Figure 2 shows that the interest rate model never forecasts better than the random walk benchmark; if anything, the random walk without drift benchmark is almost significantly better. Panels B and C show that similar results hold at the monthly and quarterly frequencies.

Since in daily data we do find predictive ability when using oil price changes as predictor but not when using interest rates as predictors, we conclude that the reason why we are able to find predictive ability is the new fundamental that we consider (the oil price) rather than the frequency of the data.

Frequency vs. Length of the Sample: Which One Matters?

In order to check whether the improved out-of-sample predictive ability at daily frequency is due to the higher frequency of the data or to 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 1 reports the results. Panel A compares daily and monthly frequencies. The 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. This means that the evidence in favor of predictive ability is much stronger in daily than in monthly data.[14] Panel B compares daily and quarterly frequencies. The Diebold and Mariano's (1995) test statistics against a random walk without drift is still significant in daily data: it equals -2.11, which implies a p-value of 0.03. For quarterly data, instead, the statistic is -1.79, and it is not significant. This means that the

[14]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.

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 observations is the same, the daily oil price model outperforms the monthly and quarterly oil price model out-of-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.[15]

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) demonstrate that macroeconomic news announcements do predict exchange rates at the daily frequency.[16] They use the International Money Market Services real-time database, which contains both expected and realized macroeconomic fundamentals, and define the "macroeconomic news announcement shock" as the difference between the two. They show, using contemporaneous in-sample regressions in 5-minute data, that macroeconomic news announcements produce significant jumps in exchange rates. It is natural to wonder whether oil prices are a better predictor for exchange rate changes than macroeconomic news announcements.[17]

To investigate this issue, we consider the following model based on Andersen et al. (2003):

$$\Delta s_t = \alpha + \beta \Delta p_t + \sum_{k=1}^{K} \gamma_k S_{k,t} + u_t, \text{ for } t = 1, ..., T, \tag{3}$$

where $S_{k,t}$ is the $k - th$ macroeconomic news announced at time t. The only difference

[15]Unreported results show that the predictive ability is still significant when predicting daily exchange rate changes *one-month-ahead* with realized oil price changes. Thus, our results are also quite robust to longer forecast horizons. However, predicting monthly exchange rate changes is much more difficult, since shocks average out over lower frequencies.

Alternatively, one could run Monte Carlo simulations to evaluate the effects of the sample length in small samples.

[16]We consider daily data and not 5-minutes data due to concerns of micro-structure noise.

[17]Interesting work by Evans and Lyons (2002) has shown that order flows are a good predictor for exchange rates. However, as discussed in Andersen et al. (2003), it leaves us ignorant about the macroeconomic determinants of order flows. In this paper, we focus on macroeconomic determinants of exchange rates, as in Andersen et al. (2003).

with Andersen et al. (2003) is that we include oil price changes among the regressors. We consider the same macroeconomic announcements as in Andersen et al. (2003), which include the unemployment rate, consumer price index, leading indicators change in non-farm payrolls and industrial production, among others. We consider a total of 32 macroeconomic announcements.[18] Table 2 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). We report results for four window sizes equal to either half, a third, a fourth or a fifth of the total sample size. Panel A report results for the model with macroeconomic news, eq. (3), whereas panel B report results for the model with only oil prices, eq. (1). The results show that the model with oil prices only forecasts better (relative to a random walk) than a model that includes both oil prices and macroeconomic fundamentals. Unreported results show that the performance of a 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.

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 analysis focuses on the U.S. Dollar-Canadian Dollar exchange rate, one might expect a correlation due to 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.[19] We collected data on the Canadian Dollar-British Pound exchange rate from WM Reuters. Our sample, which is limited by data availability, is shorter than the Canadian Dollar-U.S.

[18] More in detail, the announcements that we consider involve the following: Unemployment Rate, Consumer Price Index, Durable Goods Orders, Housing Starts, Leading Indicators, Trade Balance, Change in Nonfarm Payrolls, Producer Price Index, Advance Retail Sales, Capacity Utilization, Industrial Production, Business Inventories, Construction Spending MoM, Consumer Confidence, Factory Orders, NAPM/ISM Manufacturing, New Home Sales, Personal Consumption, Personal Income, Monthly Budget Statement, Consumer Credit, Initial Jobless Claims, GDP Annualized Advanced, GDP Annualized Preliminary, GDP Annualized Final, CPI Ex Food and Energy month-on-month (MoM), PPI Ex Food and Energy MoM, Average Hourly Earnings MoM, Retail Sales Less Autos, as well as three measures of the GDP Price Index/GDP Price Deflator.

[19] We thank M. Chinn for raising this issue.

Dollar used previously: starts on 9/15/1989 and ends in 9/16/2010. Table 3 reports the value of the Diebold and Mariano's (1995) test statistic for various in-sample window sizes, reported in the column labeled "Window". The table shows that our results are robust, since the predictive ability is present in daily data even if we use an exchange rate that does not involve the U.S. Dollar.[20]

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 – see Mork (1989), Hamilton (1996) and Hooker (1996). In particular, Mork (1989) found that the behavior of GNP growth is unstable and indeed correlated with the state of the oil market. Hooker (1996) provided sub-sample analyses and also found empirical evidence of structural instability. In addition, Maier and DePratto (2008) have noticed in-sample parameter instabilities in the relationship between the Canadian exchange rate and commodity prices. Since our focus is on out-of-sample forecasting ability, 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. Panel A in Figure 3 shows the Fluctuation test for daily data. 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 reject the null hypothesis of equal predictive ability at each point in time and conclude that the oil price model forecasts better in some periods. Visual inspection of the graph suggests that the oil price model performs significantly better than the random walk after 2005. Panels B and C in Figure 3 show the results of the Fluctuation test for monthly and quarterly data.

[20]The predictive ability, however, depends on the window size, and seems to disappears for window sizes that are very small; this might be due to the fact that the sample of data for the Canadian Dollar/British Pound is shorter.

For monthly and quarterly data, the in-sample window size is the same as in daily data and equals one-half of the total sample, whereas the out-of-sample window is chosen to be the same across frequencies. At the monthly and quarterly frequencies we do not detect significant predictive ability improvements of the oil price model over the random walk.

In-sample Fit and Clark and West's (2006) Out-of-Sample Test Analysis

To assess whether the out-of-sample predictive ability is related to the in-sample fit of the models, we estimate the oil price model, eq. (1), over the entire sample period with daily, monthly and quarterly data. Panel A in Table 4 shows empirical results. 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 monthly, and especially quarterly, frequencies does not translate into superior out-of-sample forecasting performance.[21] The main conclusion that we can draw from the in-sample analysis is 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.

Finally, we investigate the robustness of our results using the Clark and West's (2006) test statistic. Results are reported in Panel A in Table 5. 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 (2005) test.

The Importance of Timing

Our results have shown that there is a strong and significant contemporaneous relationship between oil prices and exchange rates which disappears when considering monthly or quarterly data. The reason why such relationship is much weaker at low frequencies is because when there are oil price shocks, typically exchange rates react very quickly, and it is therefore essential that the researcher focuses on daily frequencies (or high frequencies) to capture the relationship. If instead the researcher focuses on monthly or quarterly data,

[21] Panel B in Table 1 reports in-sample estimates of the interest rate model, eq. (2). The coefficient on the interest rate is never significant at any of the frequencies.

spikes in oil prices and exchange rates would be much harder to identify in the data, as they would be washed out in the sample.

To analyze the data more in detail, let's focus on an episode of a significant change in oil prices, such as July 11, 2008. The episode is selected because it is one of the largest drops in oil prices which is not immediately followed by a subsequent increase that would cancel the drop. In other words, it is a significant episode of oil price depreciation when defined as a net oil price decrease relative to the previous 30 minutes. The top panel in Figure 4 plots oil prices (in levels); the x-axis reports the minutes at 15:00h (3PM) of that day, from 15h:25 to 15h:55. The bottom panel in Figure 4 plots the exchange rate (in levels) at the same time. Clearly, oil prices reached their highest level that day at 15h:32 and then started to drop at 15h:33; at the same time, the exchange rate reaches its lowest point at 15h:32 and starts appreciating exactly at 15h:33. If the researcher considers monthly data, the contemporaneous relationship would not appear, even in population, since both oil prices and exchange rates undergo several changes during the month and the drop becomes unnoticeable.

4 Can Lagged Oil Prices Forecast Exchange Rates?

The previous section focused on regressions where the realized value of oil price changes are used to predict exchange rates contemporaneously. In reality, forecasters would not have access to realized values of oil 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 oil 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) oil price changes have predictive content for future exchange rates. We first show that the predictive ability now depends on the estimation window size being more favorable to the model with lagged oil prices, but only for large in-sample estimation window sizes. We also find that the predictive ability is now 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 at the daily frequency. On the other hand, the same model at the monthly and quarterly frequencies never forecasts significantly better than the random walk. Also, using lagged interest rates never improves the forecasting ability relative to the random walk (with or without drift). The empirical evidence in favor of the model with lagged daily oil prices clearly demonstrates that it is important not only to consider daily frequencies but also to allow for the possibility that the relative forecasting performance of the models is time varying, as the predictive ability is very transitory.

We focus on the following model with lagged oil prices:

$$\Delta s_t = \alpha + \beta \Delta p_{t-1} + u_t,\ \ t = 1, ..., T, \tag{4}$$

where Δs_t and Δp_t, which are the first difference of the logarithm, denote the Canadian-U.S. dollar exchange rate and the oil 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. (4), 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: $\Delta s^f_{t+1} = \widehat{\alpha}_t + \widehat{\beta}_t \Delta p_t$, $t = R, R+1, ..., T-1$where $\widehat{\alpha}_t, \widehat{\beta}_t$ are the parameter estimates obtained from a rolling sample of observations $\{t-R+1, t-R+2, ..., t\}$, where 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. Panel A in Figure 5 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 (4) 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.[22]

Panel B in Figure 5 reports forecast comparisons for the same model, eq. (4), 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. However, Figure 6 demonstrates that, once we allow the relative performance of the models to be time-varying, the most interesting empirical results appear. Panel A in Figure 6 reports the Fluctuation test in daily data. It is clear that there is strong significant evidence in favor of the model with lagged prices, especially around 2007, both against the random walk with and without drift. Panels B and C show, instead, that there was *never* statistically significant empirical evidence in favor of the model for monthly and quarterly data (in particular, against the toughest benchmark, the driftless random walk).

Note that the predictive ability again disappears if we use other economic fundamentals, such as interest rates differentials. Figure 7 reports the same analysis for the model with lagged interest rate differentials:

$$\Delta s_t = \alpha + \beta \Delta i_{t-1} + \varepsilon_t. \tag{5}$$

Clearly, in this case, the model's forecasts never beat the random walk's forecasts, no matter what the estimation window size is.

Finally, Panel B in Table 5 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.

[22]Note that the MSFE ratio between the model and the random walk without drift is 0.99 for most window sizes.

5 Other Commodity Prices and Exchange Rates

In this section, 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. The sample we consider is from 1/3/1994 to 9/16/2010 and the data are from Datastream. We will show that in the Norwegian krone and the South African rand case, oil prices and gold prices, respectively, statistically improve 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 models. The predictive ability is present only for the contemporaneous regression model for the other countries/commodity prices.

Figure 8 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 (see Panel I) as well as in monthly data (see Panel II), 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. The Appendix shows that the predictive ability disappears in the model with lagged fundamentals (eq. 4) under the assumption that the relative performance of the models is constant over the entire out-of-sample span of the data. However, when allowing the models' forecasting performance to change over time (Panel III), the model with lagged regressors does forecast significantly better than the random walk benchmark. Note that the performance of the lagged regressor model in monthly and quarterly frequencies is never significantly better than the random walk benchmark even if we allow the forecasting performance to change over time (Panels B and C in Figure 8, III).

Figure 9 shows that similar results hold when considering the South African rand exchange rate and gold prices. Panel I 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 II demonstrates that fluctuations in gold prices never improve the predictive ability over a random walk model. Interestingly, again, unreported results show that the model with lagged data never performs better than the random walk when we do not allow for time variation, regardless of the frequency of the data. However, when we allow for time variation (Panel III), it is clear that the model beats the driftless random walk (although it does not beat the random walk with drift) in daily data (Panel A); there is some evidence that the model also beats the driftless random walk at the quarterly frequency, but not at the monthly frequency (Panels B,C).

Figure 10(I), 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. Figure 10(II), demonstrates that such predictive ability becomes statistically insignificant when considering end-of-sample monthly and quarterly data. However, the forecasting performance disappears in the lagged regressor model even if we allow for time variation in the forecasting performance (Panel III). Results are very similar when considering predicting the Australian-U.S. dollar and oil prices – see Figure 11.[23]

6 Non-Linear Models

The recent debate on whether oil price changes have asymmetric effects on the economy motivates us to consider such models in our forecasting experiment. Hamilton (2003) found significant asymmetries of oil price changes on output. In a comprehensive study, Kilian and Vigfusson (2009) found no evidence against the null of symmetric response functions in U.S. real GDP data. Additional results in Kilian and Vigfusson (2011) (based on a longer data set) showed some empirical evidence of asymmetries in the response of real GDP to

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

very large shocks, but none in response to shocks of normal magnitude. Thus, most of the times the linear symmetric model provides a good enough approximation. Herrera, Lagalo and Wada (2010) discuss similar findings for U.S. aggregate industrial production. However, they found stronger evidence of asymmetric responses at the sectoral level than in aggregate data. Clearly, the presence (or absence) of asymmetries depends on the sample. In this section, we evaluate whether it is possible to improve upon the simple oil price model by using non-linear models that account for the asymmetric effects of oil prices. We focus on predicting exchange rates using realized oil prices. The reason is as follows: if we do not find predictive ability even for contemporaneous fundamentals, which is the easiest case to find predictability, we will not find predictive ability with lagged fundamentals either.

The model with asymmetries follows Kilian and Vigfusson (2009). We consider a model where the exchange rate response is asymmetric in oil price increases and decreases:

$$\Delta s_t = \alpha_+ + \beta_+ \Delta p_t + \gamma_+ \Delta p_t^+ + u_t \tag{6}$$

where $\Delta p_t^+ = \begin{cases} \Delta p_t \text{ if } \Delta p_t > 0 \\ 0 \text{ otherwise.} \end{cases}$ Our goal is to compare the forecasting ability of the model with asymmetries (6) with the linear model in eq. (1).[24]

In addition, we also consider a threshold model in which "large" changes in oil prices have additional predictive power for the nominal exchange rate:

$$\Delta s_t = \alpha_q + \beta_q \Delta p_t + \gamma_q \Delta p_t^q + u_t \tag{7}$$

where Δp_t^q equals Δp_t if $\Delta p_t > 80th$ quantile of Δp_t or$< 20th$ quantile of Δp_t, and equals 0 otherwise; the quantiles of Δp_t are calculated over the full sample.[25]

We focus again on the representative case of the Canadian-U.S. dollar exchange rate and oil prices. To preview our findings, the empirical evidence shows that, although both the

[24] See also Kilian (2008a,b) for analyses of the effects of oil price shocks on typical macroeconomic aggregates, such as GDP, and Bernanke, Gertler and Watson (1997), Hamilton and Herrera (2004), Herrera (2008) and Herrera and Pesavento (2009) on the relationship between oil prices, inventories and monetary policy.

[25] We calculate the thresholds over the full sample to improve their estimates. While this gives an unfair advantage to the threshold models at beating the simple model, we still find that, even with the best estimate of the threshold, the model does not beat the simple linear model, eq. (1).

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). We focus on the model with contemporaneous regressors; the Appendix shows that the same results hold when using lagged non-linear explanatory variables. Figure 12, Panel A, reports the results for the asymmetric model and the threshold model for daily data. Both figures show the test statistic for testing the difference in the MSFEs of either model (6) or model (7) versus the MSFE of the linear model, eq. (1). The figure reports the test statistics calculated using a variety of sizes for the in-sample estimation window, whose size relative to the total sample size is reported on the x-axis. Negative values in the plot indicate that the linear model, eq. (1), is better than the competitors. Panel B in Figure 12 reports results for monthly and quarterly data.

