CAN EXCHANGE RATES FORECAST COMMODITY PRICES?

Yu-chin Chen (University of Washington)
Kenneth Rogoff (Harvard University)
Barbara Rossi (Duke University)

February 14, 2008

Abstract. This paper studies the dynamic relationship between exchange rate fluctuations and world commodity price movements. Taking into account parameter instability, we demonstrate surprisingly robust evidence that exchange rates predict world commodity price movements, both in-sample and out-of-sample. Our results are consistent with a present value relationship in which the exchange rate depends on a present value of fundamentals including, for a core group of commodity exporters, the world price of their commodity exports. Because global commodity prices are essentially exogenous to these countries, we are able to avoid the endogeneity pitfalls that plague most of the related exchange rate literature. More directly, the analysis suggests that where commodity price forward markets are thin or non-existent, exchange rate-based forecasts may be a viable alternative for predicting future price movements.

J.E.L. Codes: C52, C53, F31, F47

Key words: Exchange rates, forecasting, commodity prices, random walk.

Acknowledgements. We would like to thank C. Burnside, R. Startz, and A. Tarozzi, for useful conversations. We are also grateful to various staff members of the Reserve Bank of Australia, the Bank of Canada, the Reserve Bank of New Zealand, and the IMF for helpful discussions and for providing some of the data used in this paper.

1. Introduction

Over three decades after the collapse of the Bretton Woods regime, the empirical exchange rate literature has yet to uncover any robust causal connection between the behavior of major OECD floating exchange rates and their macroeconomic fundamentals. The literature is not only deeply marred by insignificant and unstable estimates, the endogeneity of the standard fundamentals considered also makes structural interpretations practically impossible. In fact, even under admittedly implausible identification assumptions, prior research mostly concludes that exchange rates are empirically disconnected from economic fundamentals and are best approximated by a random walk.[1]

This paper advances beyond the endogeneity and instability problems afflicting prior research by moving the exchange rate-fundamentals analysis into a new laboratory, that of "commodity currencies," including the Canadian, New Zealand and Australian dollars, as well the South African rand and the Chilean peso. For all of these floating currencies, price fluctuations in world commodity markets represent exogenous terms-of-trade shocks that impact a significant share of their country's exports. By adopting testing procedures that are robust to parameter instabilities, we not only overturn the previous exchange rate-fundamental disconnect findings, we uncover an empirical regularity that has important practical implications to a wide range of developing countries.[2]

[1] There is scant empirical evidence that economic fundamentals can consistently explain movements in major OECD floating exchange rates, let alone actually forecast them, at least at horizons of one year or less. Meese and Rogoff's (1983a,b, 1988) finding that economic models are useless in predicting exchange rate changes remains an outstanding challenge for international macroeconomists, although some potential explanations have been put forward. Engel and West (2005), for example, argue that it is not surprising that a random walk forecast outperforms fundamental-based models, as in a rational expectation present-value model, if the fundamentals are I(1) and the discount factor is near one, exchange rate should behave as a near-random walk. See also Rossi (2005a, 2006) for alternative explanations. Engel, Mark and West (2007) and Rogoff and Stavreklava (2008) offer discussions of the recent evidence.

[2] Disentangling the dynamic relationsihp between the exchange rate and its fundamentals is complicated by the possibility that this relationship may not be stable over time. Mark (2001) states, "...ultimately, the reason boils down to the failure to find a time-invariant relationship between the exchange rate and the fundamentals." See also Rossi (2006).

That is, we find that exchange rates can forecast price movements in global commodity markets.

We are not the first to test present value models of exchange rate determination by running a reverse regression. Campbell and Shiller (1987), and more recently in Engel and West (2005), show that because the nominal exchange rate reflects expectations of future changes in its economic fundamentals, it should help predict them. However, previous tests have employed standard macroeconomic fundamentals such as interest rates, output and money supplies that are plagued by issues of endogeneity, rendering causal interpretation impossible.[3] This problem can be finessed for the commodity currencies, at least for one important determinant, the world price for an index of their major commodity exports.

Even after so finessing the exogeneity problem, disentangling the dynamic causality between exchange rates and commodity prices is still complicated by the possibility of parameter instability, which confounds traditional Granger causality regressions. After, and only after, controlling for the instabilities we find prevalent in these data series, we uncover robust in-sample evidence that exchange rates predict world commodity price movements. (Traditional Granger causality tests in fact give us the misleading results that there is no robust predictability in the data.) Individual commodity currencies Granger-cause their corresponding country-specific commodity price indices, and can also be combined to predict movements in the aggregate world market price index.

As a further test of the robustness of our results to parameter instability, we also look at out-of-sample commodity price forecasting. Here we find that exchange rate-based forecasts deliver substantial improvements over the random walk benchmark in mean square forecast error compar-

[3] This problem is well-stated in the conclusion of Engel and West (2005), "Exchange rates might Granger-cause money supplies because monetary policy makers react to the exchange rate in setting the money supply. In other words, the preset-value models are not the only models that imply Granger causality from exchange rates to other economic fundamentals."

isons. We even find that individual commodity currencies can help forecast important individual commodity prices as well, such as that of gold and nickel, most likely due to their correlation with the global commodity price index.

As one may be concerned that the strong ties global commodity markets have with the U.S. dollar may induce endogeneity in our data, we also conduct robustness checks using exchange rates relative to the Pound and the Yen.[4] We further consider longer-horizon predictability and alternative regression specifications as additional robustness checks. Overall, we see that even though the out-of-sample performance is weaker with the Yen cross-rates, the results in general support the conclusion that commodity currencies can forecast world commodity prices.

We also look at the reverse exercise, and test the usefulness of commodity price indices in forecasting exchange rates. In the out-of-sample tests, we find no consistent evidence that commodity prices outperform a naïve random walk in forecasting nominal exchange rate changes. Nevertheless, the fact that controlling for parameter instability makes a big difference in our in-sample results, combined with our positive results on forecasting commodity prices, suggests that the commodity currencies may ultimately prove more amenable to out-of-sample forecasting than other major floating currencies.

To summarize, we obtain the robust yet theoretically sensible finding that commodity exchange rates are not only connected to their fundamentals, they can actually forecast global commodity price movements. Since world commodity prices are essentially exogenous to these small countries' exchange rates, our finding breaks free of the reverse causality problem afflicting previous research efforts, and provides direct support for a present-value model of nominal exchange rate

[4]For example, since commodities are mostly priced in dollars, one could argue that global commodity demands and thus their prices would go down when the dollar is strong. In addition to the Yen and the Pound cross rates, we also used the nominal effective exchange rates for the commodity economies and reached the same qualitative results.

determination. Although our results are not surprising from a theoretical standpoint, their empirical robustness is, especially in view of the decades of negative findings that dominate the empirical exchange rate literature. As an important by-product of our analysis, we develop a novel approach for predicting future commodity price movements, an approach that may prove to have practical value as many commodities lack deep and liquid forward markets.

2. Background and Data Description

Although the commodity currency phenomenon may extend to a broader set of developing countries, our study focuses on five small commodity-exporting economies with a sufficiently long history of market-based floating exchange rates, and explores the dynamic relationship between exchange rates and world commodity prices.

As shown in Appendix Table A1, Australia, Canada, Chile, New Zealand, and South Africa produce a variety of primary commodity products, from agricultural and mineral to energy-related goods. Together, commodities represent between a quarter and well over a half of each of these countries' total export earnings. Even though for certain key products, these countries may have some degree of market power (e.g. New Zealand supplies close to half of the total world exports of lamb and mutton), on the whole, due to their relatively small sizes in the *overall* global commodity market, these countries are price takers for the vast majority of their commodity exports.[5] As such, global commodity price fluctuations serve as an easily-observable and *exogenous* shock to these countries' exchange rates.

From a theoretical standpoint, exchange rate responses to terms-of-trade shocks can operate

[5] In 1999, for example, Australia represents less than 5 percent of the total world commodity exports, Canada about 9 percent, and New Zealand 1 percent. Furthermore, substitution across various commodities also mitigates the market power these countries have, even within the specific market they appear to dominate. See Chen and Rogoff (2003) for a more detailed discussion and analyses.

through several well-understood channels, such as the income effect and the Balassa-Samuelson channel.[6] In practice, however, sound theories rarely translate into robust empirical support in the exchange rate literature; moreover, for most OECD countries, it is extremely difficult to actually identify an exogenous measure of terms-of-trade. Since exogenous world commodity prices can be observed daily from the few centralized exchanges, the commodity currencies we study overcome these concerns, and thus offer a unique laboratory for testing exchange rate theories.

As we discuss in more detail in Appendix 2, a direct implication of the present-value exchange rate models is that the nominal exchange rate, as an asset price, embodies expected future changes in its fundamentals and thus should help predict them. However, standard exchange rate fundamentals, such as cross-country differences in money supplies, interest rates, and inflation rates, are jointly determined with exchange rates in equilibrium; they may also directly react to exchange rate movements through policy responses. For these reasons, reduced-form testing of the dynamic present-value relationship is plagued with endogeneity problems. Commodity prices are a unique exchange rate fundamental for these countries because the causality is clear, and a direct testing of the present-value theoretical approach is thus feasible.[7] In addition, since these countries all experienced major changes in policy regimes and/or market conditions (such as the adoption of an inflation target), we also emphasize the importance of allowing for time-varying parameters.

We examine the dynamic relationship between exchange rates and commodity prices in terms of Granger causality and out-of-sample forecasting ability.[8] We regard these two tests as important alternative approaches to evaluating the predictive content of a variable. The in-sample tests

[6] See, for example, Chen and Rogoff (2003), and Chs. 4 and 9 in Obstfeld and Rogoff (1996).