In general the simple oil price model outperforms the asymmetric model. Regarding the threshold model, the evidence is not clear cut. The threshold model is statistically better than the simple oil price model when the in-sample window size is large, whereas the result is the opposite when it is small. Figure 12 shows that for monthly and quarterly data the non-linear models are never statistically better than the simple linear model, and the linear model is significantly better than the non-linear models for some window sizes.[26]

7 Conclusions

Our empirical results suggest that oil prices can predict the Canadian-U.S. dollar nominal exchange rate at a daily frequency, in the sense of having a stable out-of-sample relationship. However, the predictive ability is not evident at quarterly and monthly frequencies. When using contemporaneous realized daily oil prices to predict exchange rates, the predictive power of oil 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 oil prices to predict

[26]To evaluate whether forecast instabilities are important, we also implemented Fluctuation tests. The Appendix reports the results of the Fluctuation test for both the asymmetric and threshold models at all frequencies. The figures show that the asymmetric and threshold models are never statistically better than the linear oil price model at any point in time.

exchange rates, the predictive ability is more ephemeral and shows up only in daily data after allowing the relative forecasting performance of the oil price model and the random walk 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 oil prices, as the out-of-sample predictive ability breaks down when considering monthly and quarterly data. Following Kilian and Vigfusson (2009), we also consider two models aimed at modeling potentially important non-linearities in the oil price-exchange rate relationship. We find that non-linearities do not significantly improve upon the simple linear oil price model.

Our results suggest that the most likely explanations for why the existing literature has been unable to find evidence of predictive power in oil prices are that researchers have focused on low frequencies where the short-lived effects of oil prices wash away and that the predictive ability in oil 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.

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Figures and Tables

Table 1. Frequency Versus Number of Observations

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

Notes. The table reports the Diebold and Mariano's (1995) test statistics (with p-values in parentheses) calculated with a similar 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 (column labeled "RW w/o drift") and the random walk with drift (column labeled "RW w drift"). The critical value of the statistic is -1.96.

Table 2. 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. (3)				
Random Walk w/o drift	-2.6283	-2.2467	-2.0037	-1.6407
Random Walk w/ drift	-2.6975	-2.3084	-2.0311	-1.6829
Panel B. Model with Oil Prices only, eq. (1)				
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 report results for the model with macroeconomic news and oil prices, eq. (3), whereas panel B report results for the model with only oil prices, 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.

Table 3. 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.

Table 4. Estimates of the Basic Linear Model with Oil Prices

	Daily		Monthly		Quarterly	
	Panel A. Model With Oil Prices					
R^2	0.03		0.09		0.21	
α	-0.000	(-0.69)	-0.000	(-0.59)	-0.002	(-0.552)
β	-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	
α	-0.00001	(-0.25)	-0.0007	(-0.36)	-0.0007	(-0.13)
β	0.00002	(0.09)	0.0004	(0.54)	-0.0004	(-0.25)

Notes to the Table. The model in Panel A is eq. (1) and the model in Panel B is eq. (2); HAC robust t–statistics reported in parentheses.[27]

[27] The HAC robust variance estimate was obtained by Newey and West's (1987) HAC procedure with a bandwidth equal to $4(\frac{T}{100})^{1/4}$.

Table 5: Clark and West's (2006) Test Statistic

	A. Contemporaneous Oil P. Model			B. Lagged Oil P. Model		
Data Frequency	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 to the Table. 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 I reports results for the Contemporaneous Oil Price Model, eq. (1), whereas Panel II reports results for the Lagged Oil Price Model, eq. (4).

Figure 1A. Oil Price Model. Forecasting Ability in Daily Data

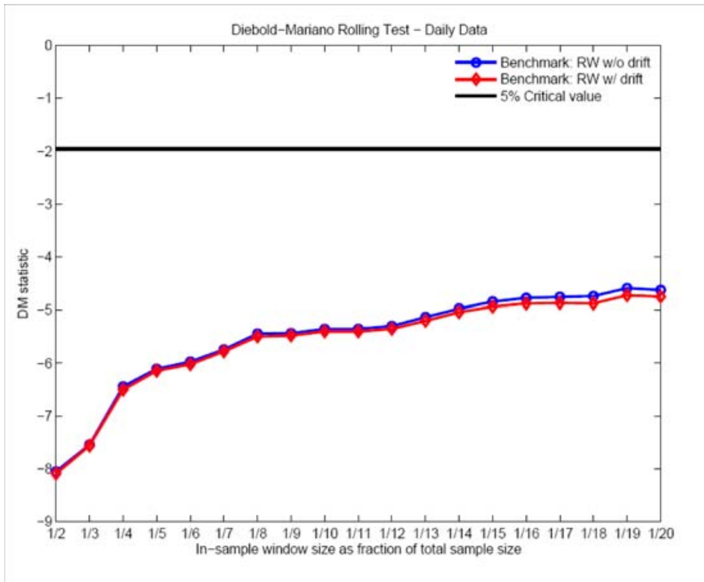
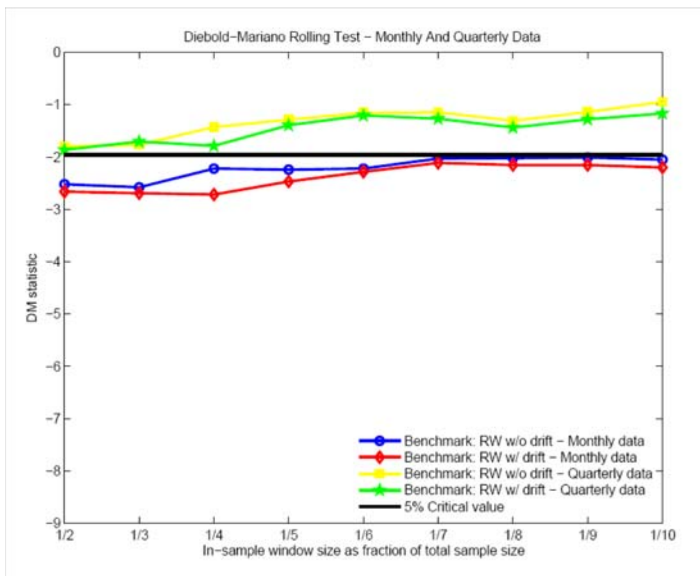
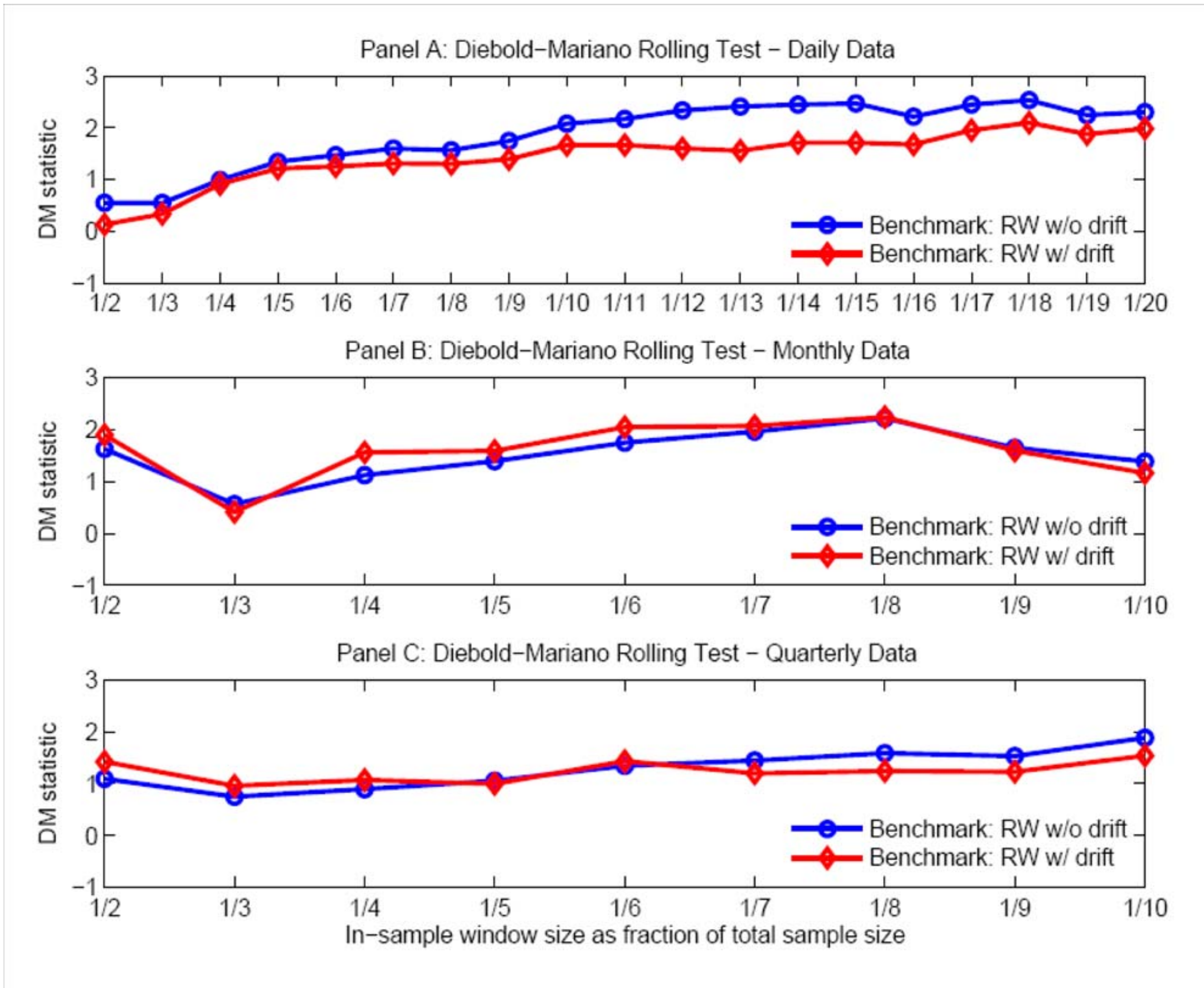


Figure 1B. Oil Price Model. Forecasting Ability in Monthly and Quarterly Data



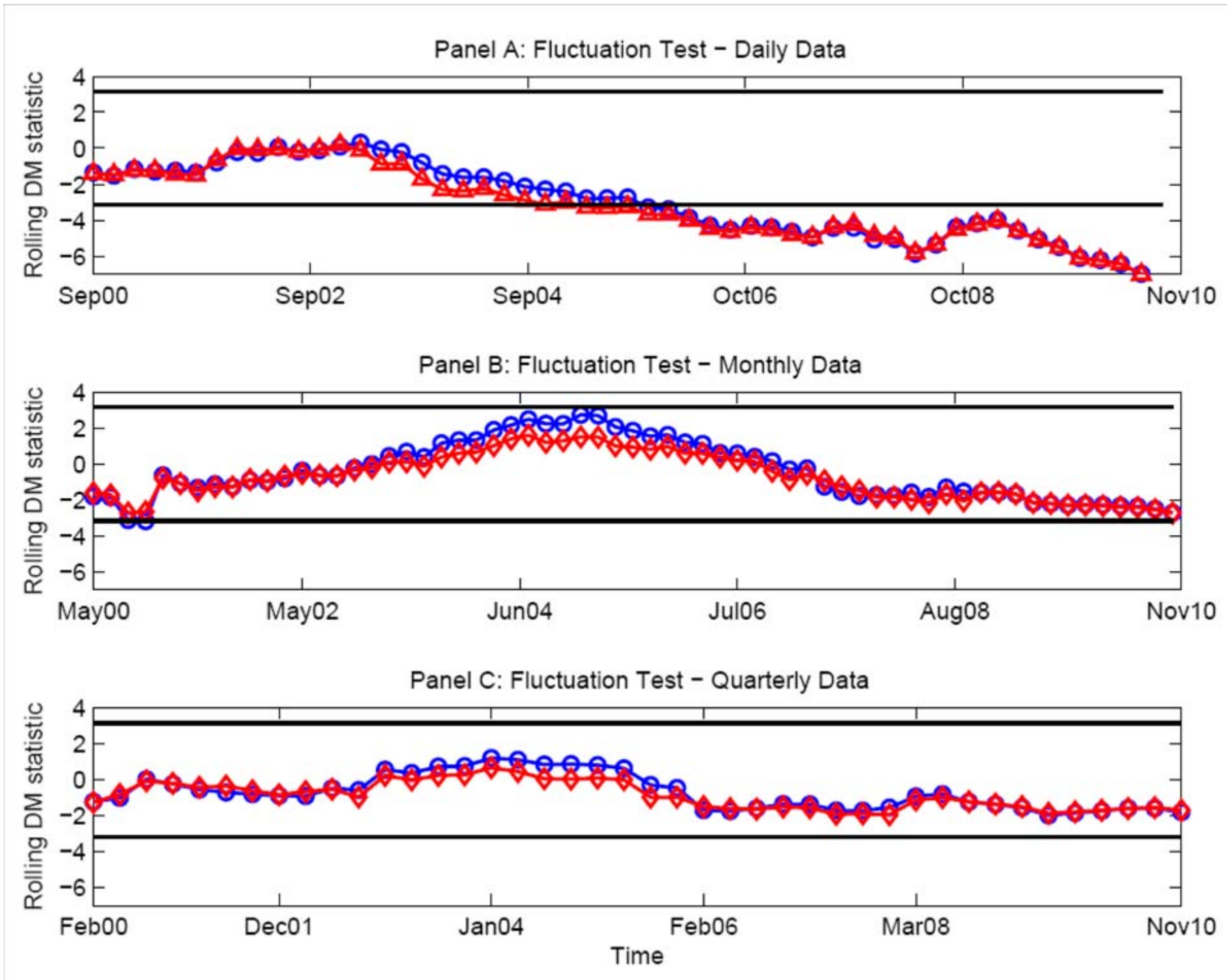
Notes. Figure 1 plots Diebold and Mariano's (1995) test statistic for comparing Model (1) to a random walk without drift (circles) and with drift (diamonds) in daily data, calculated for several in-sample window sizes (x-axis). Figure 2 similarly compares Model (1) to a random walk without drift (circles for monthly and squares for quarterly data) and with drift (diamonds for monthly and stars for quarterly data). Negative values indicate that Model (1) forecasts better. When the test statistic is below the continuous line Model (1) forecasts significantly better.

Figure 2. The Interest Rate Model.



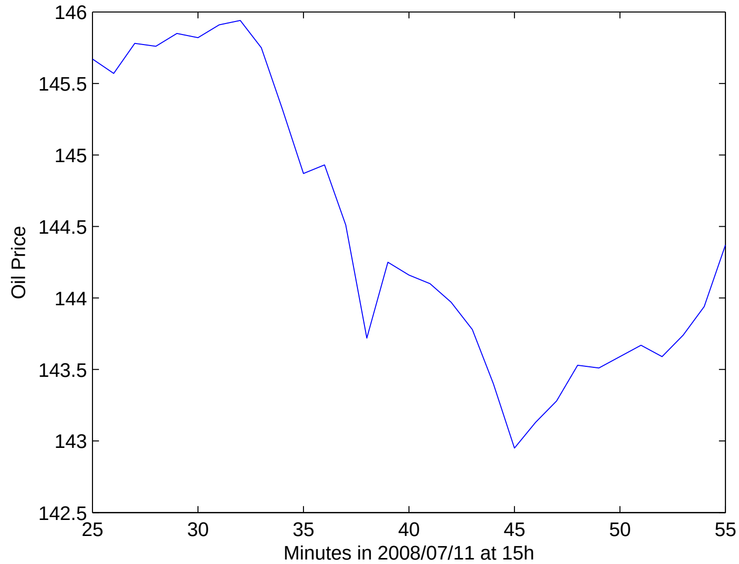
Notes to the Figure. The figure reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (2) relative to a random walk without drift benchmark (line with circles) as well as relative to the random walk with drift benchmark (line with diamonds) calculated for several in-sample window sizes (x-axis). Negative values indicate that Model (2) forecasts better. 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 (2) forecasts significantly better than its benchmark.

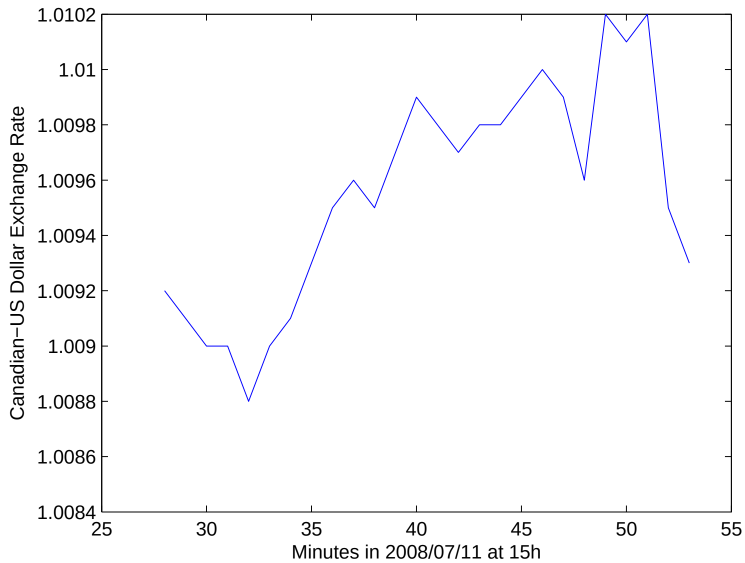
Figure 3. Fluctuation Test For the Oil Price Model



Notes to the Figure. 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 (line with circles) as well as relative to the random walk with drift benchmark (line with triangles). Negative values indicate that Model (1) forecasts better. The continuous line indicates the critical value of the Fluctuation test statistic: If the estimated test statistic is below this line, Model (1) forecasts significantly better than its benchmark.

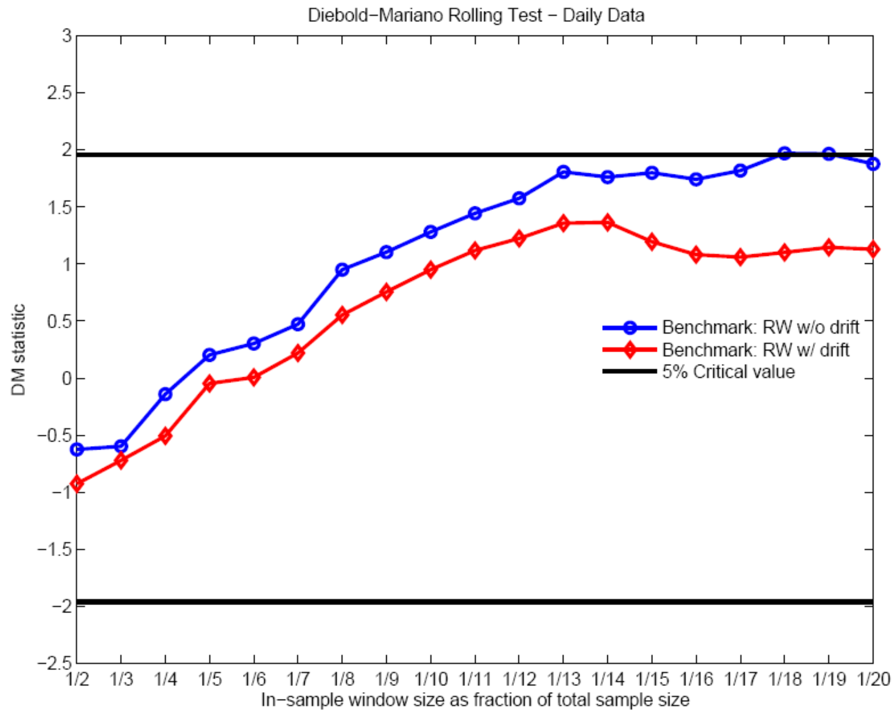
Figure 4. The Importance of Timing





Notes to Figure 4. The top panel plots oil prices (in levels); the x-axis reports the minutes at 15:00h (3PM) of July 11, 2008, from 15h:25 to 15h:55. The bottom panel in plots the Canadian-US Dollar exchange rate (in levels) at the same time.

Figure 5. Lagged Oil Price Model. Panel A. Forecasting Ability in Daily Data



Panel B. Forecasting Ability in Monthly and Quarterly Data

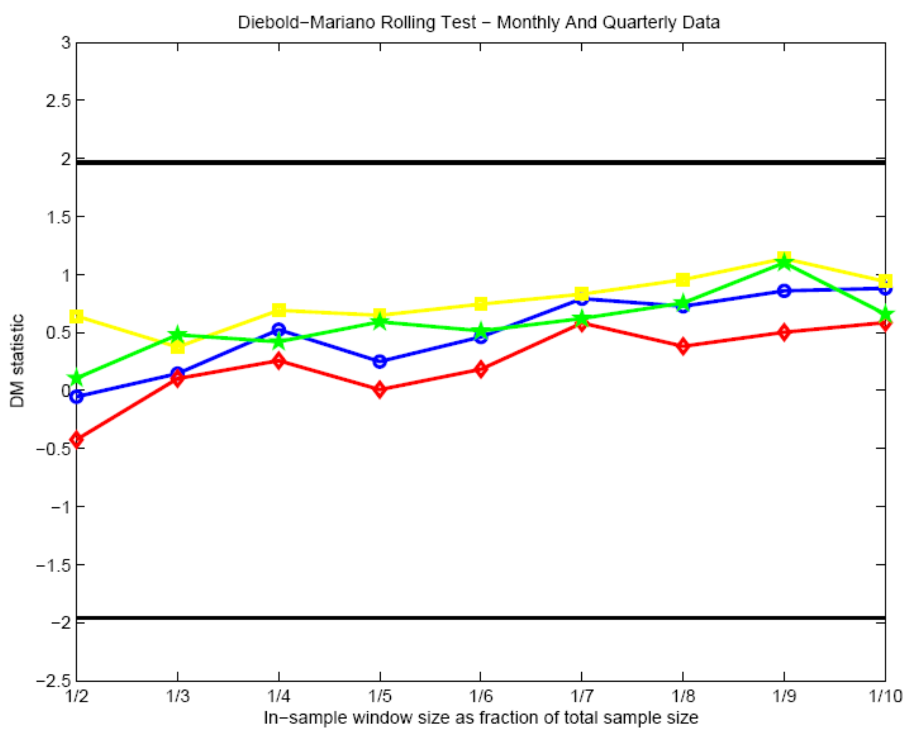


Figure 6. Fluctuation Test For the Lagged Oil Price Model

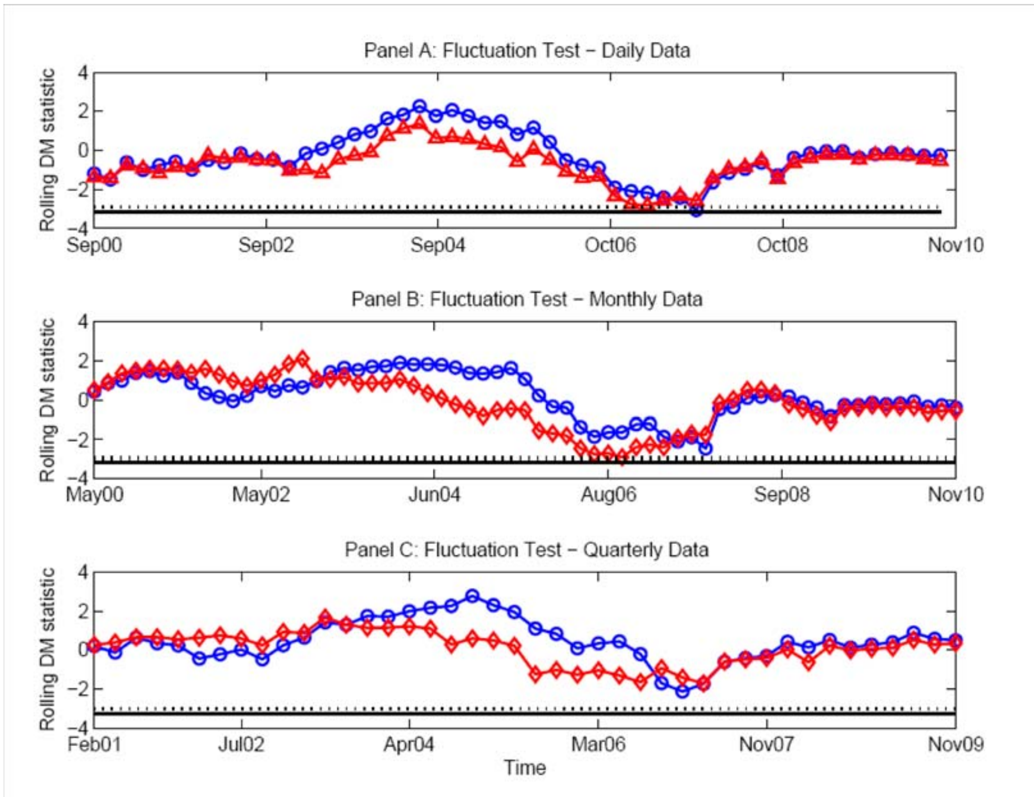
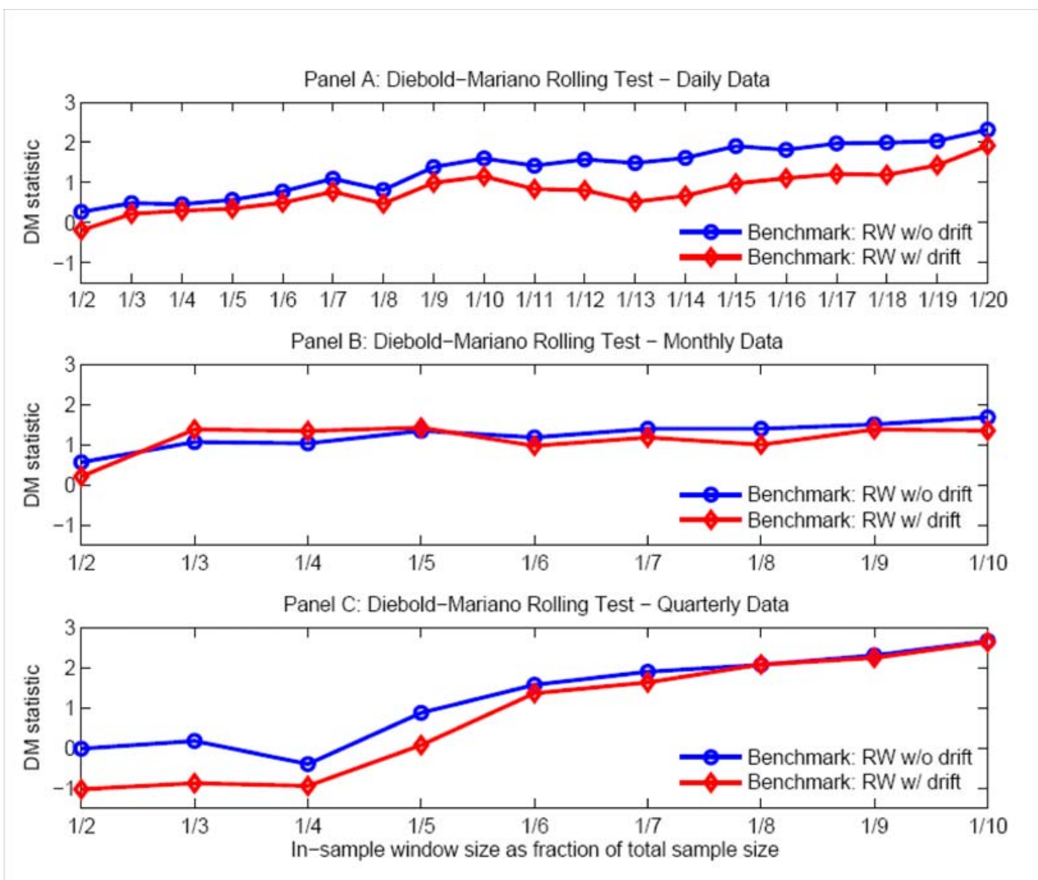


Figure 7. The Lagged Interest Rate Model



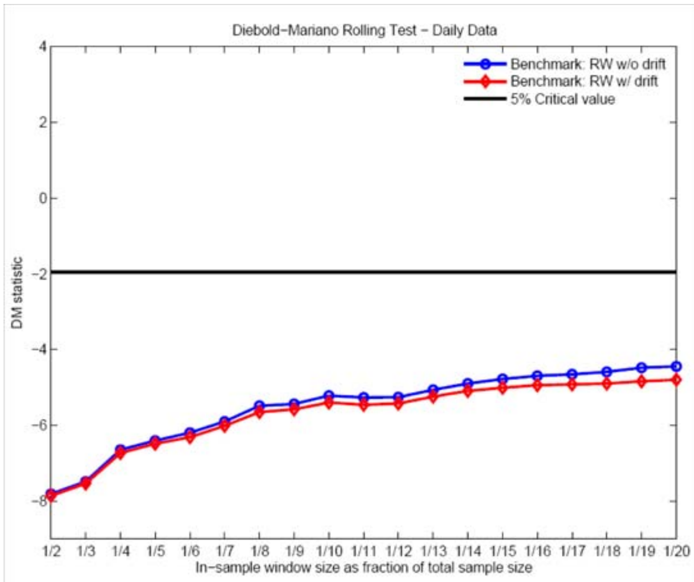
Notes to Figure 5. Panel A reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (4) relative to a random walk without drift benchmark (line with circles for monthly data and squares for quarterly data) as well as relative to the random walk with drift benchmark (line with diamonds for monthly data and stars for quarterly data) calculated for several in-sample window sizes (x-axis).

Panel B reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (4) relative to a random walk without drift benchmark (line with circles for monthly data and squares for quarterly data) as well as relative to the random walk with drift benchmark (line with diamonds for monthly data and stars for quarterly data) calculated for several in-sample window sizes. Negative values indicate that Model (4) forecasts better. 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 (4) forecasts significantly better than its benchmark.

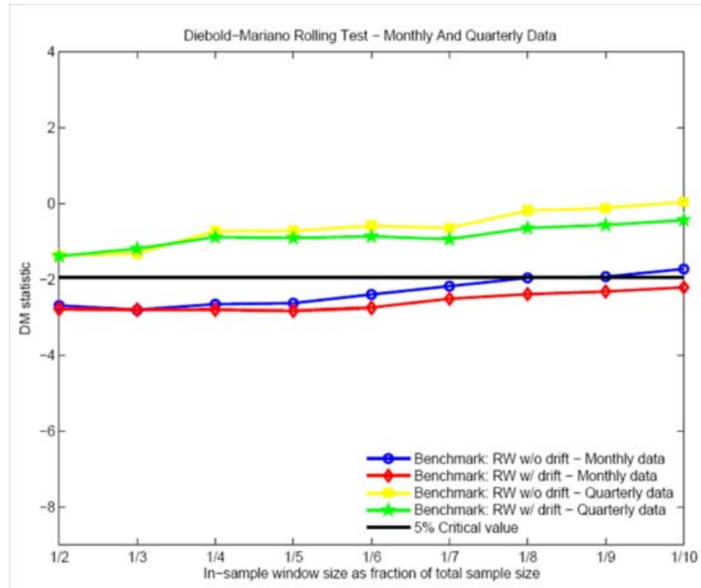
Notes to Figure 6. Figure 6 reports Giacomini and Rossi's (2010) Fluctuation test statistic for comparing forecasts of Model (4) relative to a random walk without drift benchmark (line with circles) as well as relative to the random walk with drift benchmark (line with triangles). Negative values indicate that Model (4) forecasts better. The continuous line indicates the critical value of the Fluctuation test statistic: If the estimated test statistic is below this line, Model (4) forecasts significantly better than its benchmark. The continuous and dashed lines denote, respectively, the two-sided 5% and 10%-level critical values.

Notes to Figure 7. Figure 7 reports Giacomini and Rossi's (2010) Fluctuation test statistic for comparing forecasts of Model (5) relative to a random walk without drift benchmark (line with circles) as well as relative to the random walk with drift benchmark (line with triangles). Negative values indicate that Model (5) forecasts better. The continuous line indicates the critical value of the Fluctuation test statistic: If the estimated test statistic is below this line, Model (5) forecasts significantly better than its benchmark.