[7] Amano and van Norden (1993), Chen and Rogoff (2003, 2006), and Cashin, Cespedes, and Sahay (2004), for example, establish commodity prices as an exchange rate fundamental for these commodity currencies

[8] Previous studies on commodity currencies emphasize the strong contemporaneous causal relationship from commodity prices to exchange rates. There has been little success in finding stable dynamic relationships in various exchange rate forecasting exercises (see Chen (2005), for example.)

take advantage of the full sample size and thus are likely to have higher power, while the out-of-sample forecast procedure may prove more practical as it mimics the data constraint of real-time forecasting.[9] We use quarterly data over the following time-periods: Australia (from 1984:1 to 2005:4), Canada (from 1973:1 to 2005:4), Chile (from 1989:3 to 2005:4), New Zealand (from 1987:1 to 2005:4), and South Africa (from 1994:1 to 2005:4).[10] For each commodity economy, we aggregate the relevant dollar spot prices in the world commodity markets to construct country-specific, export-earnings-weighted commodity price indices (labeled "cp").[11] For nominal exchange rates ("s"), we use the end-of-period U.S. dollar rates from the IFS for the majority of our analyses. We also consider cross rates relative to the Japanese yen and the British pound as a robustness check. We use the *All Commodities and Oil Index* in US dollars ("cp^W") from the IMF to measure movements in the overall aggregate world commodity markets. It is a world export-earnings-weighted price index for over forty products traded on various exchanges.[12]

As standard unit root tests cannot reject that these series contain unit roots, we proceed to analyze the data in first-differences, which we denote with a preceding Δ.[13] In Section 4, we

[9] As is well-known in the literature, in-sample predictive tests and out-of-sample forecasting tests can and often provide different conclusions, which could result from their differences in the treatment of time-varying parameters, the possibility of over-fitting, sample sizes, and other biases...etc. See Inoue and Kilian (2004). We do not promote one over the other here, but recognize the trade-offs.

[10] Canada began floating its currency in 1970, and Astralia and New Zealand abandoned their exchange rate pegs in 1983 and 1985 respectively. For Chile and South Africa, our sample periods are chosen a bit more arbitrarily: Chile operated under a crawling peg for most of the 1990s, and the starting point for South Africa roughly corresponds to the end of apartheid. We note that we also conducted all the analyses presented in this paper using monthly data up to the end of 2007 for the subset of countries that we have all the data. The results are qualitatively similar and are available upon request.

[11] Individual commodity price data are collected from the IMF, Global Financial Database, the Bank of Canada, and the Reserve Bank of New Zealand. Appendix Table A1 provides the country-specific weights used to aggregate individual world commodity prices into country-specific indices.

[12] The IMF series underwent significant revisions in recent years (see IMF's website for details). We splice the series in order to have a relatively consistent series going as far back as possible (to 1980).

[13] Here we do not consider cointegration but first differences since we are not testing any specific models. Chen and Rogoff (2003) showed that, in analyzing real exchange rates, DOLS estimates of cointegrated models and estimates of models in differences produce very similar results. (From a practical point of view, real exchange rates and nominal ones behave very similarly.) Chen (2005) examines commodity-priced augmented monetary models in the cointegration framework.

present an alternative predictive regression specification that is robust to the possibility that the autoregressive roots in these data may not be exactly one, although very close to it (i.e. they are "local-to-unity"). We see that our findings are robust to these different assumptions. In addition, we note that even in the individual data series, we observe strong evidence of structural breaks, found mostly in early 2000's.[14] This finding foreshadows one of our major conclusions that controlling for parameter instabilities is crucial in analyzing the exchange rate-fundamental connection.

3. Exchange Rates and Commodity Prices: Which Predicts Which?

In this section, we analyze the dynamic relationship between nominal exchange rates and commodity prices by looking at both in-sample predictive content and out-of-sample forecasting ability. We first examine whether the exchange rate can explain future movements in commodity prices, as a test of the present-value theoretical approach. Following the Meese-Rogoff (1983a,b) literature, we next look at the reverse analyses of exchange rate predictability by commodity prices.

Using Rossi's (2005b) procedure that is robust to time-varying parameters, we first see that individual exchange rates Granger-cause movements in their corresponding country-specific commodity price indices, and that this predictive content translates to superior out-of-sample forecast performance relative to a random walk benchmark. We then look into multivariate analyses using several exchange rates and forecast combinations. We find these commodity currencies together forecast price fluctuations in the aggregate world commodity market quite well. Figures 1 and 2 present a quick visual preview to this key finding. World commodity price forecasts based on the exchange rates - whether entered jointly in a multivariate model or individually under a forecast

[14] A more detailed analysis of the time series properties of these series, as well as the other fundamentals typically used in the canonical exchange rate literature, are not included in this draft but are available upon request.

combination approach - track the actual data dramatically better than the random walk.

Concerning the reverse exercise of forecasting exchange rates, addressing parameter instability again plays a crucial role in uncovering evidence for in-sample exchange rate predictability from commodity prices. The out-of-sample analyses, however, show essentially no evidence of exchange rate forecastability.

All the analyses in this section are based on U.S. dollar exchange rates. The next section provides additional evidence by looking at different anchor-currencies, longer-horizon predictive regressions robust to "local-to-unity" regressors, and implications for individual commodity markets. Appendix 3 provides an overview of the time series methods that we use.

3.1. Can Exchange Rates Predict Commodity Prices?. We first investigate the empirical evidence on Granger-causality, using both the traditional testing procedure and one that is robust to parameter instability. We demonstrate the prevalence of structural breaks and emphasize the importance of controlling for them. Our benchmark Granger causality analyses below include one lag each of the explanatory and dependent variables, though our findings are robust to the inclusion of additional lags.[15]

In-Sample Granger-Causality (GC) Tests. Present value models of exchange rate determination imply that exchange rates must Granger-cause fundamentals. In other words, ignoring issues of parameter instabilities, we should reject the null hypothesis that $\beta_0 = \beta_1 = 0$ in the regression:[16]

$$E_t \Delta f_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta f_t \qquad (1)$$

[15] Additional lags are mostly found to be insignificant based on the BIC criterion.

[16] We note that the qualitative results are the same if one tests for only $\beta_1 = 0$. Our choice here is more consistent with the driftless random walk benchmark commonly used in the exchange rate literature. Our finding is also robust to the inclusion of additional lags, or even the exclusion, of Δf_t.

Panel A in Table 1 reports the results based on the above standard Granger-causality regression for the five exchange rates and their corresponding commodity price indices. All variables are first differenced, and the estimations are heteroskedasticity and serial correlation-consistent.[17] The table reports the p-values for the tests, so a number below 0.05 implies evidence in favor of Granger causality (at the 5% level). We note that overall, traditional Granger-causality tests find essentially no evidence for exchange rates Granger-causing commodity prices.

An important drawback in these Granger-causality regressions is that they do not take into account potential parameter instabilities. We find that structural breaks are a serious concern not only theoretically as discussed above, but also empirically as observed in the individual time series data under consideration.[18] Table 2 reports results from the parameter instability test, based on Andrews (1993), for the bivariate Granger-causality regressions. We observe strong evidence of time-varying parameters in several of these relationships. As such, we next consider the joint null hypothesis that $\beta_{0t} = \beta_0 = 0$ and $\beta_{1t} = \beta_1 = 0$ by using Rossi's (2005b) $Exp - W^*$ test, in the following regression setup:[19]

$$E_t \Delta f_{t+1} = \beta_{0t} + \beta_{1t} \Delta s_t + \beta_2 \Delta f_t \tag{2}$$

Table 3, Panel A shows that this test of Granger-causality, which is robust to time-varying parameters, indicates strong evidence in favor of a time-varying relationship between exchange rates and commodity prices.

[17] Results are based on the Newey and West (1987) procedure with bandwidth $T^{1/3}$ (where T is the sample size.)

[18] Results from structural break analyses using Andrews' (1993) QLR test and Rossi's (2005b) Exp-W* test are available upon request.

[19] We confirmed (by testing only $\beta_{1t} = \beta_1 = 0$) that our positive Granger causality findings are not the result of random walk fundamentals with time-varying drifts.

We emphasize again that in general, positive Granger-causality findings merely indicate that exchange rate changes precede movements in the particular fundamental; they are not necessarily a valid test for the causal relationship from fundamentals to exchange rates, as specified in a present-value model. Even when a present-value relationship exists, the positive Granger-causality finding could be observationally equivalent to other explanations, unless the fundamental under consideration is exogenous to the exchange rate (see Appendix 2 for more discussion.) The positive Granger-causality finding from exchange rates to commodity prices, on the other hand, is not confounded by this endogeneity problem. Because world commodity prices are essentially exogenous to these exchange rates, we interpret our findings as evidence in favor of a net present value approach to exchange rate determination.

INSERT TABLES 1, 2 AND 3 HERE

Out-of-Sample Forecasts. We now ask whether in-sample Granger-causality translates into out-of-sample forecasting ability. We adopt a rolling forecast scheme based on eq (1), without the lagged dependent variable Δf_t, and test for forecast encompassing relative to a random walk ($E_t \Delta f_{t+1} = 0$). Here we present results based on a random walk benchmark due to its significance in the exchange rate literature.[20] Specifically, we use a rolling window with size equal to half of the total sample size to estimate the model parameters and generate one-quarter ahead forecasts recursively (what we call "model-based forecasts"). Table 4 reports the difference between the associated mean square forecast errors (MSFE) from this procedure and the MSFE of the random walk benchmark, after re-scaling by a measure of their variability.[21] A negative number indicates

[20] Our findings are robust to the inclusion of lagged dependent variables in both forecast specifications, as one may do in the spirit of an out-of-sample Granger causality test. We also extend the comparison to a random walk with drift, and find similar results.

[21] This procedure produces a statistic similar to the standard Diebold and Mariano (1995) test statistic.

that the model outperforms a driftless random walk, and for proper inference, we use Clark and McCracken's (2001) 'ENCNEW' test of equal MSFEs to compare these nested models. A rejection of the null hypothesis, which we indicate with asterisks, implies that the regressor contains out-of-sample forecasting power for the dependent variable.

Panel A in Table 4 shows that exchange rates help forecast commodity prices, even out of sample. The exchange rate-based models outperform a random walk in forecasting changes in world commodity prices, and this result is quite robust across the five countries.[22] The strong evidence of commodity price predictability in both in-sample and out-of-sample tests is quite remarkable, given the widely documented pattern in various forecasting literature that in-sample predictive ability often fails to deliver out-of-sample success.

INSERT TABLE 4 HERE

3.2. Can Exchange Rates Predict Aggregate World Commodity Price Movements? Multivariate Predictions and Forecast Combinations. Having found that individual exchange rates can forecast the price movements of its associated country's commodity export basket, we next consider whether combining the information from all of our commodity currencies can help predict price fluctuations in the aggregate world commodity market. For the world market index, we use the IMF's "All Commodities and Oil Index" (cp^W) discussed earlier.[23]

We first look at the in-sample predictability of the world price index and consider multivariate Granger causality regressions using the three longest exchange rate series (South Africa and Chile

[22] We note that the sample size for South Africa, being quite a bit shorter than the other countries, may not be sufficient for meaningful testing of out-of-sample forecast power.

[23] The index only goes back to 1980, so the sample size we are able to analyze is shorter in this exercise for Canada.

are excluded to preserve a larger sample size):

$$E_t \Delta cp^W_{t+1} = \beta_0 + \beta_{11}\Delta s^{AUS}_t + \beta_{12}\Delta s^{CAN}_t + \beta_{13}\Delta s^{NZ}_t + \beta_2 \Delta cp^W_t \tag{3}$$

Panels A through C in Table 5 reveal results consistent with our earlier findings using single currencies. This time, traditional Granger causality tests suggest that the commodity currencies have predictive power (panel A), and controlling for time-varying parameters reinforces the evidence in favor of the three exchange rates jointly predicting the aggregate commodity price index (panel C).

We next extend the analysis to look at out-of-sample forecasts. We consider two approaches: multivariate forecast and combination of univariate forecasts. The multivariate forecast uses the same three exchange rates as in equation (3) above to implement the rolling regression forecast procedure described in the previous section. We again use Clark and McCracken's (2001) ENC-NEW test to evaluate the model's forecast performance relative to a random walk forecast. Table 5 Panel D shows that using the three commodity currencies together, we can forecast the world commodity price index significantly better than a random walk at the 1% level. This forecast power is also quite apparent when we plot the exchange rates-based forecasts along with the actual realized changes of the (log) global commodity price index in Figure 1. The random walk forecast is simply the x-axis (forecasting no change). We see that overall, the commodity currency-based forecasts track the actual world price series quite well, and fit strikingly better than a random walk.[24]

[24] We can improved the forecast performance of the model even more by further including lagged commodity prices in the forecast specifications.

INSERT TABLE 5 AND FIGURE 1 HERE

We next consider forecast combination, which is an alternative way to exploit the information content in the different exchange rates. The approach involves computing a weighted average of different forecasts, each obtained from using a single exchange rate. That is, we first estimate the following three regressions and generate one-step ahead world commodity price forecasts, again using the rolling procedure:

$$E_t \Delta cp_{t+1}^{W,i} = \beta_{0,i} + \beta_{1,i} \Delta s_t^i \quad \text{where } i = AUS, CAN, NZ \tag{4}$$

While there are different methods to weigh the individual forecasts, it is well known that simple combination schemes tend to work best (Stock and Watson 2003 and Timmermann 2006.) We consider equal weighting here, and compare our out-of-sample forecast of future global commodity prices, $\left(\Delta cp_{t+1}^{W,AUS} + \Delta cp_{t+1}^{W,CAN} + \Delta cp_{t+1}^{W,NZ}\right)/3$, with the random walk forecast. We report the result in Table 5 Panel E. Again, we observe that the MSFE difference is negative and significant, indicating that the commodity price forecasts constructed from individual exchange rate-based forecasts outperform the random walk.[25] This finding is illustrated graphically in Figure 2, which plots the forecasted global commodity price obtained via forecast combination, along with the actual data (both in log differences). The random walk forecast, of no change, is the x-axis. The figure shows that the combined forecast tracks the actual world price series much better than the random walk.

INSERT FIGURE 2 HERE

[25] To judge the significance of forecast combinations, we used critical values based on Diebold and Mariano (1995).

Finally, as a robustness check, we also examine whether each individual exchange rate series by itself can predict the global market price index. We note that this exercise is perhaps more a test to see whether there is strong co-movement amongst individual commodity price series, rather than based on any structural model. The first lines (labeled "s_t GC cp_{t+1}") in Table 6 report results for the predictive performance of each country-specific exchange rates. Remarkably, the finding that exchange rates predict world commodity prices appears extremely robust: the Australian, Canadian, and New Zealand exchange rates each have predictive power for the aggregate global commodity price index, and they also all outperform a random walk in out-of-sample forecasts.

INSERT TABLE 6 HERE

3.3. Can Commodity Prices Predict Exchange Rates?. Having found strong and robust evidence that exchange rates can forecast future commodity prices, we now consider the reverse exercise of forecasting these exchange rates. We have already shown promising in-sample results by allowing for structural breaks. In terms of out-of-sample forecasting ability, however, commodity currencies exhibit the same Meese-Rogoff puzzle as other major currencies studied in the literature; none of the fundamentals, including commodity prices, consistently forecasts exchange rate movements better than a random walk.[26]

The lower panels (Panel B) in Tables 1-4, and Table 6 present results on exchange rate predictability by commodity prices. We first consider whether commodity prices Granger-cause nominal exchange rate changes, using standard tests that ignore the possibility of parameter instability.

[26]We conducted, but excluded from this draft, the same analyses presented in Tables 1-4 using the standard exchange rate fundamentals as well. (These include the short-run interest rate differential, the long-run interest rate differential, the inflation rate differential, the log real GDP differential, and the log money stock differential between the relevant country-pairs.) We observe exactly the Meese-Rogoff puzzle, consistent with findings in the literature.

We look for rejection of the null hypothesis that the $\beta_0 = \beta_1 = 0$ in the following regression:

$$E_t \Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta s_t \tag{5}$$

Similarly to the results in Panel A, Table 1 Panel B shows that traditional Granger-causality tests do not find any evidence that commodity prices Granger-cause exchange rates. We do find strong evidence of instabilities in the regressions, however, as seen in Table 2 Panel B. We then test the joint null hypothesis of $\beta_{0t} = \beta_0 = 0$ and $\beta_{1t} = \beta_1 = 0$, using Rossi's (2005b) $Exp - W^*$ test in the following regression:

$$E_t \Delta s_{t+1} = \beta_{0t} + \beta_{1t} \Delta cp_t + \beta_2 \Delta s_t \tag{6}$$

Results in Table 3, Panel B, show that when looking at in-sample Granger causality, exchange rates are predictable by their country-specific commodity price indices, once we allow for time-varying parameters. This is a very promising result given previous failures to connect the exchange rate and its fundamentals dynamically. We note that there does not appear to be significant differences between using exchange rates to predict commodity prices or vice versa, when we look at in-sample Granger causality regressions robust to parameter instability.

The major difference between the two directions comes from comparing out-of-sample forecasting ability. Comparing Panel B to Panel A in Table 4, we see that there are hardly any negative numbers in Panel B, giving us exactly the Meese-Rogoff stylized fact. We note the same pattern in Table 6, where individual exchange rates forecast aggregate world commodity price index better than a random walk, but world commodity price index does not help forecast exchange rates.

This asymmetry in forecastability can be the result of many factors, ranging from potential non-linearities to the relative depth of the exchange rate markets, which may contribute to the exchange rates being more closely approximated by a random walk than commodity prices.[27]

4. Robustness Analyses

The previous section shows strong evidence that the U.S. dollar-based exchange rates of the five commodity-exporters can forecast price movements in global commodity markets. This novel finding raises some questions as well as potentially interesting implications, which we explore in this section. First, we consider whether this dynamic connection between movements in the currencies and in the commodity prices may result from a "dollar effect", as both are priced in U.S. dollars. In addition, we consider an alternative predictive regression specification that is robust to highly persistent regressors, and examine longer-horizon predictions, up to two years ahead. Lastly, since we observe such robust results that exchange rate-based models can forecast various aggregated commodity price indices, we explore whether the forecastability extends to the prices of individual commodity products.

4.1. Alternative Benchmark Currencies. Since commodity products are priced in dollars, there may be some endogeneity induced by our use of dollar cross rates in the analyses above. For instance, one could imagine that when the dollar is strong, global demand for dollar-priced commodities would decline, inducing a drop in the associated commodity prices. Any aggregate uncertainty about the U.S. dollar may also simultaneously affect commodity prices and the value of the dollar (relative to the commodity currencies.) To remove this potential reverse causality or endogeneity, this section re-examines the predictive Granger causality regressions and out-of-

[27] See Appendix 2 for further discussions.

sample forecast exercises using exchange rates vis-a vis the British Pound and the Japanese Yen. Table 7 reports results parallel to those in Tables 1-4. Panels A and B report the p-values for the Granger causality and Andrews' (1993) QLR tests for the predictive regressions. Panel C shows predictability results robust to parameter instabilities, using Rossi's (2005b) $Exp-W^{*}$ test. Lastly, Panel D reports the relative MSFEs from comparing exchange rate-based models to the random walk in out-of-sample forecasts.