Figure 8, Panel I. Norw. Krone and Oil. Daily Data, Contemp. Model



Panel II. Norw. Krone and Oil. Monthly and Quarterly Contemp. Model



Panel III. Norw. Krone and Oil. Fluctuation Test, Lagged P. Model

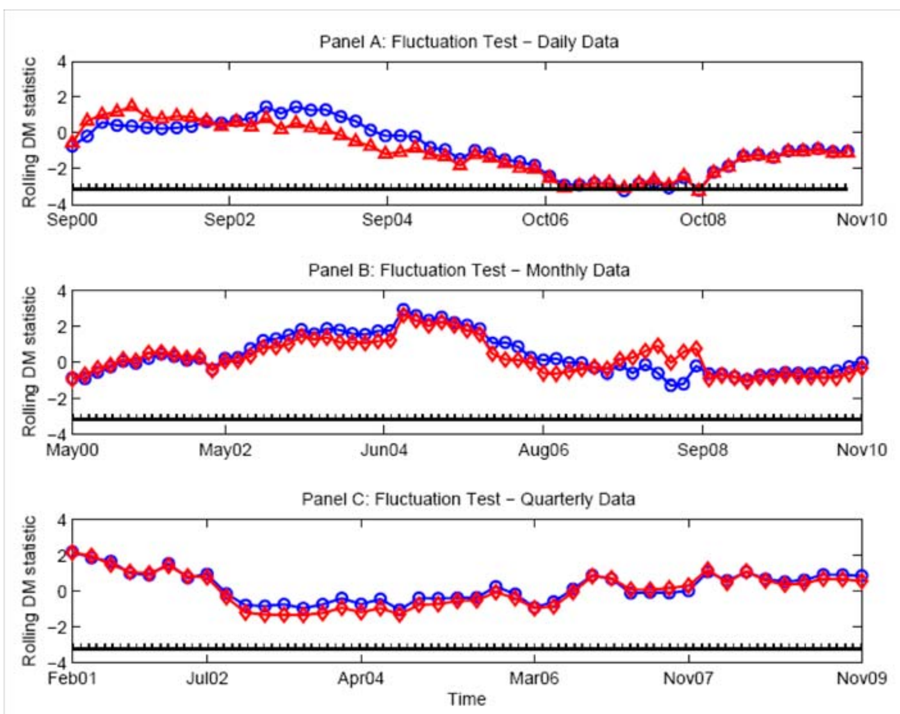
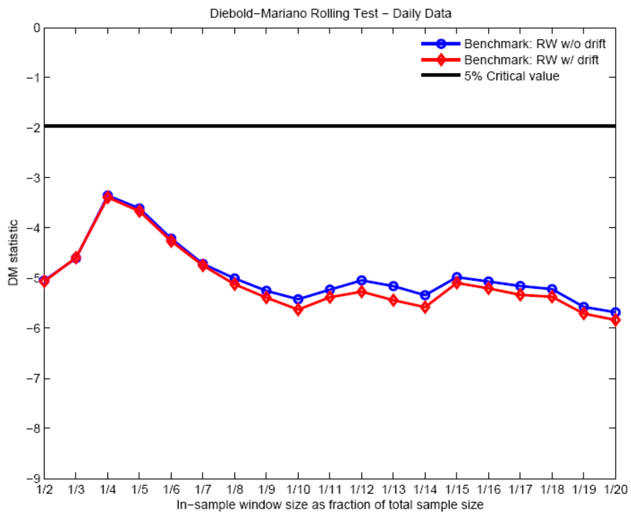


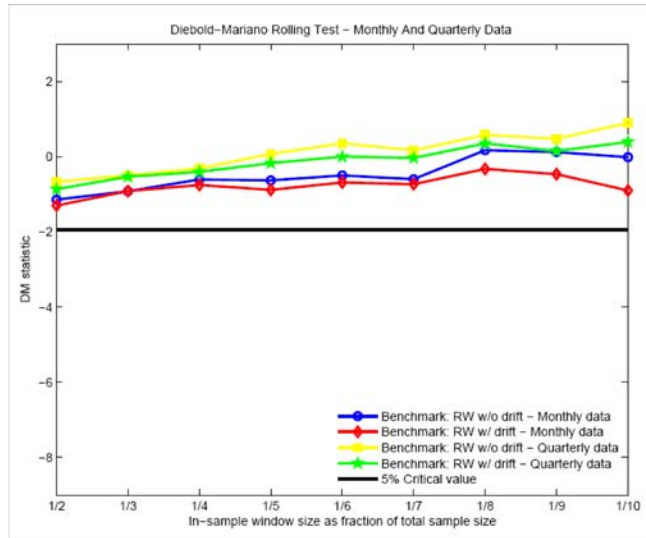
Figure 9, Panel I. S.A. Rand and Gold.

Daily Data, Contemp. Model



Panel II. S.A. Rand and Gold.

Monthly and Quarterly Contemp. Model



Panel III. S.A. Rand and Gold. Fluctuation Test, Contemp. Model

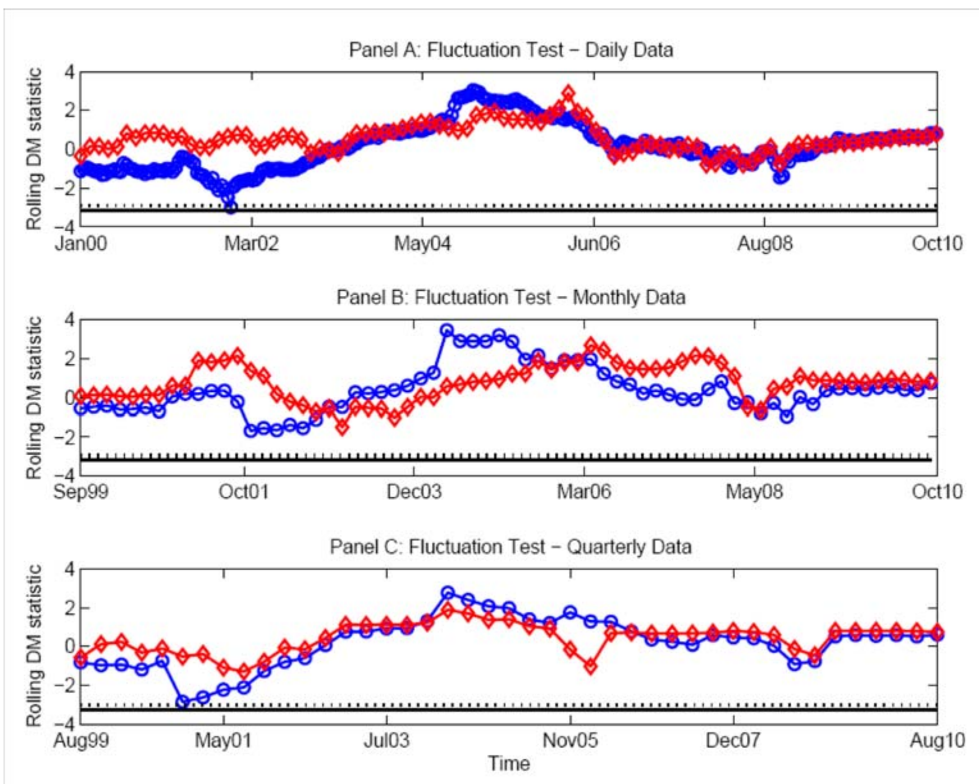
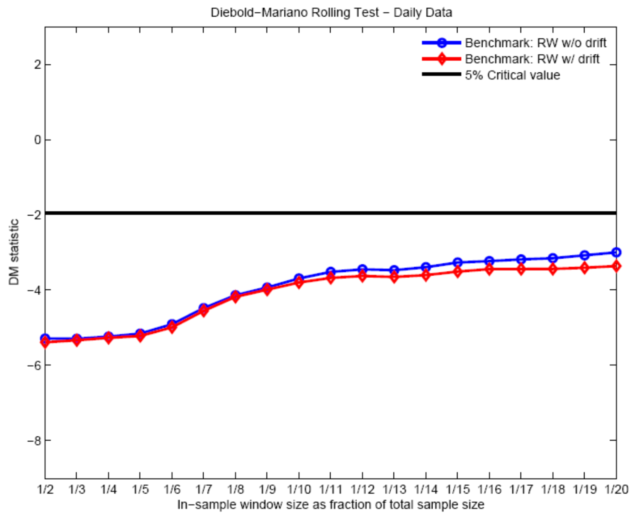
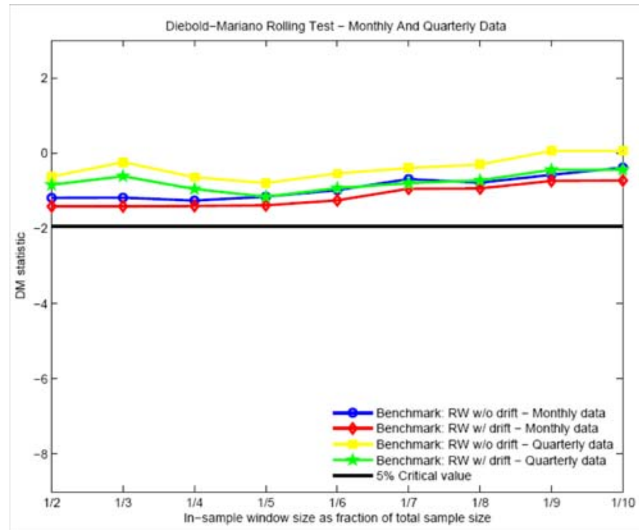


Figure 10, Panel I. Chilean Peso and Copper. Daily Data, Contemp. Model

Panel II. Chilean Peso and Copper. Monthly and Quarterly Contemp. Model





Panel III. Chilean Peso and Copper. Fluctuation Test, Contemp. Model

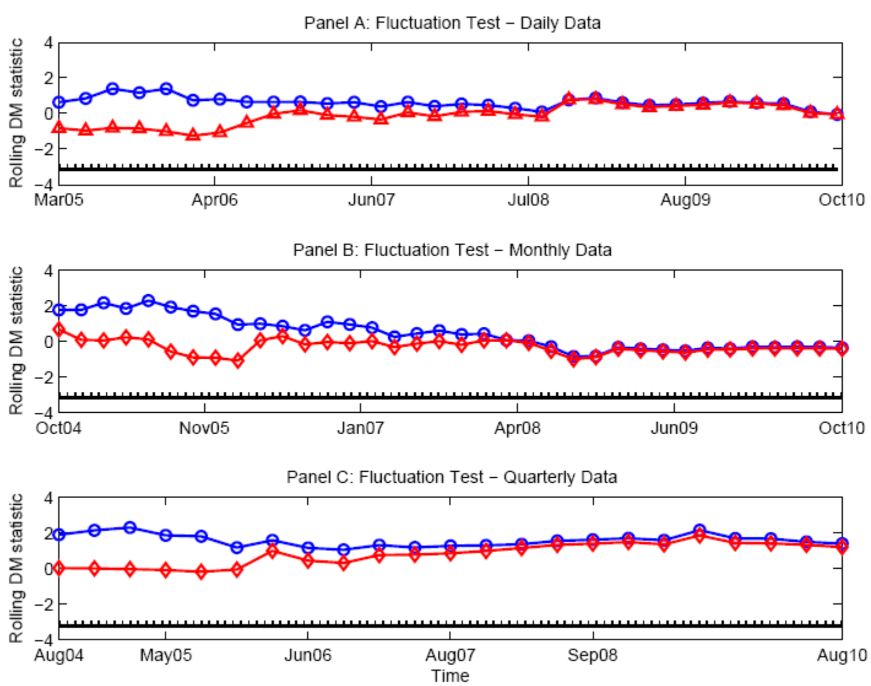
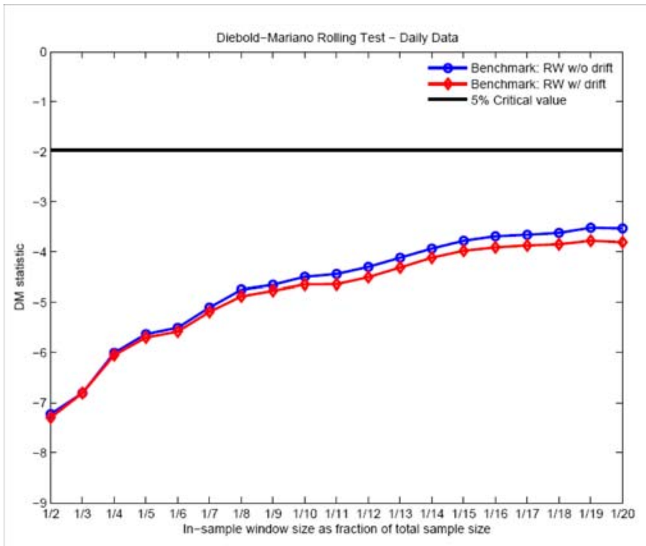
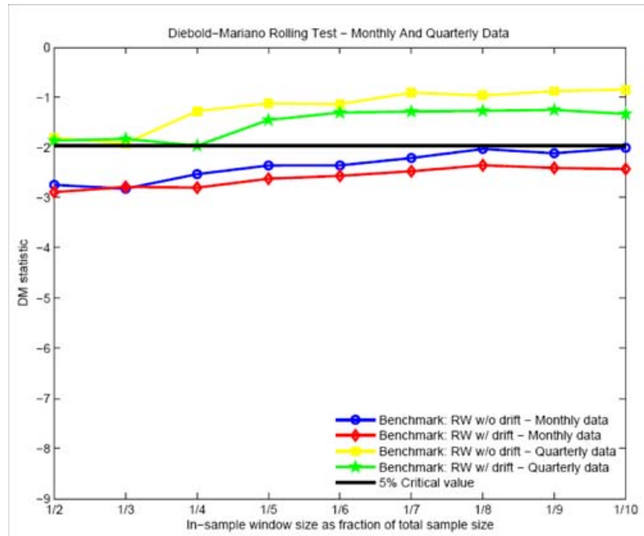


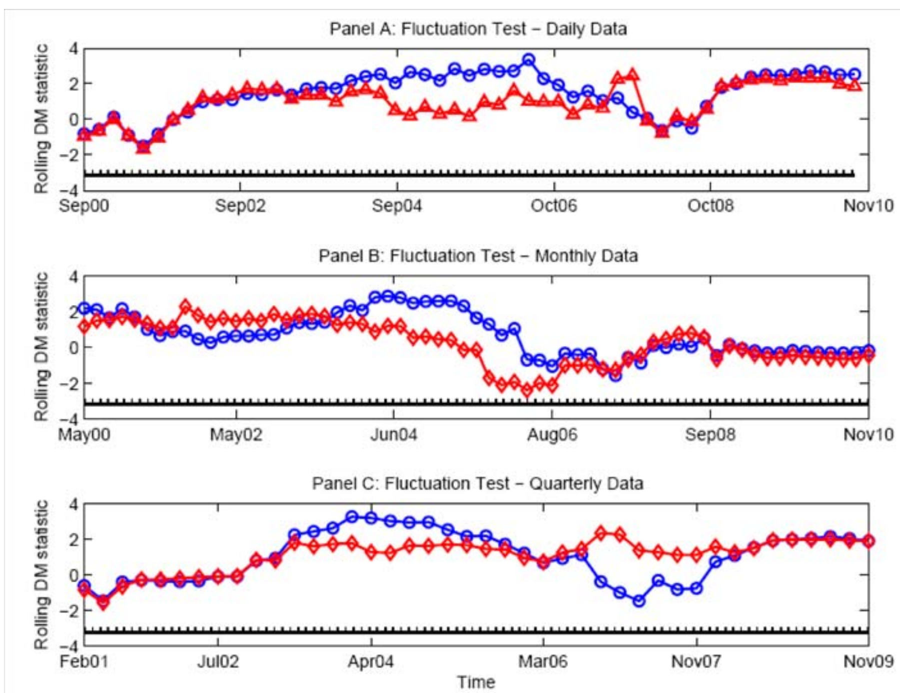
Figure 11, Panel I. Austr. $ and Oil. Daily Data, Contemp. Model



Panel II. Austr. $ and Oil. Monthly and Quarterly Contemp. Model



Panel III. Australian $ and Oil. Fluctuation Test, Contemp. Model

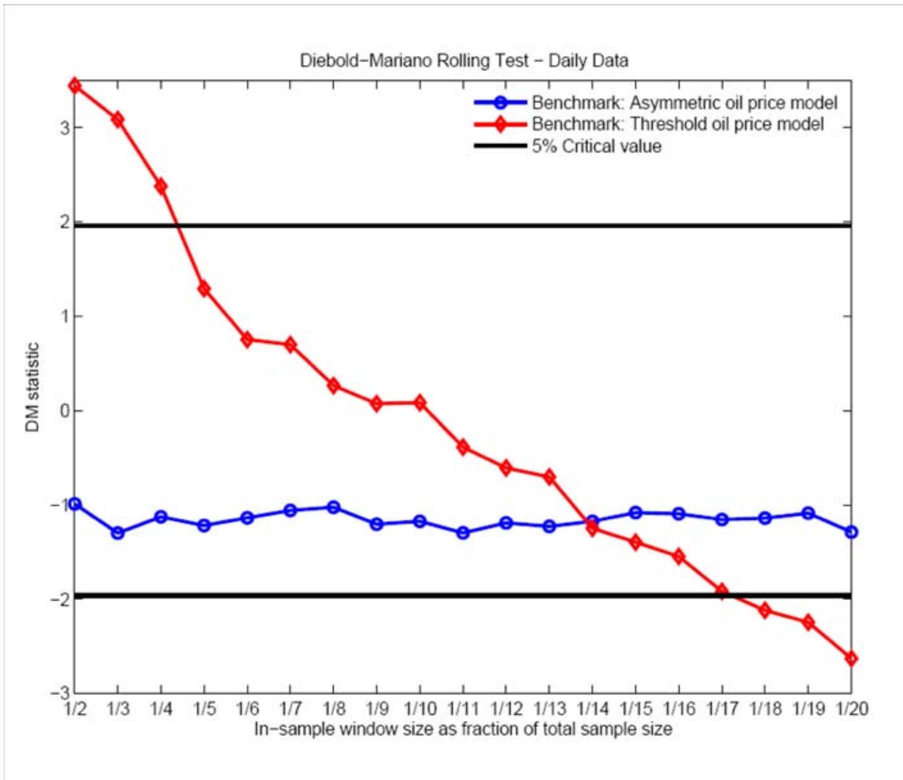


Notes to Figures 8-11. Panels (I,II) report Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) relative to a random walk without drift benchmark (line with circles) as well as relative to the random walk with drift benchmark (line with diamonds) calculated for daily (panel I), monthly and quarterly data (panel II), and 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 (4) forecasts significantly better than its benchmark. Panel III reports the Fluctuation test statistic for comparing forecasts of Model (4) relative to a random walk without drift benchmark (line with circles) as well as relative to the random walk with drift benchmark (line with diamonds) calculated at daily, monthly and quarterly frequencies, and several in-sample window sizes (x-axis). Negative values indicate that Model (1) forecasts better. 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) forecasts significantly better than its benchmark.

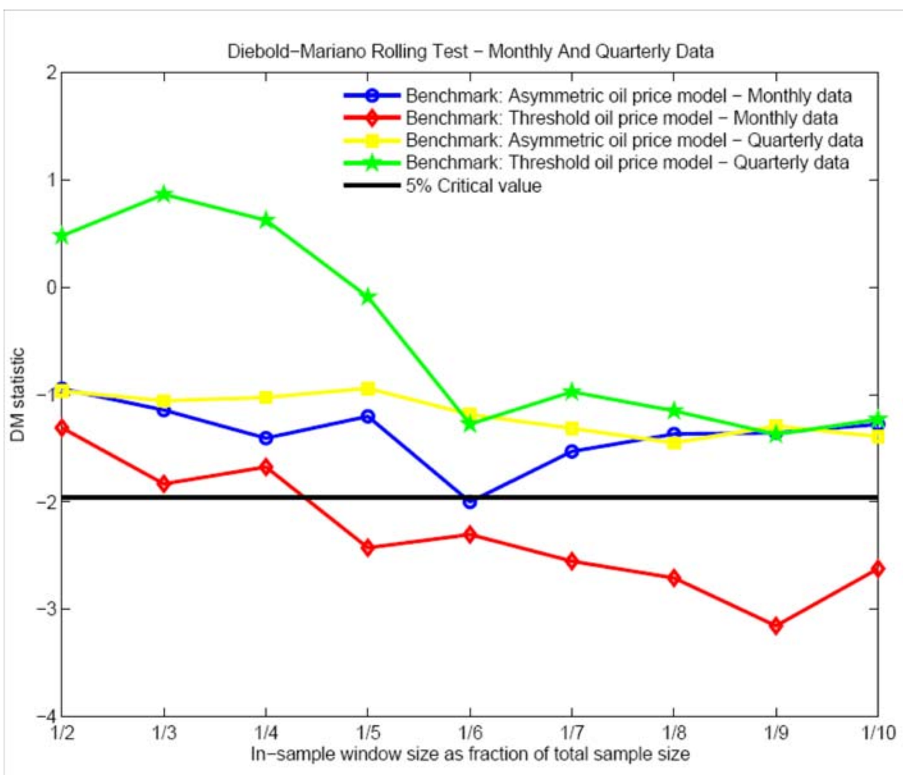
Notes to Figure 12. Panel A reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) relative to Model (6) (line with circles) as well as the forecasts of Model (1) relative to Model (7) (line with diamonds) calculated for daily data and several in-sample window sizes (x-axis). Panel B reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (1) relative to Model (6) (line with circles for monthly data and line with squares for quarterly data) as well as the forecasts of Model (1) relative to Model (7) (line with diamonds for monthly data and line with stars for quarterly data) calculated for several in-sample window sizes (x-axis). Negative values indicate that Model (1) forecasts better. 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) forecasts significantly better than its benchmark, and when it is above this line Model (1) forecasts worse.

Figure 12. Asymmetric and Threshold Models. Forecasting Ability

Panel A. Daily Data

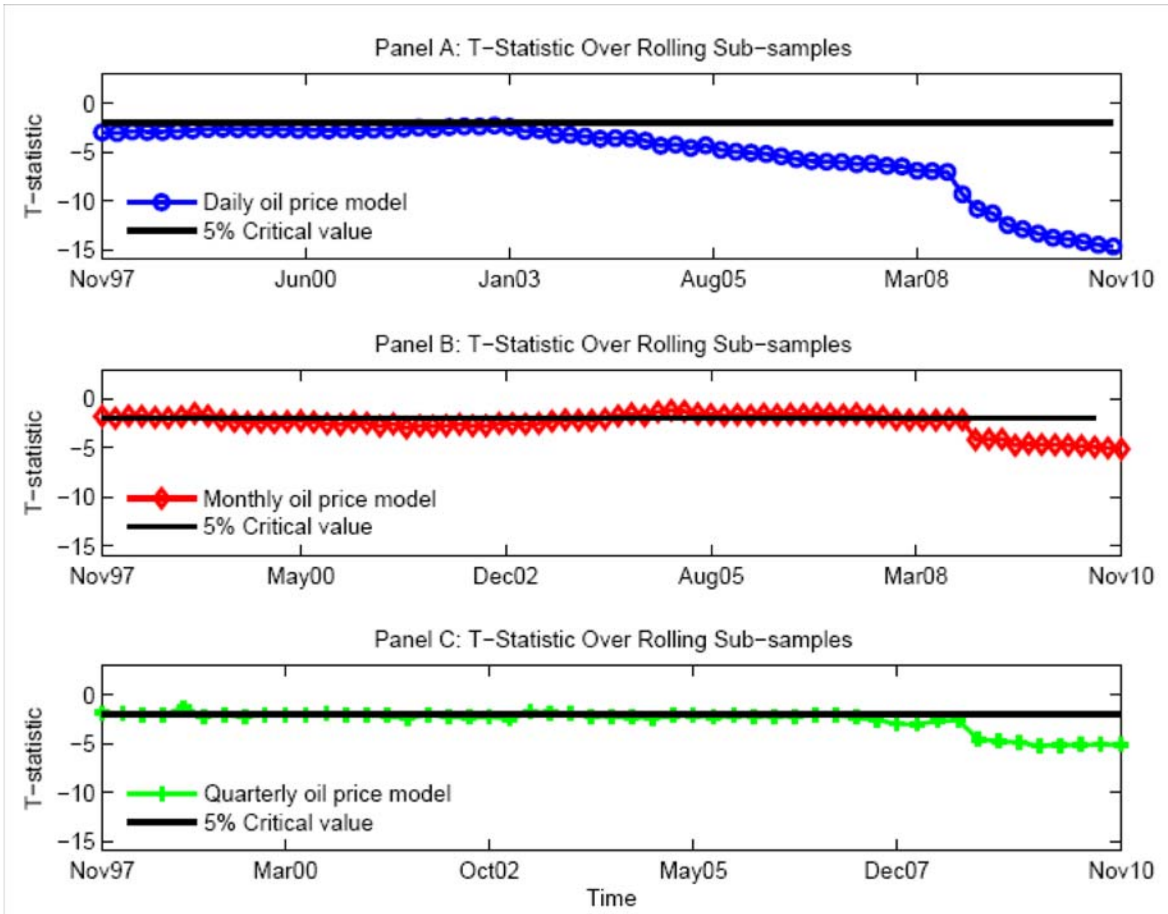


Panel B. Monthly and Quarterly Data



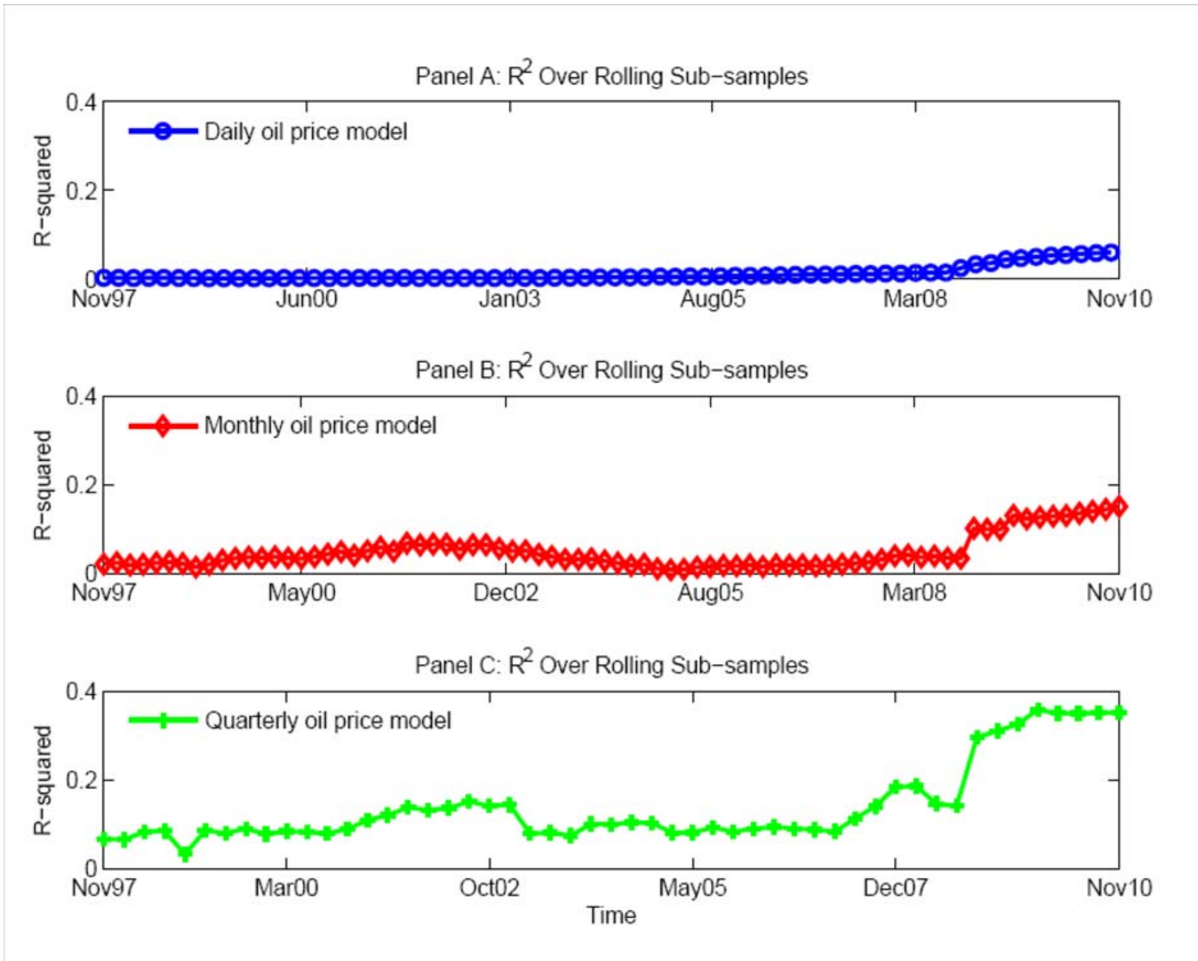
Not-for-Publication Appendix to: "Can Oil Prices Forecast Exchange Rates?" by Domenico Ferraro, Ken Rogoff and Barbara Rossi

Figure A.1. In-sample Fit of Oil Price Model – T-statistics Over Time



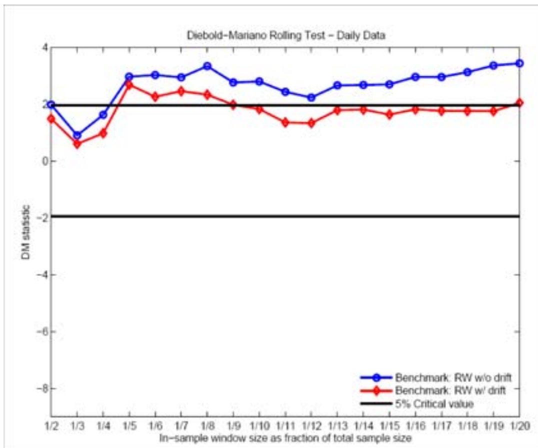
Notes to the Figure. The figure reports in-sample t-statistics for comparing forecasts of Model (1) calculated over rolling samples (dates reported on the x-axis). The continuous line indicates the critical value of the t-statistic: if the estimated test statistics is below this line, the coefficient on the oil price in Model (1) is statistically significantly negative. The top panel is for daily data, the middle panel for monthly and the bottom panel for quarterly data.

Figure A.2. In-sample Fit of Oil Price Model – R^2statistics Over Time

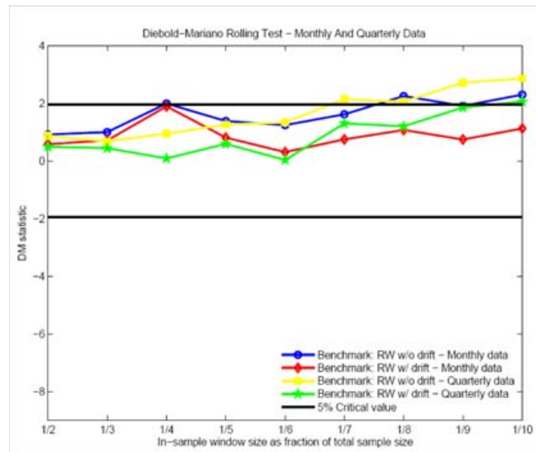


Notes to the Figure. The figure reports in-sample R^2 statistics for comparing forecasts of Model (1) calculated over rolling samples (dates reported on the x-axis).