Overall, we see that our earlier conclusions are quite robust under the two alternative benchmark currencies. We first observe that ignoring structural breaks, none of the traditional Granger causality tests in Panel A rejects the null hypothesis that there is no relationship between exchange rates and commodity prices. However, as before, we uncover substantial instabilities in such regressions (Panel B), found mostly around 2002. When such instability is taken into account, we see extremely strong evidence in favor of Granger-causality. In particular, we see the evidence is slightly stronger when we use exchange rates to predict the commodity price indices than the other way around. Panel D shows that the predictive power of exchange rates for future commodity prices carries over to out-of-sample forecasts as well. The results based on the British Pound are strongly supportive of the forecasting power of exchange rates for future commodity prices, whereas those for the Yen are somewhat weaker.[28]

INSERT TABLE 7 HERE

4.2. Highly Persistent Regressors and Long-Horizon Predictability. We have analyzed the dynamic connections between nominal exchange rates and fundamentals using data in first-

[28] Using monthly data up to the end of 2007 for a subset of countries we have the full set of data, we observe strong predictability of commodity prices , both in- and out-of-sample, using nominal effective exchange rates. This is another indication that "the dollar effect" is not dominating our findings.

differences thus far. This approach is consistent with the view that the series contain unit roots, which both has overwhelming empirical support and is theoretically sensible.[29] In this section, we consider an alternative specification and inference procedure that is robust to the possibility that the largest autoregressive (AR) roots in these series may not be *exactly* one, despite being very close to one. That is, we model the regressors in the predictive regressions as highly persistent and use tests statistics based on local-to-unity asymptotics.[30] We consider the robustness of our main findings (in Section 3) to this form of high persistence in the regressors, and also to longer-horizon predictive analyses. Results below show that our earlier findings are very robust.

We focus on three countries only: Canada, Australia and New Zealand, as they have longer sample periods which are necessary for more meaningful testing of long-horizon predictability. Letting s_t and f_t denote the levels of nominal exchange rate and fundamental (commodity prices) at time t, the short horizon exchange rate predictive regression can be expressed as follows:

$$\Delta s_{t+1} = \mu_1 + \beta f_t + \gamma \Delta s_t + \epsilon_{1,t+1} \tag{7}$$

$$b(L)^{-1}(1 - \rho L) f_{t+1} = \mu_2 + \epsilon_{2,t+1}$$

where $\epsilon_{1,t+1}$ and $\epsilon_{2,t+1}$ are assumed to be contemporaneously but not serially correlated, and ρ is assumed to be "local-to-unity" (very close to 1). The inference procedure robust to highly persistent regressors for this short-horizon predictive regressions is based on Campbell and Yogo (2006).

[29] See Obstfeld and Rogoff (1996), Mark (2001), for example. A not-for-publication appendix providing detailed empirical analyses on the time series properties of the fundamentals we consider is available upon request.

[30] See Elliott (1998), Campbell and Yogo (2006), for example. The local-to-unity asymptotics allows us to obtain reliable small sample approximations to the distribution of the test statistics when, empirically, the largest root is close to unity, and conveniently avoids problems arising from pre-test bias.

Assuming the same stochastic process for f_t above, the corresponding long-horizon regression can be expressed as:[31]

$$\Sigma_{j=1}^{h}\Delta s_{t+j} = \beta_h f_t + \lambda \Delta s_t + \xi_{t,h} \tag{8}$$

The long horizon regression analyses are based on Rossi's (2007) procedure, which consists of inverting Elliott, Rothemberg and Stock's (1995) test in the first stage, and adopting Campbell and Yogo's (2006) test in the second stage.

For the reverse direction - using exchange rates to predict commodity prices - the regression robust to highly persistent regressor can be specified as:

$$\Sigma_{j=1}^{h}\Delta f_{t+j} = \beta_h s_t + \lambda \Delta f_t + \xi_{t,h} \tag{9}$$

where s_t would then be assumed to "highly persistent":

$$b(L)^{-1}(1-\rho L)\, s_{t+1} = \mu_1 + \epsilon_{2,t+1}$$

Table 8 reports the 95% confidence intervals for β estimated from (7) in the rows with "$h = 1$"(one quarter-ahead forecast), and confidence intervals for β_h estimated from (8) and (9) in the rows under "$h = 4$" and "$h = 8$", for one- and two-year-ahead forecasts, respectively.[32] When the confidence intervals do not contain zero, we consider them as evidence in favor of predictive ability. The table shows that the predictability at long horizons is quite strong, both from exchange rates to commodity prices and vice-versa (with the exception of predicting the Australian commodity

[31] Regression (7) includes the lagged endogenous variable, where we assume $|\gamma| < 1$. The formula in Rossi (2007) has to be modified to take this into account. Her expression (4.14) becomes: $\beta_h = \beta \sum_{j=1}^{h} \rho^{j-1} (1-\gamma)^{-1}$, and the confidence interval follows straightforwardly from this. Direct calculations show that $\lambda \equiv h\Sigma_{j=1}^{h}\gamma^j$.

[32] We note the h =1 case is just a special case of the other two.

price index). This supports our earlier findings, based on first-differenced specifications, that the in-sample dynamic connection between commodity prices and exchange rates is very strong and robust.[33]

INSERT TABLE 8 HERE

4.3. Individual Commodity Prices. Having found robust evidence that exchange rate-based models can forecast various aggregated commodity price indices, we now explore whether the forecasting ability extends to some individual commodity products of interest. Positive results may have significant policy implications and could be very useful to the many commodity-exporting countries that care about forecasting price movements in world commodity markets. While it would be interesting to compare exchange rate-based commodity price forecasts with other methods (such as using commodity forwards), we do not explore the comparisons here. We note that some commodity markets do not have forwards, in which case exchange rate-based forecasts may be one viable alternative to gauge future market movements.

We consider both in-sample Granger causality regressions (robust to parameter instability) and out-of-sample forecasts, focusing on the connection between a selected group of mineral and energy-related products and the exchange rates of Australia, Canada, and New Zealand.[34] Panel A in Table 9 reports the p-values from regression (2), and Panel B the p-values from regression (6) for gold, silver, nickel, and natural gas. Asterisks denote significance level of 10%. We find that all three exchange rates have predictive ability for price movements of silver and gold, and the price

[33] We also conducted additional analyses using standard fundamentals, although these are highly endogenous, as we have noted. In the interest of space, we do not report the full table here. Overall, we find that for most countries and most fundamentals, we are able to reject the null hypothesis of no predictivability (i.e. most confidence intervals exclude zero).

[34] Unreported results show that for all commodities and countries, we do not reject the null hypothesis that the parameter is insignificant in either regression (5) or regression (1). However, when we take into account the possibility that the parameter is time-varying, the results change substantially.

of nickel is predictable by the Australian and New Zealand exchange rates as well. Evidence for the reverse, i.e. for gold or silver prices to Granger-cause exchange rates, appears weaker.

INSERT TABLE 9

Table 10 reports the p-values, based on Clark and West's (2006) test statistic, for the out-of-sample forecast comparisons with a random walk. The forecasts are conducted using the same rolling procedure described in Section 3. The null hypothesis in Panel A is that individual commodity prices are best forecasted by a random walk, while the alternative hypothesis is that exchange rate-based models outperform a random walk commodity price forecast. Panel A shows the p-values for this one-sided test: asterisks light p-values smaller than 0.10, which indicate that exchange rates provide significant predictive content for forecasting commodity prices out of sample. Panel B reports the p-values for the reverse exercise of exchange rate forecast, comparing individual commodity price-based forecasts with a random walk. Again, asterisks light p-values smaller than 0.10, indicating that lagged commodity prices provide significant predictive content for forecasting exchange rates out of sample. We see from Table 10 that nickel prices appear to be forecastable by all three exchange rates, while natural gas prices are also forecastable by the Australian and New Zealand currencies. Interestingly, the in-sample predictability of silver prices did not carry over out-of-sample.

INSERT TABLE 10 HERE

While we only explore a small set of commodity products in these simple bilateral tests, we consider these findings to be very promising. They provide a simple and viable method of forecasting price movements in individual commodity markets where alternative indicators may not be available. We leave more comprehensive explorations, such as using the multivariate forecast procedure discussed in Section 3 on a broader set of commodity products, to future research.

5. Conclusion

This paper investigates the dynamic relationship between commodity price movements and exchange rate fluctuations. After controlling for time-varying parameters, we not only find robust a relationship, we also uncover a surprising finding that exchange rates are very useful in forecasting future commodity prices. From a technical perspective, because our approach is robust to parameter instabilities and because commodity prices are essentially exogenous to the exchange rates we consider, our findings can be given a causal interpretation and thus represent a substantial advance over the existing literature. We are able in particular to overcome the greatest difficulty in testing single-equation, reduced-form, exchange rate models, namely, that the standard fundamentals may be endogenous and that omitted variables may lead to parameter instabilities. For these reasons, we argue that commodity currencies offer an ideal laboratory for cutting-edge work on exchange rate models. There simply is no other instance of such a consistently clear and identifiable shock as world commodity prices.

Our results are robust to multivariate regressions, alternative benchmark currencies, forecast combinations, highly persistent (local-to-unit root) regressors, and longer-horizon predictions. One might eventually extend the approach to look at countries that have few or no commodities, such as most of Asia, to see if commodity prices affect the value of their currencies, and if their currency fluctuations may offer predictive power for, say, oil prices. Our findings raise a broader question of whether one can exploit information from the nexus of global foreign exchange markets to predict commodity prices. We do not attempt such analysis here, and leave it for future research.

6. References

Amano, R., Norden, S., (1993), "A Forecasting Equation for the Canada-U.S. Dollar Exchange Rate," *The Exchange Rate and the Economy*, 201-65. Bank of Canada, Ottawa.

Andrews, D.W.K. (1993), "Tests for Parameter Instability and Structural Change with Unknown Change Point", *Econometrica* 61(4), 821-856.

Campbell, J. Y., and R. Shiller (1987), "Cointegration and Tests of Present Value Models," *Journal of Political Economy* 95(5), 1062-88.