Figure A.3 Panel I. Norw. Krone and Oil. Daily Data, Lagged Model



Panel II. Norw. Krone and Oil. Monthly and Quarterly Lagged Model



Panel III. Norw. Krone and Oil. Fluctuation Test Contemporaneous Price Model

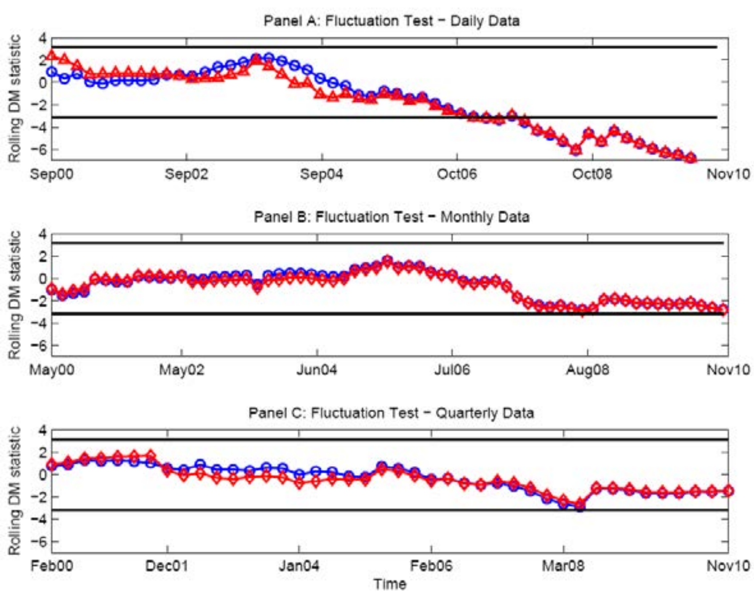
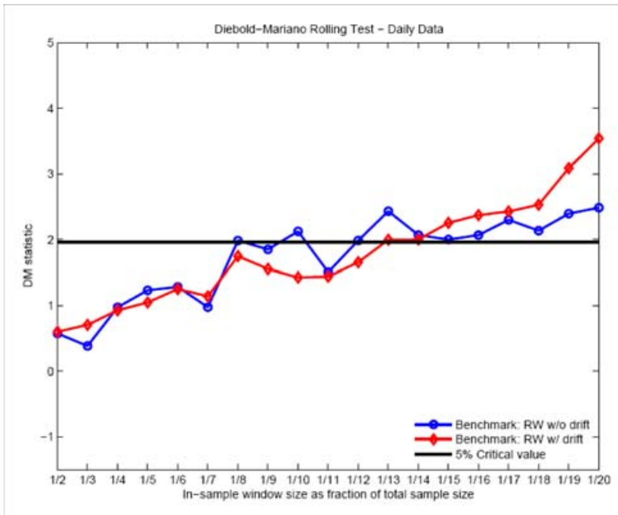
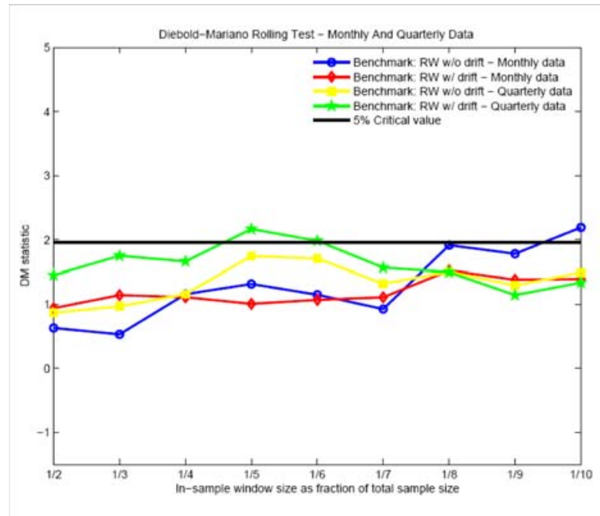


Figure A.4. Panel I. S.A. Rand and Gold. Daily Data, Lagged Model



Panel II. S.A. Rand and Gold. Monthly and Quarterly Lagged Model



Panel III. S.A. Rand and Gold. Fluctuation Test Contemporaneous Model

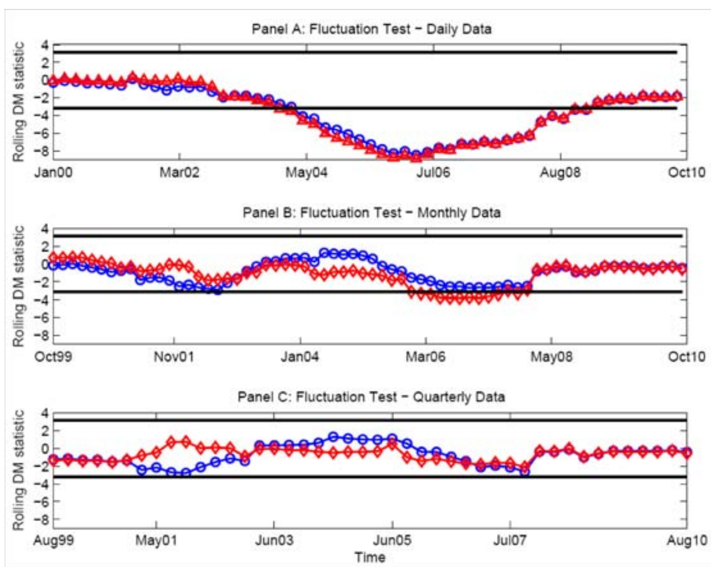
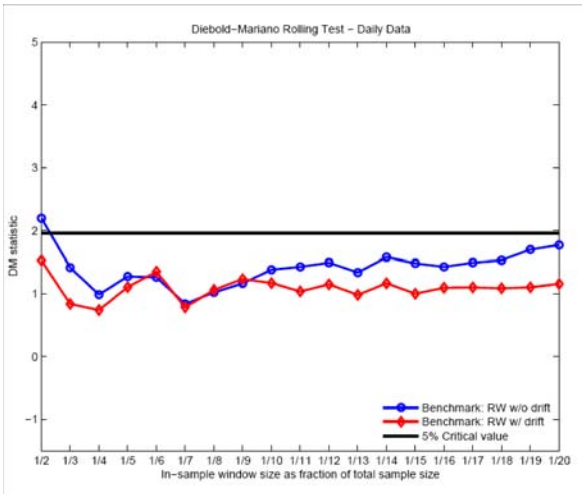
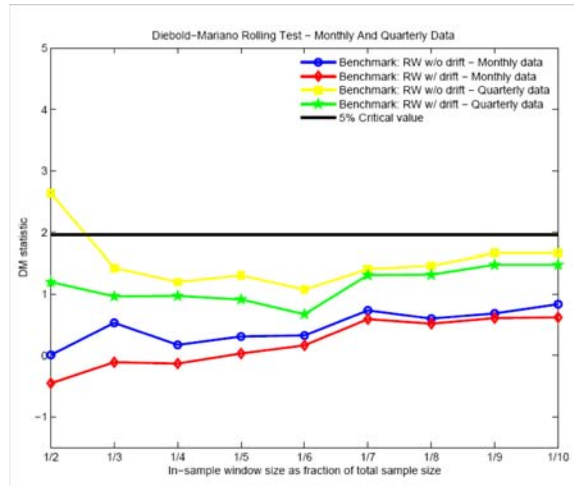


Figure A.5. Panel I. Chilean Peso and Copper. Daily Data, Lagged Model



Panel II. Chilean Peso and Copper. Monthly and Quarterly Lagged Model



Panel III. Chilean Peso and Copper. Fluctuation Test Contemporaneous Model

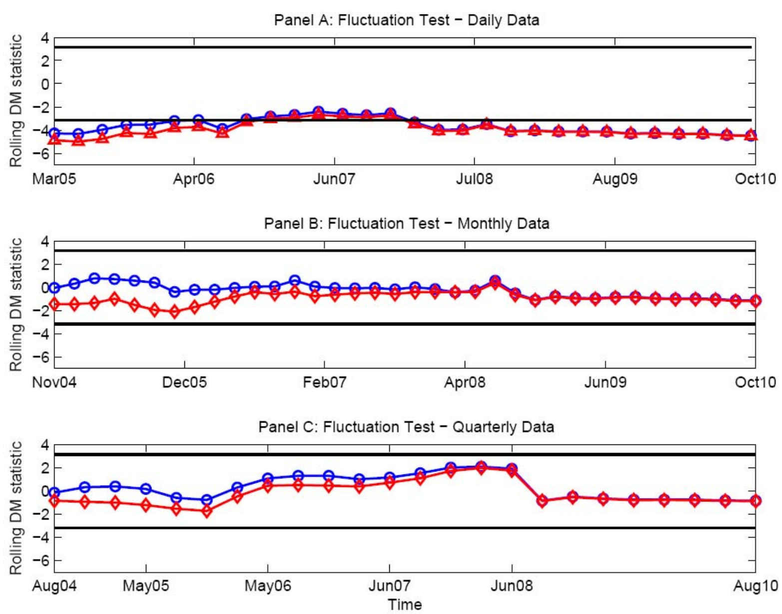
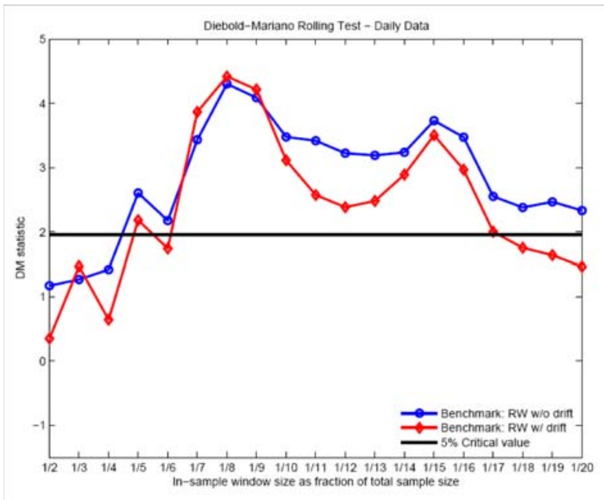
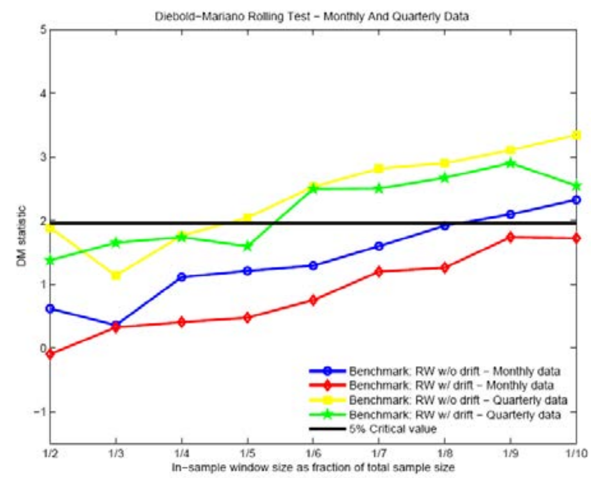


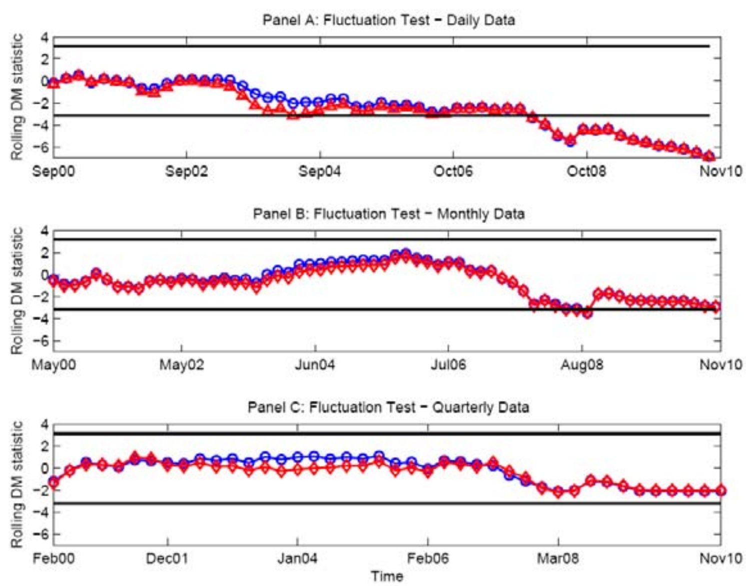
Figure A.6. Panel I. Austr. Dollar and Oil. Daily Data, Lagged Model



Panel II. Austr. Dollar and Oil. Monthly and Quarterly Lagged Model



Panel III. Australian Dollar and Oil. Fluctuation Test Contemporaneous Model



Notes to Figures A.3-A.6. Panels (I,II) report the same analysis for Model (4). Negative values indicate that Model (1) or (4) forecasts better. 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 (4) forecast significantly better than its benchmark. Notes to the Figure. Panel (III) reports the Fluctuation test statistic for comparing forecasts of Model (1) relative to a random walk without drift benchmark (line with circles) as well as relative to the random walk with drift benchmark (line with diamonds) calculated at daily, monthly and quarterly frequencies, and several in-sample window sizes (x-axis). Negative values indicate that Model (1) forecasts better. 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) forecasts significantly better than its benchmark.

Asymmetric and threshold models with lagged fundamentals.

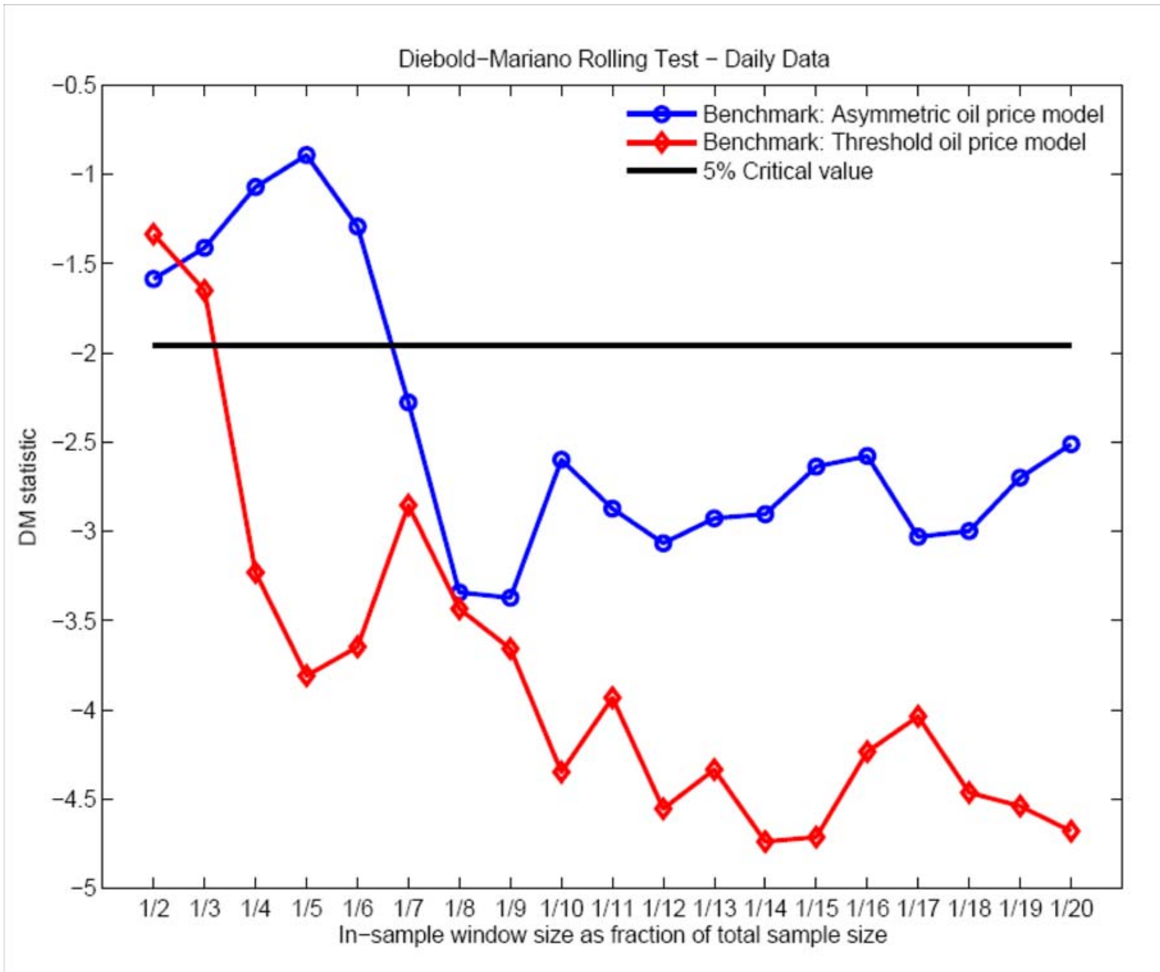
The asymmetric model with lagged fundamentals is:

$$\Delta s_t = \alpha_+ + \beta_+ \Delta p_{t-1} + \gamma_+ \Delta p_{t-1}^+ + u_t, \tag{8}$$

whereas the threshold model with lagged fundamentals is:

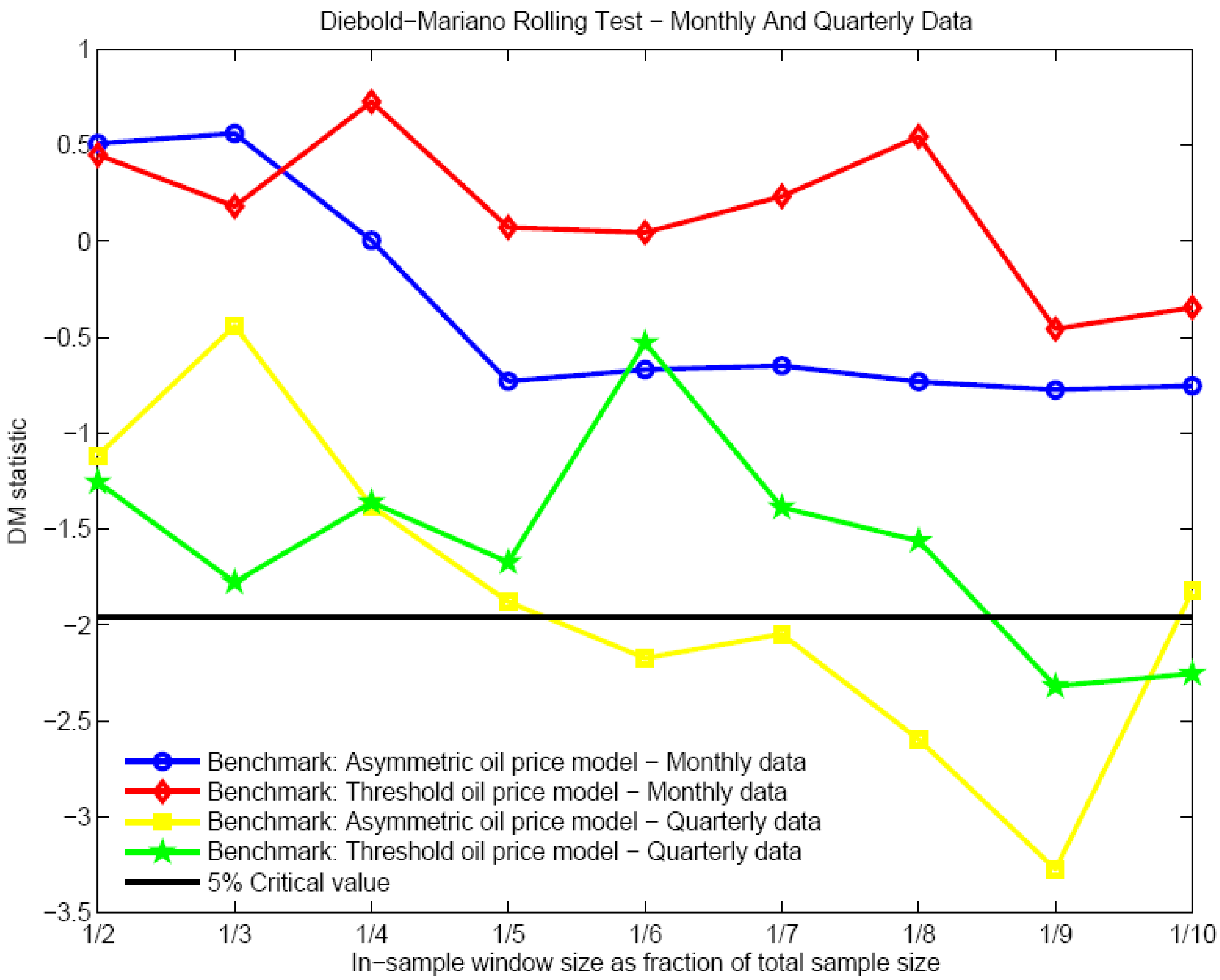
$$\Delta s_t = \alpha_q + \beta_q \Delta p_{t-1} + \gamma_q \Delta p_{t-1}^q + u_t. \tag{9}$$

Figure A.7. Asymmetric and Threshold Models. Forecasting Ability in Daily Data, Lagged Model



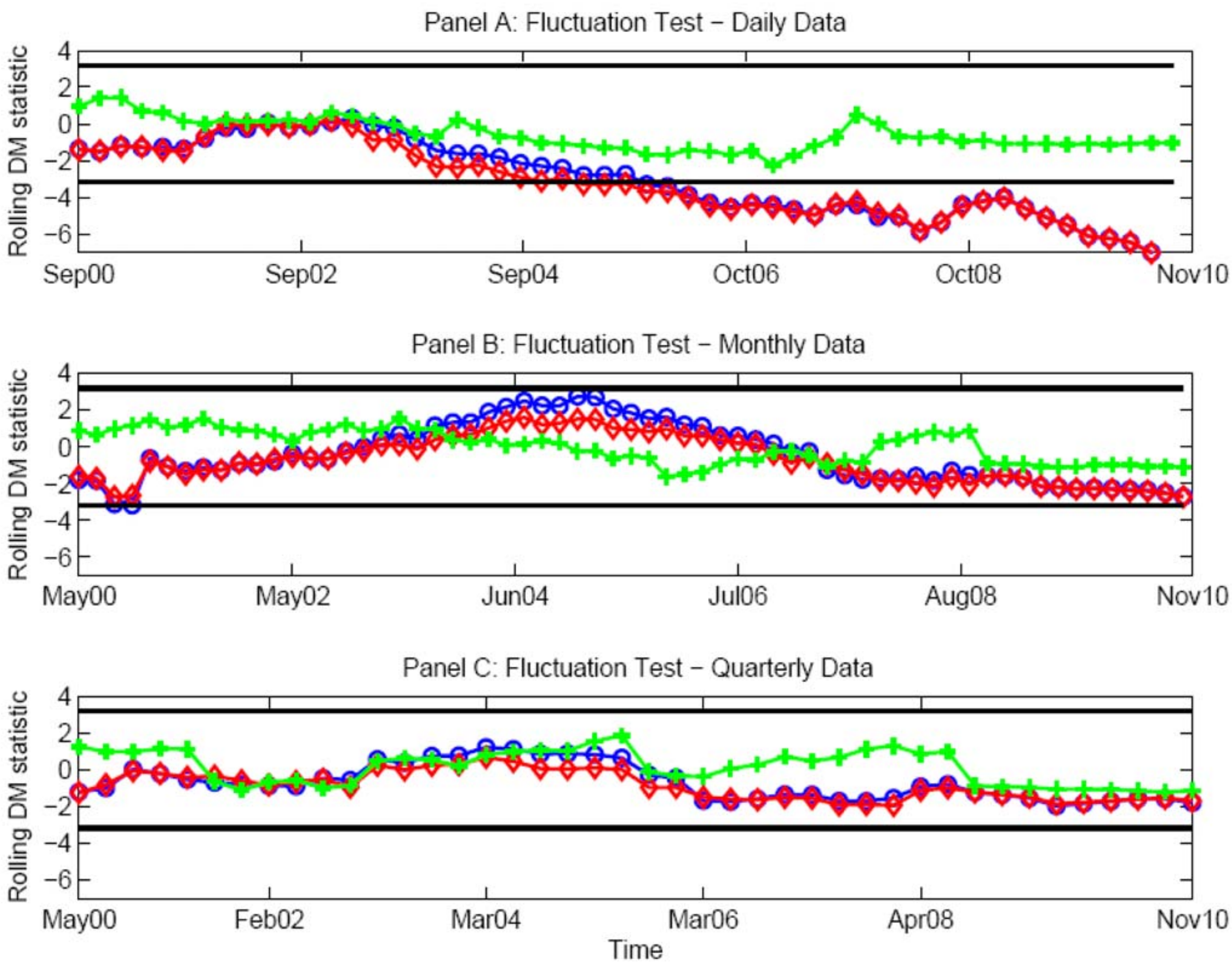
Notes to the Figure. The figure reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (4) relative to Model (6) (line with circles for monthly data and line with squares for quarterly data) as well as the forecasts of Model (4) relative to Model (7) (line with diamonds for monthly data and line with stars for quarterly data) calculated for several in-sample window sizes (x-axis). Negative values indicate that Model (4) forecasts better. 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 (4) forecasts significantly better than its benchmark.

Figure A.8. Asymmetric and Threshold Models. Forecasting Ability in Monthly and Quarterly Data, Lagged Model



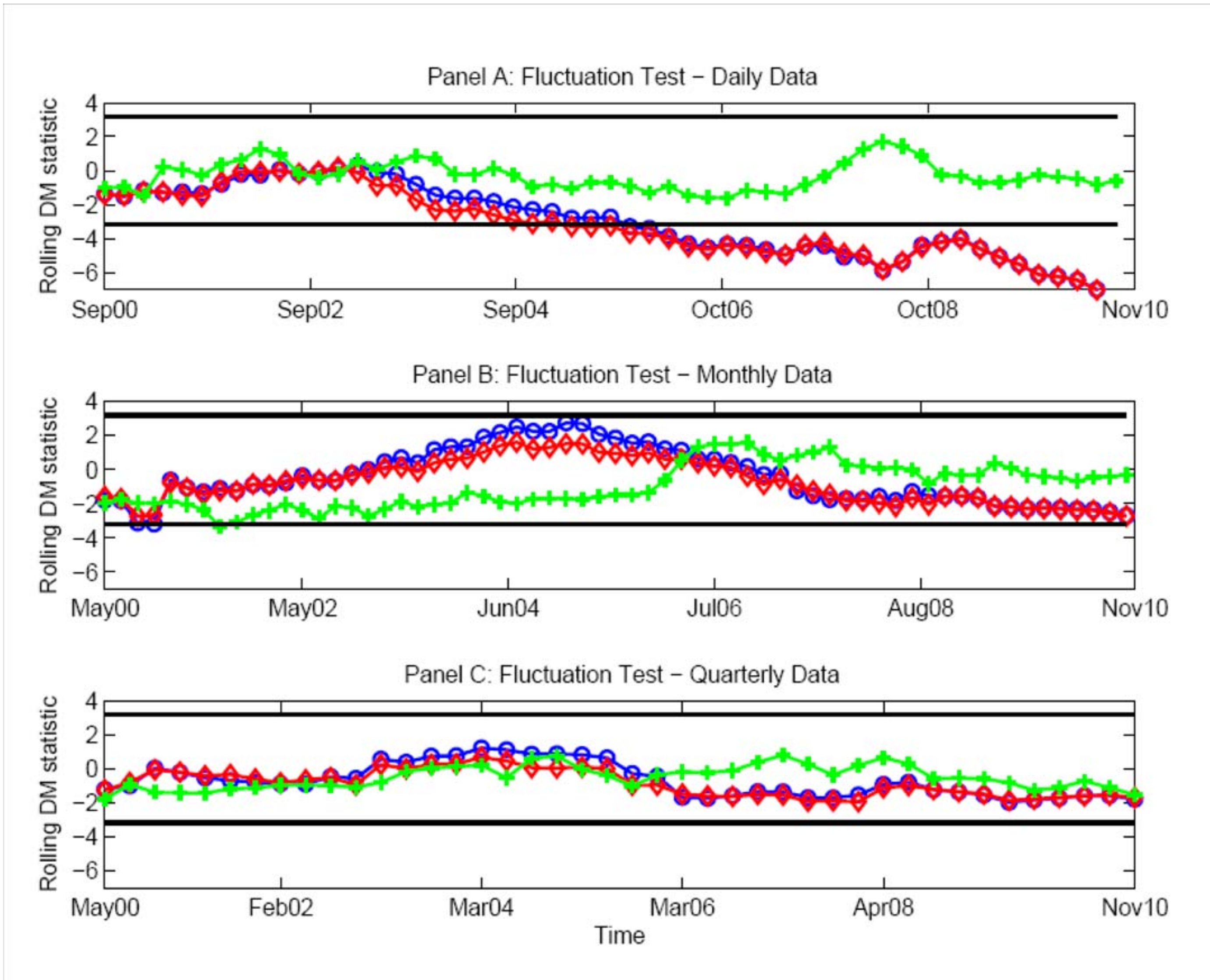
Notes to the Figure. The figure reports Diebold and Mariano's (1995) test statistic for comparing forecasts of Model (4) relative to Model (6) (line with circles for monthly data and line with squares for quarterly data) as well as the forecasts of Model (4) relative to Model (7) (line with diamonds for monthly data and line with stars for quarterly data) calculated for several in-sample window sizes (x-axis). Negative values indicate that Model (4) forecasts better. 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 (4) forecasts significantly better than its benchmark.

Figure A.9. Fluctuation Test on the Asymmetric Model



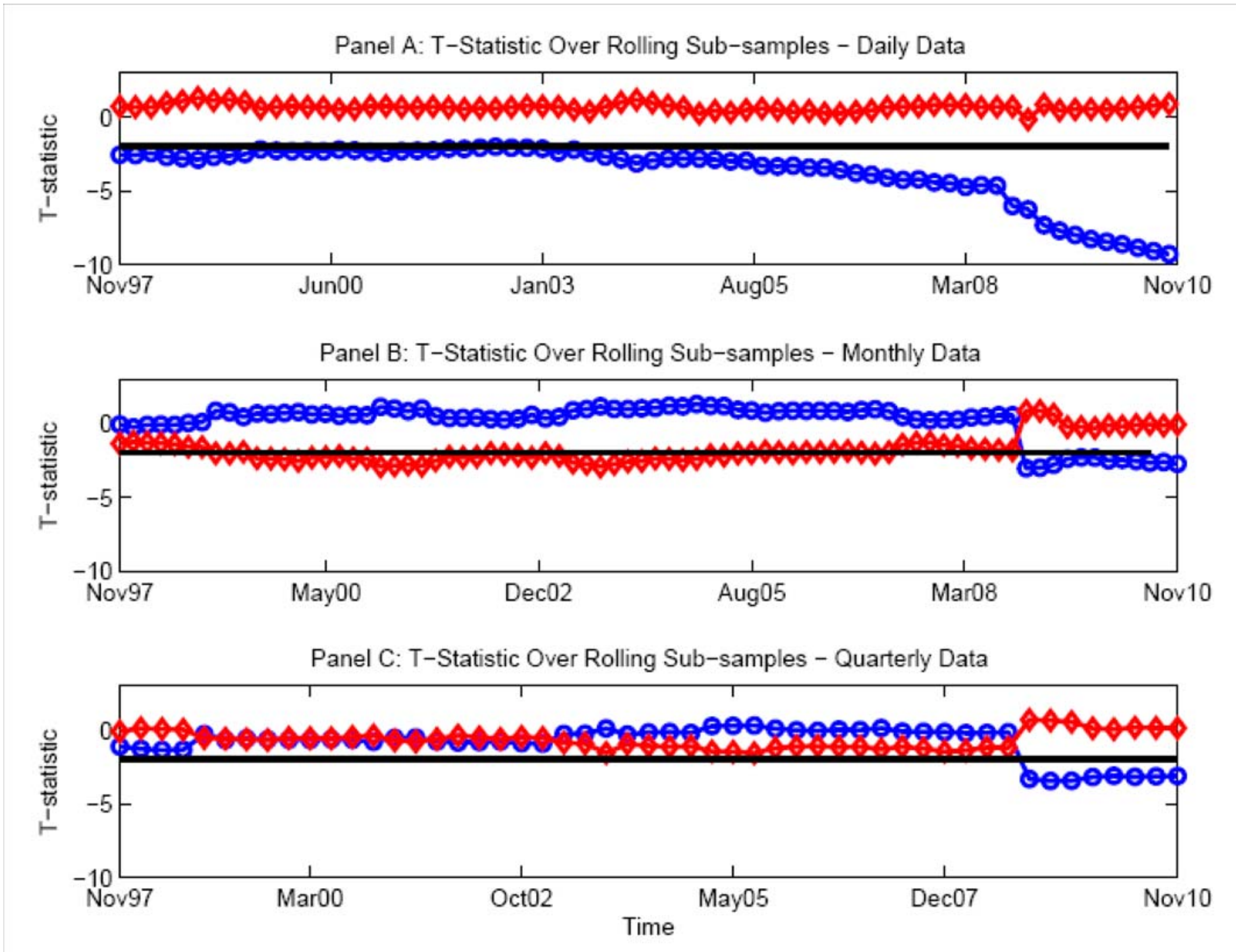
Notes to the Figure. The figure reports Giacomini and Rossi's (2010) Fluctuation test statistic for comparing forecasts of Model (1) relative to a random walk without drift benchmark (line with circles) as well as relative to the random walk with drift benchmark (line with diamonds) and the Asymmetric Model (line with pluses). Negative values indicate that Model (6) forecasts better. The continuous line indicates the critical value of the Fluctuation test statistic: If the estimated test statistic is below this line, Model (6) forecasts significantly better than its benchmark.