Campbell, J.Y., and M. Yogo (2006), "Efficient Tests of Stock Return Predictability", *Journal of Financial Economics 81,* 27-60.

Cashin, P., L. Céspedes, and R. Sahay (2004) "Commodity Currencies and the Real Exchange Rate" *Journal of Development Economics*, Vol. 75, pp. 239-68.

Chen,Y. (2005), "Exchange Rates and Fundamentals: Evidence from Commodity Currencies", *University of Washington Working Paper.*

Chen,Y., and K. Rogoff (2003), "Commodity Currencies", *Journal of International Economics* 60, 133-169.

Chen,Y., and K. Rogoff (2006), "Are the Commodity Currencies an Exception to the Rule?", *University of Washington Working Paper.*

Clark, T., and M. McCracken (2001), "Tests of Equal Forecast Accuracy and Encompassing for Nested Models", *Journal of Econometrics* 105(1), 85-110.

Clark, T., and K.D. West (2006), "Using Out-of-sample Mean Squared Prediction Errors to Test the Martingale Difference Hypothesis", *Journal of Econometrics* 135, 155-186.

Diebold, F.X., and R. Mariano (1995), "Comparing Predictive Accuracy", *Journal of Business and Economic Statistics* 13(3), 253-263.

Elliott, G. (1998), “On the Robustness of Cointegration Methods When Regressors Almost Have Unit Roots”, *Econometrica* 66(1), 149-158.

Elliott, G., T.J. Rothenberg and J.H. Stock (1996), “Efficient Tests for an Autoregressive Unit Root”, *Econometrica*, 64, 813-836.

Engel, C., N. Mark and K.D. West (2007), “Exchange Rate Models Are Not as Bad as You Think”, in D. Acemoglu, K. S. Rogoff and M. Woodford (eds.), *NBER Macroeconomics Annual.*

Engel, C., and K.D. West (2005), “Exchange Rates and Fundamentals”, *The Journal of Political Economy* 113(3), 485-517.

Inoue, A., and L. Kilian (2004), "In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use?" *Econometric Reviews* 23, 371–402.

Mark, N. (2001), *International Macroeconomics and Finance: Theory and Econometric Methods*. Oxford: Blackwell.

Meese, R., and K. Rogoff (1983a), “Exchange Rate Models of the Seventies. Do They Fit Out of Sample?”, *The Journal of International Economics* 14, 3-24.

Meese, R., and K. Rogoff (1983b), “The Out of Sample Failure of Empirical Exchange Rate Models”, in Jacob Frankel (ed.), *Exchange Rates and International Macroeconomics*, Chicago: University of Chicago Press for NBER.

Meese, R., and K. Rogoff (1988), “Was it Real? The Exchange Rate-Interest Differential Relation Over the Modern Floating Rate Period”, *The Journal of Finance* 43(3), 923-948.

Newey, W., and K.D. West (1987), “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix”, *Econometrica* 55, 703-708.

Obstfeld, M., and K. S. Rogoff (1996), *Foundations of International Macroeconomics.* Cambridge, MA: MIT Press.

K. S. Rogoff (2007), Comment to: "Exchange Rate Models Are Not as Bad as You Think", in D. Acemoglu, K. S. Rogoff and M. Woodford (eds.), *NBER Macroeconomics Annual.*

K. S. Rogoff and V. Stavreklava (2008), "New Evidence on Short-Horizon Exchange Rate Forecasting: Is it as Good as It Seems?", *mimeo.*

Rossi, B. (2005a), "Testing Long-Horizon Predictive Ability, and the Meese-Rogoff Puzzle", *International Economic Review* 46(1), 61-92.

Rossi, B. (2005b), "Optimal Tests for Nested Model Selection with Underlying Parameter Instability", *Econometric Theory* 21(5), 962-990.

Rossi, B. (2006), "Are Exchange Rates Really Random Walks? Some Evidence Robust to Parameter Instability", *Macroeconomic Dynamics* 10(1), 20-38.

Rossi, B. (2007), "Expectations Hypotheses Tests at Long Horizons", *Econometrics Journal* 10(3), 1-26.

Stock, J. H. and M. W. Watson (2003), "Combination Forecasts of Output Growth in a Seven-Country Data Set," forthcoming *Journal of Forecasting.*

Timmermann, A. (2006), "Forecast Combinations", in: C. Granger, G. Elliott and A. Timmermann (eds.), *Handbook of Economic Forecasting*, Volume 1, North Holland.

7. Tables

Table 1. Bivariate Granger Causality Tests

AUS	NZ	CAN	CHI	SA
A. P-values of $H_0 : \beta_0 = \beta_1 = 0$ in $\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$				
0.51	0.12	0.03**	0.10	0.29
B. P-values of $H_0 : \beta_0 = \beta_1 = 0$ in $\Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta s_t$				
0.25	0.93	0.06*	0.17	0.35

Note: The table reports p-values for the Granger-causality test. Astrisks mark rejection at the1% (***), 5% (**), and 10% (*) significance levels respectively, indicating evidence of Granger-causality.

Table 2. Andrews' (1993) QLR Test for Instabilities

AUS		NZ		CAN	CHI		SA	
A. P-values for stability of (β_{0t}, β_{1t}) in: $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t} \Delta s_t + \beta_2 \Delta cp_t$								
0***	(2002:1)	1.00		0.47	0.08*	(2002:4)	0***	(2003:3)
B. P-values for stability of (β_{0t}, β_{1t}) in: $\Delta s_{t+1} = \beta_{0t} + \beta_{1t} \Delta cp_t + \beta_2 \Delta s_t$								
0***	(2002:1)	0***	(2002:3)	0.23	0***	(2002:4)	0***	(2003:3)

Note: The table reports p-values for Andrew's (1993) QLR test of parameter stability. Astrisks mark rejection at the 1% (***), 5% (**), and 10% (*) significance levels respectively, indicating evidence of instability. When the test rejects the null hypothesis of parameter stability, the estimated break date is reported in the parentheses.

Table 3. Granger-Causality Tests Robust to Instabilities, Rossi (2005b)

	AUS	NZ	CAN	CHI	SA
A. P-values for $H_0 : \beta_t = \beta = 0$ in $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \beta_2 \Delta cp_t$					
	0.09*	0.34	0.10*	0***	0***
B. P-values for $H_0 : \beta_t = \beta = 0$ in $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t + \beta_2 \Delta s_t$					
	0***	0***	0.19	0***	0***

Note: The table reports p-values for testing the null of no Granger-causality that are robust to parameter instabilities. Astrisks mark rejection at the 1% (***), 5% (**), and 10% (*) significance levels respectively, indicating evidence in favor of Granger-causality.

Table 4. Tests for Out-of-Sample Forecasting Ability

	AUS	NZ	CAN	CHI	SA
A. MSFE difference between the model: $E_t \Delta cp_{t+1} = \beta_{0t} + \beta_{1t} \Delta s_t$ and the random walk: $E_t \Delta cp_{t+1} = 0$					
	-1.40***	-0.22***	-0.39***	-0.52***	0.55
B. MSFE difference between the model: $E_t \Delta s_{t+1} = \beta_{0t} + \beta_{1t} \Delta cp_t$ and the random walk: $E_t \Delta s_{t+1} = 0$					
	0.50	0.81	0.01**	0.42	0.55

Note. The table reports rescaled MSFE differences between the model and the random walk forecasts. Negative values imply that the model forecasts better than the random walk. Asterisks denote rejections of the null hypothesis that random walk is better in favor of the alternativehypothesis that the fundamental-based model is better at 1% (***), 5% (**), and 10% (*) significance levels, respectively, using Clark and McCracken's (2001) critical values.

Table 5. Exchange Rates and the Aggregate Global Commodity Price Index

Panel A. Multivariate Granger-Causality Tests
0***
Panel B. Andrews' (1993) QLR Test for Instabilities
0.29
Panel C. Multivariate Granger-Causality Tests Robust to Instabilities, Rossi (2005b)
0***
Panel D. Out-of-Sample Forecasting Ability
-1.76***
Panel E. Forecast Combination
-2.4***

Notes: The table reports results from different tests using the AUS, NZ and CAN exchange rates to jointly predict aggregate global future commodity prices (cp^W).

Panels A-C report the p-values, and Panels D and E report the differences between the model-based forecasts and Random Walk forecasts. *** indicates significance at the 1% level.

Table 6. Aggregate Global Commodity Price Index

and Individual Exchange Rates

	AUS	NZ	CAN
		Panel A. Granger-Causality Tests	
s_t GC cp^W_{t+1}	0.06**	0***	0***
cp^W_t GC s_{t+1}	0.41	0.17	0.81
		Panel B. Andrews' (1993) QLR Test for Instabilities	
s_t GC cp^W_{t+1}	0.33	0.77	0.25
	- -	- -	- -
cp^W_t GC s_{t+1}	0***	0***	0***
	(2001:3)	(2001:3)	(2001:3)
		Panel C. Granger-Causality Tests Robust to Instabilities, Rossi (2005b)	
s_t GC cp^W_{t+1}	0.05**	0.05**	0***
cp^W_t GC s_{t+1}	0***	0***	0***
		Panel D. Out-of-Sample Forecasting Ability	
$s_t \Rightarrow cp^W_{t+1}$	-2.04***	-2.11***	-0.17***
$cp^W_t \Rightarrow s_{t+1}$	0.88	0.89***	1.52

Note. Panels A-C report p-values for tests for $\beta_0 = \beta_1 = 0$ based on two regressions: (i) $\Delta cp^W_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp^W_t$ (labeled s_t GC cp^W_{t+1}) and (ii) $\Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp^W_t + \beta_2 \Delta s_t$ (labeled cp^W_t GC s_{t+1}). Estimated break-dates are reported in parentheses. Panel D reports the differences between model-based out-of-sample forecasts and the RW forecasts, where the model is $E_t \Delta y_{t+1} = \beta_0 + \beta_1 \Delta x_t$ (labeled $x \Rightarrow y$). Astrisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively.

Table 7. Alternative Benchmark Currencies

	U.K. Pound					**Japanese Yen**				
	AUS	NZ	CAN	CHI	SA	AUS	NZ	CAN	CHI	SA
	Panel A. Multivariate Granger-Causality Tests									
s_t GC cp_{t+1}	0.33	0.63	0.20	0.07*	0.36	0.45	0.42	0.21	0.02**	0.42
cp_t GC s_{t+1}	0.48	0.36	0.37	0.30	0.22	0.77	0.52	0.12	0.17	0.03**
	Panel B. Andrews' (1993) QLR Test for Instabilities									
s_t GC cp_{t+1}	0.03**	0***	0.45	0***	0***	0.01***	0.04**	0.87	0.03**	0***
	(2002:1)	- -	- -	(2002:4)	(2003:3)	(2002:1)	(2002:3)	- -	(2002:4)	(2003:3)
cp_t GC s_{t+1}	0	0.04**	1	0***	0.03**	0.08*	0.08*	0.62	0***	0.56
	(2002:1)	- -	- -	(2002:4)	(2003:3)	(2002:1)	(2002:3)	- -	(2002:4)	- -
	Panel C. Granger-Causality Tests Robust to Instabilities, Rossi (2005b)									
s_t GC cp_{t+1}	0.15	0***	0.03**	0***	0***	0.41	0***	0.43	0***	0***
cp_t GC s_{t+1}	0.12	0***	1	0***	0***	0.39	0.15	0.04**	0***	0.01***
	Panel D. Out-of-Sample Forecasting Ability									
$s_t \Rightarrow cp_{t+1}$	-1.21***	0.63**	-0.17	-0.51**	0.04	-1.56***	0.79	-1.06	-0.42	-0.00
$cp_t \Rightarrow s_{t+1}$	1.20	0.77**	1.52	1.10**	0.21***	2.02	-0.24	1.27	0.23	0.26***

Note. Panels A-C report p-values for tests of $\beta_0 = \beta_1 = 0$ based on two regressions: (i) $\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$ (labeled s_t GC cp_{t+1}) and (ii) $\Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta s_t$ (labeled cp_t GC s_{t+1}). Estimated break-dates are reported in parentheses. Panel D reports the differences between model-based out-of-sample forecasts and the RW forecasts, where the model is $E_t \Delta y_{t+1} = \beta_0 + \beta_1 \Delta x_t$ (labeled $x \Rightarrow y$). Astrisks indicate 1% (***), 5% (**), and 10% (*) significance levels.

Table 8. Short- and Long-Horizon Predictive Regressions

(Robust to Highly Persistent Regressors)

	A. Confidence Interval for β_h in: $E_t \Sigma_{j=1}^{h} \Delta cp_{t+j} = \beta_h s_t + \gamma \Delta cp_t$		
h:	1	4	8
AUS	(-0.01;0.01)	(-0.02;0.02)	(-0.02;0.02)
NZ	(-0.06;-0.05)	(-0.12;-0.16)	(-0.13;-0.22)
CAN	(0.18;0.19)	(0.24;0.33)	(0.24;0.35)
CHI	(0.44;0.53)	(0.54;0.89)	(0.54;0.92)
SA	(0.05;0.08)	(0.06;0.14)	(0.06;0.15)
	B. Confidence Interval for β_h in: $E_t \Sigma_{j=1}^{h} \Delta s_{t+j} = \beta_h cp_t + \gamma \Delta s_t$		
h:	1	4	8
AUS	(0.22;0.24)	(0.44;0.72)	(0.47;1.04)
NZ	(0.15;0.18)	(0.25;0.46)	(0.26;0.56)
CAN	(0.010;0.016)	(0.0;0.04)	(0.02;0.05)
CHI	(-0.06;-0.03)	(-0.08;-0.07)	(-0.08;-0.07)
SA	(0.14;0.19)	(0.17;0.32)	(0.17;0.34)

Note. The table reports confidence intervals for the long horizon regression parameter β_h at different horizons h.

Table 9. Granger-Causality Tests Robust to Instabilities

for Individual Commodity Prices, Rossi (2005b)

	P-values of $H_0 : \beta_t = \beta = 0$ in:					
Commodity:	A. $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \beta_2 \Delta cp_t$			B. $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t + \beta_2 \Delta s_t$		
	AUS	NZ	CAN	AUS	NZ	CAN
silver	0***	0.05*	0.01***	0.64	0.03**	0.06*
gold	0***	0***	0.01***	1.00	0.31	0.04**
natural gas	0.72	0.77	0.15	0.13	0.13	0***
nickel	0.02**	0***	0.31	0.80	0.02**	1.00

Note. The table reports p-values for testing the null hypothesis of Granger causality robust to instability. Astrisks mark rejection at the 1% (***), 5% (**), and 10% (*) significance levels, respectively. Panel A tests whether exchange rates Granger causes commodity prices, and panel B tests if commodity prices Granger causes exchange rates.

Table 10. Tests for Out-of-Sample Forecasting Ability

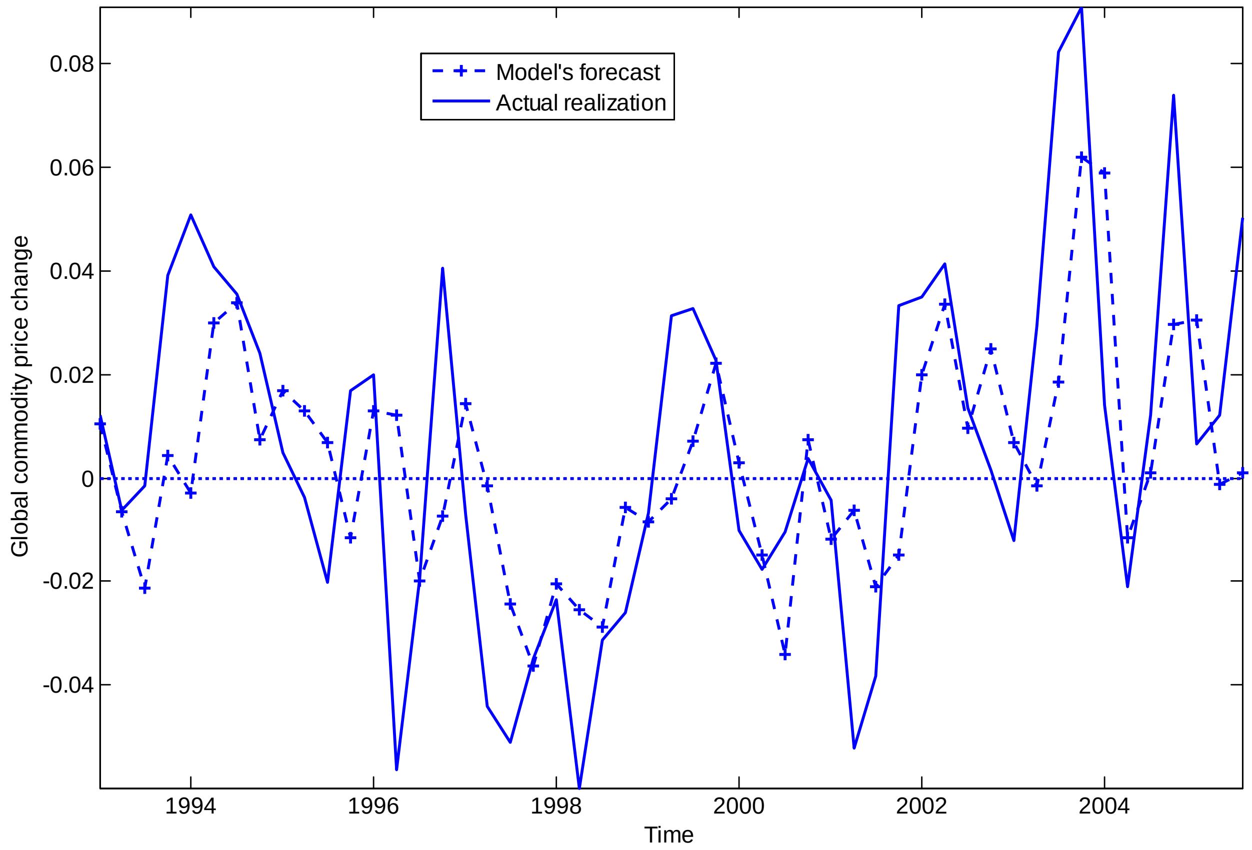
Individual Commodity Prices

Commodity:	A. $\Delta s_t \Rightarrow \Delta cp_{t+1}$			B. $\Delta cp_t \Rightarrow \Delta s_{t+1}$		
	AUS	NZ	CAN	AUS	NZ	CAN
silver	0.19	0.38	0.40	0.87	0.69	0.95
gold	0.09*	0.21	0.76	0.97	0.45	0.62
natural gas	0.02**	0.05*	0.47	0.95	0.12	0.90
nickel	0.07*	0.03**	0.09*	0.86	0.32	0.98

Note. The table reports p-values for testing the null hypothesis that the MSFE of the model is the same as that of the random walk, against the alternative that the model has additional forecasting ability. Astrisks denote rejection at the 1% (***), 5% (**), and 10% (*) significance levels, respectively. $x \Rightarrow y$ indicates using x to forecast y out of sample. Panel A compares forecasts of the model $E_t\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t$ and those of the random walk ($E_t\Delta cp_{t+1} = 0$).Panel B compares forecasts of the model $E_t\Delta s_{t+1} = \beta_{0t}$ $+\beta_{1t}\Delta cp_t$ and those of the random walk ($E_t\Delta s_{t+1} = 0$).