Figure A.10. Fluctuation Test on the Threshold Model



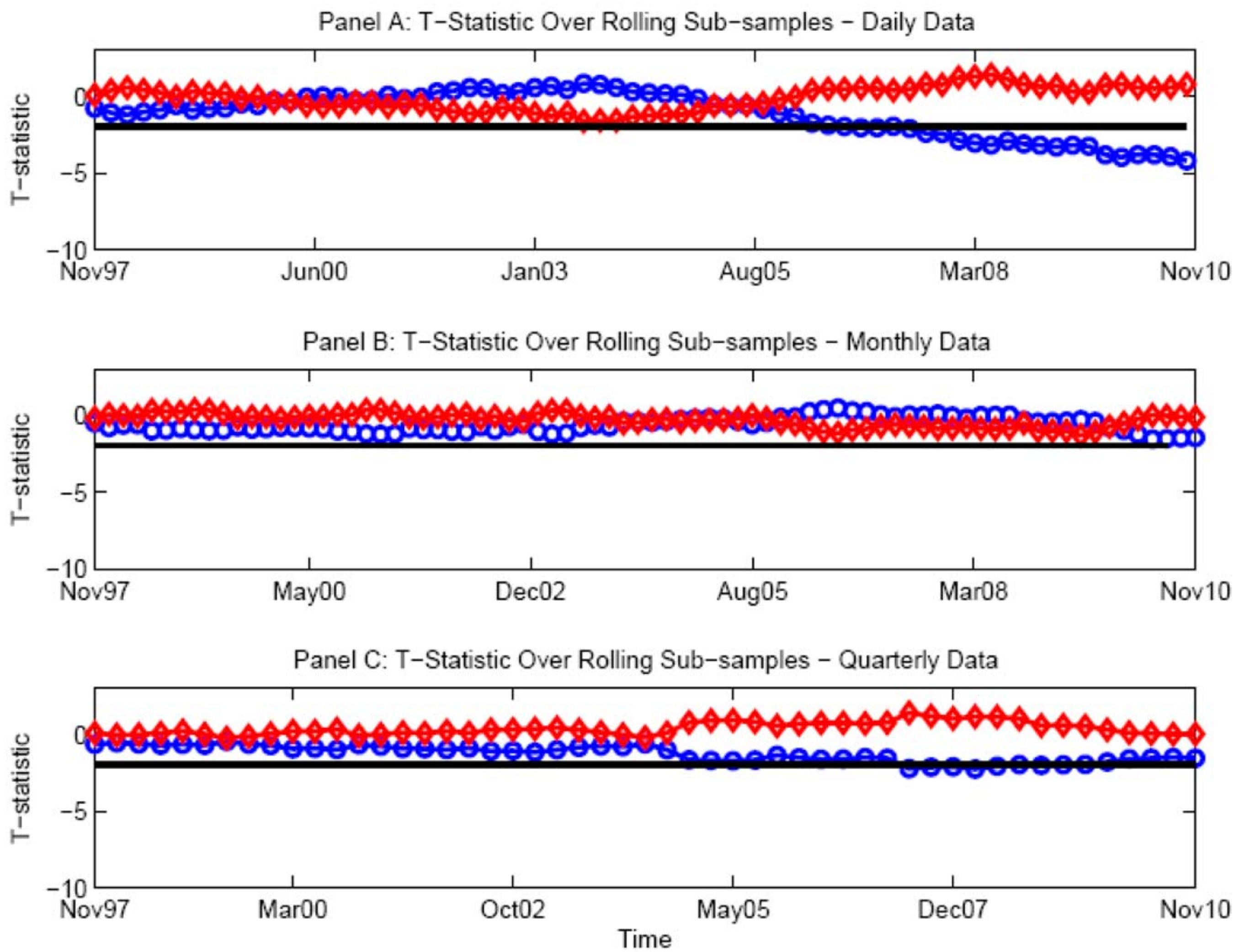
Notes to the Figure. The figure reports Giacomini and Rossi's (2010) Fluctuation test statistic for comparing forecasts of Model (1) relative to a random walk without drift benchmark (line with circles) as well as relative to the random walk with drift benchmark (line with diamonds) and the Threshold Model (line with pluses). Negative values indicate that Model (7) forecasts better. The continuous line indicates the critical value of the Fluctuation test statistic: If the estimated test statistic is below this line, Model (7) forecasts significantly better than its benchmark.

Figure A11. In-sample Fit of the Asymmetric Model – t-statistics Over Time



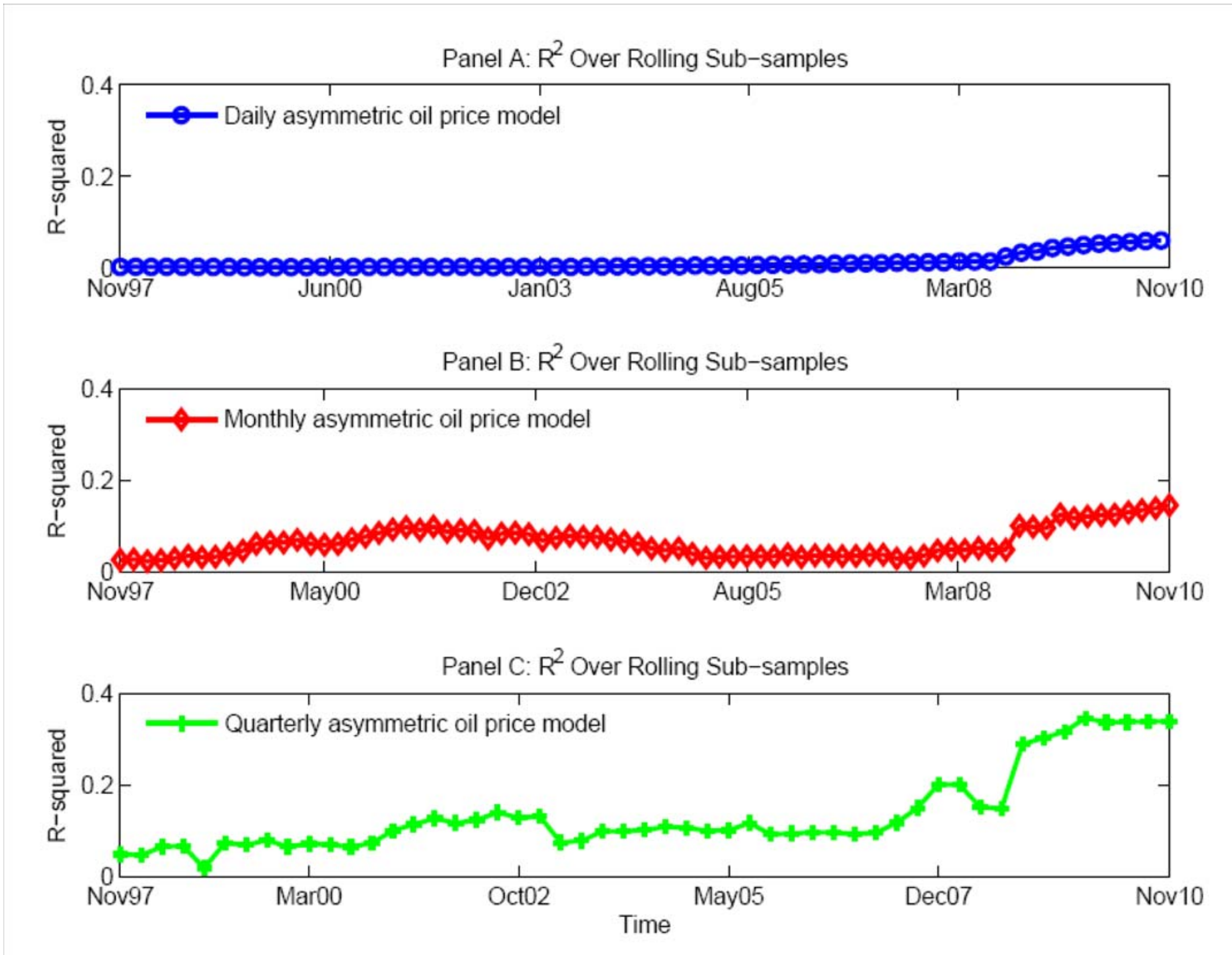
Notes to the Figure. The figure reports in-sample t-statistics for comparing forecasts of Model (1) calculated over rolling samples of size equal to one-half of the total sample size (dates reported on the x-axis). The line with circles is the t-statistic on the coefficient on the oil price growth rate and the line with diamonds is the t-statistic on the coefficient of the non-linear variable, calculated over rolling samples of data. The continuous line indicates the critical value of the t-statistic: If the estimated test statistic is below this line, the relevant coefficient in Model (1) is statistically significantly negative.

Figure A.12. In-sample Fit of the Threshold Model – t-statistics Over Time



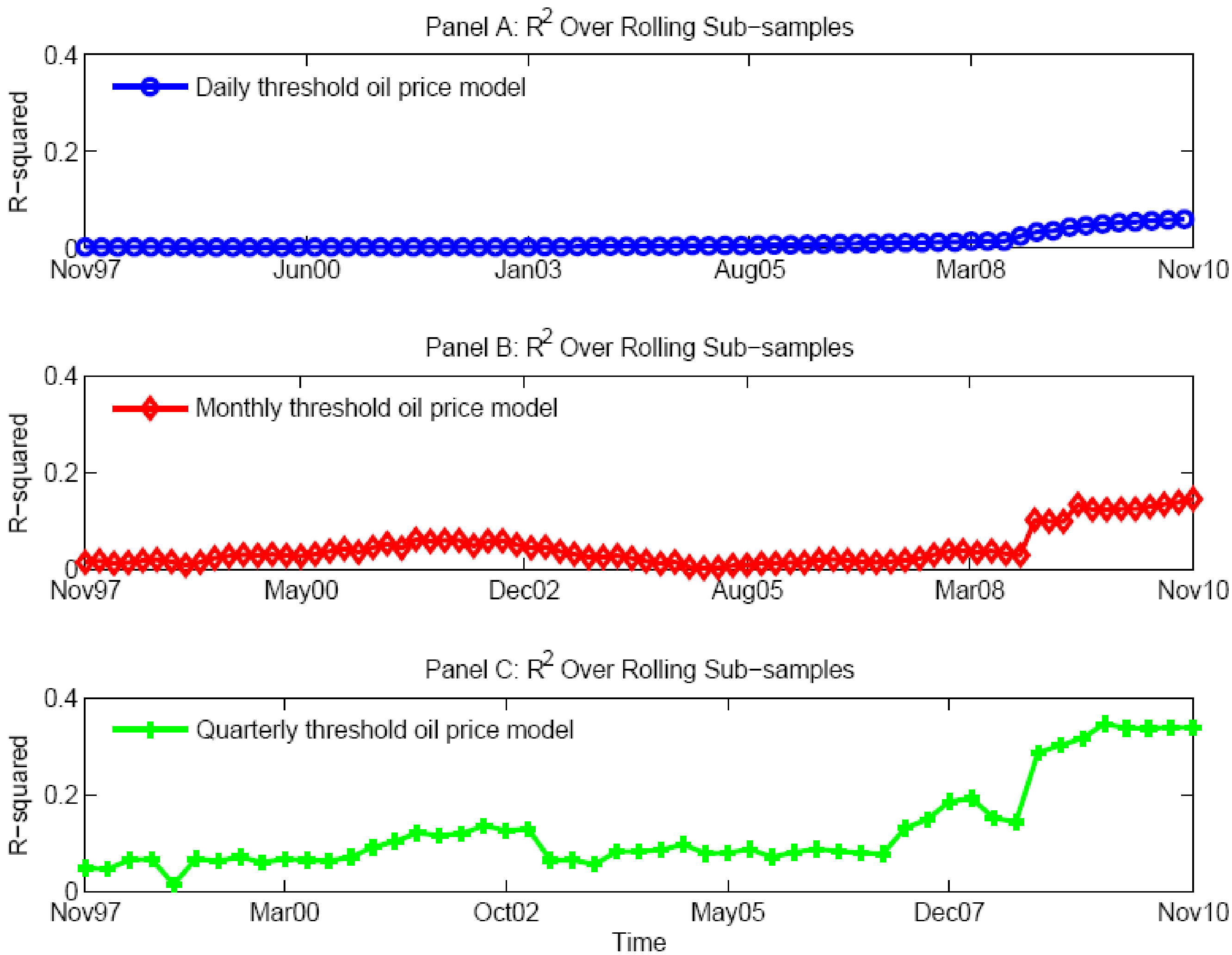
Notes to the Figure. The figure reports in-sample t-statistics for comparing forecasts of Model (1) calculated over rolling samples of size equal to one-half of the total sample size (dates reported on the x-axis). The line with circles is the t-statistic on the coefficient on the oil price growth rate and the line with diamonds is the t-statistic on the coefficient of the non-linear variable, calculated over rolling samples of data. The continuous line indicates the critical value of the t-statistic: If the estimated test statistic is below this line, the coefficient on the oil price in Model (1) is statistically significantly negative.

Figure A.13. In-sample Fit of the Asymmetric Model – R^2 Statistics Over Time



Notes to the Figure. The figure reports in-sample R^2 statistics for comparing forecasts of Model (1) calculated over rolling samples of one-half of the total sample size (dates reported on the x-axis).

Figure A.14. In-sample Fit of the Threshold Model – R^2 Statistics Over Time



Notes to the Figure. The figure reports in-sample R^2 statistics for comparing forecasts of Model (1) calculated over rolling samples (dates reported on the x-axis).

Table A.1 Recursive Estimation for Model 1

Estimation Method	Rolling		Recursive	
Benchmark	RW w/o Drift	RW w/ Drift	RW w/o Drift	RW w/ Drift
1/2	-8.051	-8.094	-8.744	-8.760
1/3	-7.543	-7.563	-8.716	-8.735
1/4	-6.441	-6.504	-8.668	-8.720
1/5	-6.108	-6.145	-8.645	-8.691
1/6	-5.974	-6.023	-8.627	-8.682
1/7	-5.744	-5.780	-8.627	-8.675
1/8	-5.443	-5.499	-8.655	-8.703
1/9	-5.434	-5.479	-8.645	-8.688
1/10	-5.355	-5.402	-8.642	-8.687

Notes. The table reports Diebold and Mariano's (1995) test statistic for comparing the contemporaneous oil price model, eq. (1), with a random walk without drift (column labeled "RW w/o Drift") and a random walk with drift (column labeled "RW w/ Drift") benchmark, for different first starting window sizes as a fraction of the total sample size ("R/T"). The columns labeled "Rolling" report results for a rolling window estimation scheme and those labeled "Recursive" report results for a recursive estimation scheme.

Table A.2. Estimates of the Asymmetric Model

	Daily	Monthly	Quarterly
R^2	0.029	0.08	0.20
α	- 0.000	0.000	-0.002
	(-0.51)	(0.22)	(-0.40)
β	-0.030	-0.046	-0.08
	(-5.84)	(-1.16)	(-1.90)
γ	0.000	-0.029	-0.001
	(0.03)	(-0.48)	(-0.02)

Notes to the Table. The model is eq. (6); HAC robust t–statistics reported in parentheses.

Table A.3. Estimates of the Threshold Model

	Daily	Monthly	Quarterly
R^2	0.03	0.08	0.20
α	-0.000	-0.000	-0.002
	(-0.63)	(-0.63)	(-0.57)
β	-0.04	-0.05	-0.08
	(-4.16)	(-1.46)	(-1.73)
γ	0.008	-0.014	-0.002
	(0.85)	(-0.39)	(-0.03)

Notes to the Table. The model is eq. (7); HAC robust t–statistics reported in parentheses.