Figure 1. Forecasting Aggregate Global Commodity Price with Multiple Exchange Rates

$$\text{Model}: E_t \Delta cp^W_{t+1} = \beta_0 + \beta_{11} \Delta s^{AUS}_t + \beta_{12} \Delta s^{CAN}_t + \beta_{13} \Delta s^{NZ}_t$$

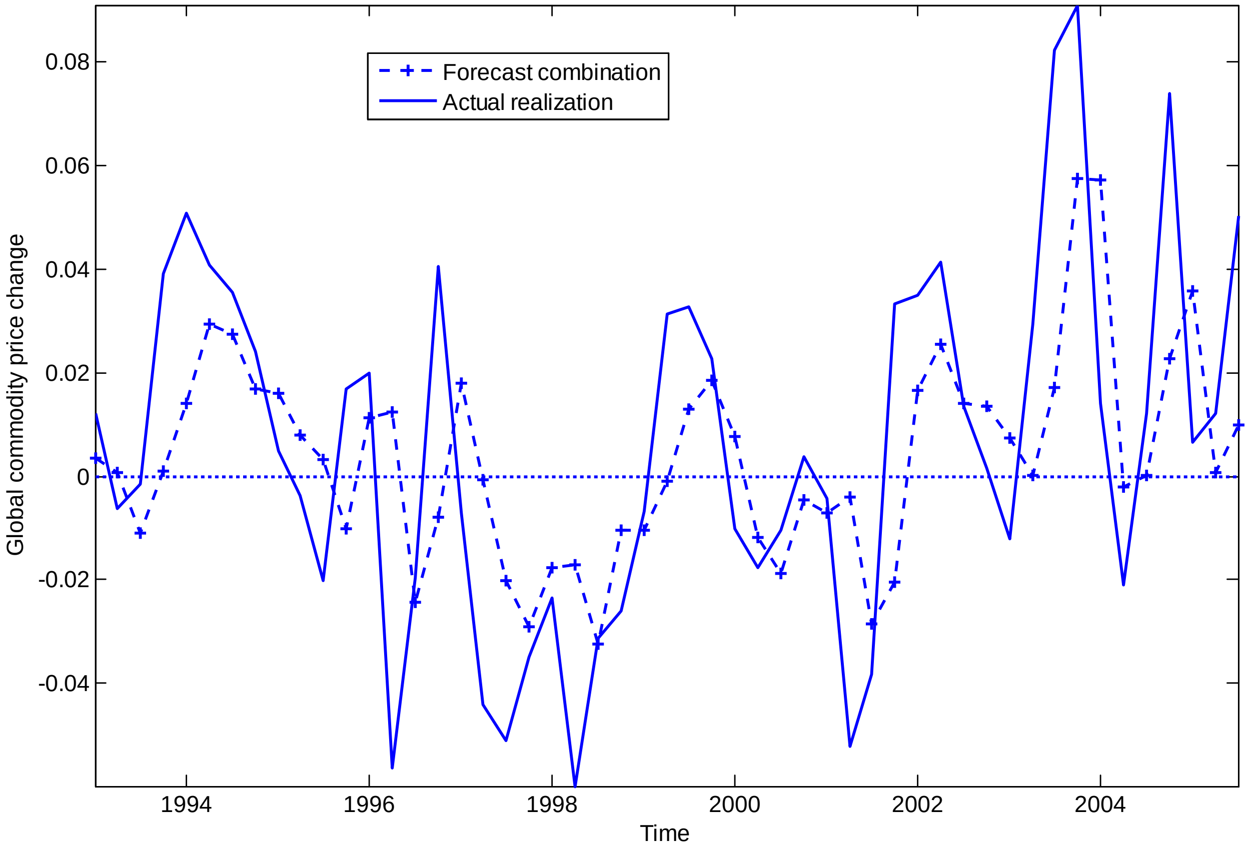


Note. The figure plots: the realized change in the global commodity price level (labeled 'Actual realization'), and their forecasts based on: 1) exchange rates (labeled 'Model's forecast') and 2) the random walk (the "X-axis")

Figure 2. Forecasting Aggregate Global Commodity Price Using Forecast Combination:

$$\text{Model: } (\Delta cp^{W,AUS}_{t+1} + \Delta cp^{W,CAN}_{t+1} + \Delta cp^{W,NZ}_{t+1})/3,$$

$$\text{where } E_t \Delta cp^{W,i}_{t+1} = \beta_{0,i} + \beta_{1,i} \Delta s^i_t,\ i = AUS, CAN, NZ$$



Note. The figure plots: the realized change in the global commodity price level (labeled 'Actual realization'), and their forecasts based on: 1) exchange rates (labeled 'Forecast combination') and 2) the random walk (the "X-axis")

8. Appendix 1. Composition of the Commodity Price Indices

Table A1. Weights

Australia		Canada		New Zealand		South Africa	
1983Q1-2005Q4		1972Q1-2005Q4		1986Q1-2005Q4		1994Q1-2005Q4	
Product	Wt.	Product	Wt.	Product	Wt.	Product	Wt.
Wheat	8.3	Aluminum	5	Aluminum	8.3	Coal	22
Beef	7.9	Beef	7.8	Apples	3.1	Gold	48
Wool	4.1	Canola	1.2	Beef	9.4	Platinum	30
Cotton	2.8	Coal	1.8	Butter	6.5		
Sugar	2.5	Copper	2	Casein	6.7		
Barley	1.9	Corn	0.5	Cheese	8.3		
Canola	1	Crude Oil	21.4	Fish	6.7		
Rice	0.5	Fish	1.3	Kiwi	3.7		
Aluminum	8.1	Gold	2.3	Lamb	12.5	Chile	
Copper	2.8	Hogs	1.8	Logs	3.5	1989Q1-2005Q4	
Nickel	2.6	Lumber	13.6	Pulp	3.1	Product	Wt.
Zinc	1.5	Nat. Gas	10.7	Sawn Timber	4.6	Copper	100
Lead	0.7	Newsprint	7.7	Skim MP	3.7		
Coking coal	14.7	Nickel	2.4	Skins	1.6		
Steaming coal	9.7	Potash	1.6	Wholemeal MP	10.6		
Gold	9.4	Pulp	12.8	Wool	7.7		
Iron ore	9.3	Silver	0.3				
Alumina	7.4	Wheat	3.4				
LNG	4.8	Zinc	2.3				

9. Appendix 2: The Present Value Models and Asset Pricing

One insight that emerged from decades of exchange rate determination literature is that the nominal exchange rate should be viewed as an asset price (e.g. Obstfeld and Rogoff 1996, p.529). The asset-pricing approach encompasses a variety of structural models that relate nominal exchange rate s_t to its fundamentals f_t and to its expected future value, giving rise to a present-value relation between the nominal exchange rate and the discounted sum of its expected future fundamentals[35]:

$$s_t = \gamma \sum_{j=0}^{\infty} \psi^j E_t(f_{t+j}|I_t)$$

where γ and ψ are parameters dictated by the specific structural model, and E_t is the expectation operator given information I_t. It is this present-value equation that shows that exchange rate s should Granger-cause its fundamentals f.

While the present-value representation is well accepted from a theoretical standpoint, there is so far little convincing empirical support for it in the exchange rate literature. The difficulty lies in the actual testing, as the standard exchange rate fundamentals considered in the literature are essentially all endogenous and jointly determined with exchange rates in equilibrium. When f is not exogenous, a positive finding that exchange rate s Granger-causes fundamental f could simply be the result of endogenous response or reverse causality, and is thus observationally equivalent to a present-value model. In other words, exchange rates Granger-causing money supply or interest changes may simply be the result of monetary policy responses to exchange rate fluctuations, as would be the case with a Taylor interest rate rule that targets CPI-inflation. Exchange rate changes may also precede inflation movements if prices are sticky and pass-through is gradual. As

[35] The transversality or "no-bubbles" condition is imposed here.

such, positive Granger causality results for these standard fundamentals are difficult to interpret and cannot be taken as evidence for the present-value framework, *unless* the fundamental under consideration is clearly exogenous to exchange rate movements. For this reason, our findings that exchange rates Granger-cause exogenous world commodity prices represents a significant step forward in the empirical literature.

In terms of out-of-sample forecasts, we observe an asymmetry between commodity prices and the exchange rates. We find exchange rates to forecast commodity prices well, but not vice versa. Exchange rates, even for these commodity economies, are still best approximated by a random walk. One possible explanation for this would be due the result of unit roots in the exchange rate fundamentals (e.g. in commodity prices), combined with a high discount rate, as argued in Engel and West (2005). According to this view, we may be able to overcome the Meese-Rogoff struggle with long enough data and more powerful tests to distinguish models from random walks. The predictability of commodity prices may also be due to the less liquid nature of commodity products (e.g. storage, production time), putting more predictable patterns into their pricing. We do not explore this issue fully in this paper, and will leave it as a topic for future research.

10. Appendix 3: Time Series Methods

This section provides a description of the test statistics used in this paper. Let the model be: $y_t = x'_{t-1}\beta_t + \varepsilon_t$, $t = 1, ..T$, where x_{t-1} is a $p \times 1$ vector of explanatory variables.[36]

[36] The Granger-causality test described below is valid under the following assumptions: (i) $\{y_t, x_t\}$ are stationary and ergodic, (ii) $E(x_t x'_t)$ is nonsingular, (iii) $E(x_t \varepsilon_t) = 0$ and (iv) $\{x_t \varepsilon_t\}$ satisfies Gordin's condition (p. 405, Hayashi, 2000) and his long-run variance is non-singular. Condition (iii) allows the data to be serially correlated, but rules out endogeneity. Rossi (2005b) relaxes these conditions.

10.1. Granger-causality tests. Traditional Granger-causality regressions assume that the parameter $\beta_t = \beta$, that is β is constant. They are implemented as:

$$GC : W_T = T\left(\widehat{\beta} - 0\right)' \widehat{V}_\beta^{-1}\left(\widehat{\beta} - 0\right),$$

where $\widehat{V}_\beta$ is a consistent estimate of the covariance of $\widehat{\beta}$, for example, $\widehat{V}_\beta = S_{xx}^{-1}\widehat{S}S_{xx}^{-1}$, $S_{xx} \equiv \frac{1}{T-1}\sum_{t=1}^{T-1} x_{t-1}x_{t-1}'$,

$$\widehat{S} = \left(\frac{1}{T}\sum_{t=2}^{T} x_{t-1}\widehat{\varepsilon}_t\widehat{\varepsilon}_t x_{t-1}'\right) + \sum_{j=2}^{T-1}\left(1 - |\frac{j}{T^{1/3}}|\right)\left(\frac{1}{T}\sum_{t=j+1}^{T} x_{t-1}\widehat{\varepsilon}_t\widehat{\varepsilon}_{t-j}x_{t-1-j}'\right), \tag{10}$$

$\widehat{\varepsilon}_t \equiv y_t - x_{t-1}'\widehat{\beta}$ and $\widehat{\beta}$ is the full-sample OLS estimators:

$$\widehat{\beta} = \left(\frac{1}{T}\sum_{t=1}^{T-1} x_{t-1}x_{t-1}'\right)^{-1}\left(\frac{1}{T}\sum_{t=1}^{T-1} x_{t-1}y_t\right)^{-1}.$$

Under the null hypothesis of no Granger-causality ($\beta = 0$), W_T is a chi-square distribution with p degrees of freedom. If there is no serial correlation in the data, only the first component in (10) is relevant.

10.2. Rossi (2005b). Rossi (2005b) shows that traditional Granger-causality tests above may fail in the presence of parameter instabilities. She therefore develops optimal tests for model selection between two nested models in the presence of underlying parameter instability in the data. The procedures are based on testing jointly the significance of additional variables that are present only under the largest model and their stability over time.[37] She is interested in testing

[37] Rossi (2005b) considered the general case of testing possibly nonlinear restrictions in models estimated with General Method of Moments. Here, we provide a short description in the simple case of no Granger-causality

whether the variable x_t has no predictive content for y_t in the situation where the parameter β_t might be time-varying. Among the various forms of instabilities that she considers, we focus on the case in which β_t may shift from β to $\overline{\beta} \neq \beta$ at some unknown point in time.

The test is implemented as follows. Suppose the shift happens at a particular point in time τ. Let $\widehat{\beta}_{1\tau}$ and $\widehat{\beta}_{2\tau}$ denote the OLS estimators before and after the time of the shift:

$$\begin{aligned}
\widehat{\beta}_{1\tau} &= \left(\frac{1}{\tau}\sum_{t=1}^{\tau-1} x_{t-1}x_{t-1}'\right)^{-1}\left(\frac{1}{\tau}\sum_{t=1}^{\tau-1} x_{t-1}y_t\right)^{-1}, \\
\widehat{\beta}_{2\tau} &= \left(\frac{1}{T-\tau}\sum_{t=\tau}^{T-1} x_{t-1}x_{t-1}'\right)^{-1}\left(\frac{1}{T-\tau}\sum_{t=\tau}^{T-1} x_{t-1}y_t\right)^{-1}.
\end{aligned}$$

The test builds on two components: $\frac{\tau}{T}\widehat{\beta}_{1\tau} + \left(1-\frac{\tau}{T}\right)\widehat{\beta}_{2\tau}$ and $\widehat{\beta}_{1\tau} - \widehat{\beta}_{2\tau}$. The first is simply the full-sample estimate of the parameter, $\frac{\tau}{T}\widehat{\beta}_{1\tau} + \left(1-\frac{\tau}{T}\right)\widehat{\beta}_{2\tau} = \widehat{\beta}$; a test on whether this component is zero is able to detect situations in which the parameter is constant but different from zero. However, if the regressor Granger-causes the dependent variable in such a way that the parameter changes but in a way in which the average of the estimates equals zero, then the first component would not be able to detect such situations. The second component is introduced to perform that task. It is the difference of the parameters estimated in the two subsamples; a test on whether this component is zero is able to detect situations in which the parameter changes at time τ. The test statistic is the following:

$$Exp - W_T^* =$$

$$\frac{1}{T}\sum_{\tau=[0.15T]}^{[0.85T]} \frac{1}{0.7}\exp\left(\frac{1}{2}\right)\left(\begin{array}{cc} \left(\widehat{\beta}_{1\tau} - \widehat{\beta}_{2\tau}\right)' & \left(\frac{\tau}{T}\widehat{\beta}_{1\tau} + \left(1-\frac{\tau}{T}\right)\widehat{\beta}_{2\tau}\right)' \end{array}\right) \widehat{V}^{-1} \left(\begin{array}{c} \left(\widehat{\beta}_{1\tau} - \widehat{\beta}_{2\tau}\right) \\ \left(\frac{\tau}{T}\widehat{\beta}_{1\tau} + \left(1-\frac{\tau}{T}\right)\widehat{\beta}_{2\tau}\right) \end{array}\right)$$

---

restrictions in models whose parameters are consistently estimated with Ordinary Least Squares (OLS), like the Granger-causality regressions implemented in this paper. She also considers the case of tests on subsets of parameters, that is the case where $y_t = x_{t-1}'\beta_t + z_{t-1}'\delta + \varepsilon_t$ and the researcher is interested in testing only whether x_t Granger-causes y_t.

$$\text{where } \widehat{V} = \begin{pmatrix} \frac{\tau}{T} S'_{xx} \widehat{S}_1^{-1} S_{xx} & 0 \\ 0 & \frac{T-\tau}{T} S'_{xx} \widehat{S}_2^{-1} S_{xx} \end{pmatrix},$$

$$\widehat{S}_1 = \left(\frac{1}{\tau} \sum_{t=2}^{\tau} x_{t-1} \widehat{\varepsilon}_t \widehat{\varepsilon}_t x'_{t-1} \right) + \sum_{j=2}^{\tau-1} \left(1 - \left| \frac{j}{\tau^{1/3}} \right| \right) \left(\frac{1}{\tau} \sum_{t=j+1}^{\tau} x_{t-1} \widehat{\varepsilon}_t \widehat{\varepsilon}_{t-j} x'_{t-1-j} \right), \tag{11}$$

$$\widehat{S}_1 = \left(\frac{1}{T-\tau} \sum_{t=\tau+1}^{T-\tau} x_{t-1} \widehat{\varepsilon}_t \widehat{\varepsilon}_t x'_{t-1} \right) + \sum_{j=\tau+1}^{T-\tau} \left(1 - \left| \frac{j}{(T-\tau)^{1/3}} \right| \right) \left(\frac{1}{T-\tau} \sum_{t=j+1}^{T-\tau} x_{t-1} \widehat{\varepsilon}_t \widehat{\varepsilon}_{t-j} x'_{t-1-j} \right). \tag{12}$$

Under the joint null hypothesis of no Granger-causality and no time-variation in the parameters ($\beta_t = \beta = 0$), $Exp - W_T^*$ has a distribution whose critical values are tabulated in Rossi's (2005b) Table B1. If there is no serial correlation in the data, only the first component in (11) and (12) is relevant.

10.3. Tests of out-of-sample rolling MSFE comparisons. To compare the out-of-sample forecasting ability of:

$$Model \;:\; y_t = x'_{t-1}\beta_t + \varepsilon_t \tag{13}$$

$$Random\ Walk \;:\; y_t = \varepsilon_t, \tag{14}$$

we generate a sequence of $1-$step-ahead forecasts of y_{t+1} using a rolling out-of-sample procedure. The procedure involves dividing the sample of size T into an in-sample window of size m and an out-of-sample window of size $n = T - m - \tau + 1$. The in-sample window at time t contains observations indexed $t-m+1, \ldots, t$. We let $f_t(\widehat{\beta}_t)$ be the time-t forecast for y_t produced by estimating the model over the in-sample window at time t, with $\widehat{\beta}_t = \left(\sum_{s=t-m+1}^{t-1} x_s x_s'\right)^{-1} \sum_{s=t-m+1}^{t-1} x_s y_{s+1}$ indicating the parameter estimate; we let f_t^{RW} denote the forecast of the random walk (for which, $f_t^{RW} = 0$).

To compare the out-of-sample predictive ability of (13) and (14), Diebold and Mariano (1995), West (1996) suggest focusing on:

$$d_t \equiv \left(y_t - f_t(\widehat{\beta}_t)\right)^2 - \left(y_t - f_t^{RW}\right)^2 \tag{15}$$

Diebold and Mariano (1995) and West (1996) show that the sample average of d_t, appropriately rescaled, has an asymptotic standard Normal distribution. However, this is not the case when the models are nested, as in our case. Clark and McCracken's (2001) show that, under the null hypothesis that the model is (14), the tests of Diebold and Mariano (1995) and West (1996) do not have a Normal distribution. They propose a new statistic, ENCNEW, which is the following:

$$ENCNEW = n \frac{\left[\frac{1}{n} \sum_{t=m+1}^{T} \left(\left(y_t - f_t(\widehat{\beta}_t)\right)^2 - \left(y_t - f_t(\widehat{\beta}_t)\right)\left(y_t - f_t^{RW}\right)\right)\right]}{\left[\frac{1}{n} \sum_{t=m+1}^{T} \left(\left(y_t - f_t^{RW}\right)^2 - \frac{1}{n} \sum_{t=m+1}^{T} \left(y_t - f_t^{RW}\right)^2\right)^2\right]}$$

Its limiting distribution is non-standard, and critical values are provided in Clark and McCracken (2001). Clark and West (2006) propose a correction to (15) that results in an approximately normally distributed test statistic.