CAN EXCHANGE RATES FORECAST COMMODITY PRICES?[1] AN UPDATE

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This note provides an update to the relationship between "commodity currency" exchange rates and global commodity prices that we reported in Chen, Rogoff, and Rossi (2010; hereinafter CRR). The global financial crisis clearly constitutes a major shock and test of the commodity price/exchange rate relationship. In addition to the obvious changing economic conditions that motivate a re-examination, we provide more clarifications in response to some of the helpful comments and questions we have received.[2]

Using updated data until the end of 2013 and additional testing, we see that the main findings in CRR (2010) remain very robust. That is, we find that the currencies of Australia, Canada, Chile, New Zealand and South Africa can predict world commodity prices one quarter ahead, with strong in-sample results even after the volatile financial crisis years are included. As before, the evidence from out-of-sample testing is positive but less robust. Predictability in the reverse direction, from commodity prices to exchange rates, is much weaker both in-sample and out-of-sample. More specifically, we observe some changes in the currency-specific patterns in our updated results.

[1] Updated data and replication codes are available on authors' websites.

[2] We thank, in particular, graduate students at Duke University, Universitat Pompeu Fabra and University of Washington that have worked through the programs over the last couple of years, and for pointing out a few typoes. We note that due to data access limitation, we only updated the main results and not everything in the original robustness or appendix sections.

For example, the predictive power of the Canadian dollar has weakened considerably, and the same is true when the commodity currencies are measured against the British Pound instead of the U.S. dollar. In terms of out-of-sample forecasting comparisons, the general macro-forecasting literature has shown that it is often difficult for any model to have a sustained superior forecast performance against statistical benchmarks, due to underlying structural instabilities. The exact methodology and forecasting samples can also play an important role, making success even more elusive.[3] Forecasting commodity prices with exchange rates is no exception.[4] Nevertheless, five years after the onset of the Global Financial Crisis, we continue to observe generally superior out-of-sample forecasting performance for our exchange rate-based models against the three statistical benchmarks (a random walk, a random walk with drift, and an AR(1) process), though the pattern is far from uniform. The Australian and the New Zealand dollars, in particular, outperform the benchmarks consistently, while the Canadian and South African results are overall poor. Combining multiple currencies in a multivariate setting continues to forecast price movements in the aggregate commodity markets quite well, regardless of whether we use aggregate market index constructed by the IMF, Goldman Sachs, or other major sources. As an alternative approach, forecast combination using equal weighting can deliver smaller mean squared forecast errors than the benchmarks, although the improvements lack statistical significance. Overall, we conclude that the theoretical relationship identified in CRR (2010) is robust in the long-term, even though this update uncovers more nuanced issues that future research should address, such as the reason behind the elusive or fickle real-time forecasting power for certain currencies or specifications.

[3] See Stock and Watson (1996, 2007), Rossi (2013) and references therein.

[4] CRR (2010) stated that their out-of-sample results are not robust over sub-samples. Since then, Groen and Pesenti (2011), for example, provided one of the first comprehensive robustness checks of the forecasting power of commodity prices. They show how the out-of-sample results change depending on alternative commodity price indices and econometric specifications.

Below we report the updated results that parallel the main tables reported in CRR (2010) which was based on pre-Global Financial Crisis data. For some tables, we provide additional testing results as well as clarifications, and sometimes slight modifications, to our original methodology. We refer readers to our original paper for the motivations and more detailed discussions.

1. Data Description

We use quarterly data over the following time-periods: Australia (from 1984:1 to 2013:3), Canada (from 1973:1 to 2013:3), Chile (from 1989:3 to 2013:3), New Zealand (from 1987:1 to 2013:3), and South Africa (from 1994:1 to 2013:3).

- Bilateral nominal exchange rates (labeled s^i) are end-of-period rates from Global Financial Data. We used bilateral rates relative to the U.S. dollar, the British pound, as well as the Japanese yen.

- Nominal effective exchange rates are from the International Finance Statistics.

- Country-specific commodity price indexes (labeled cp^i) are obtained from the Bank of Canada, the Reserve Bank of Australia, ANZ, as well as Global Financial Data (copper for Chile, and gold, platinum, and coal for South Africa).

- Aggregate world commodity price index (labeled cp^W) is the PNFUEL series (Non-Fuel Price Index) from the IMF. The IMF has updated its series and no longer provides data prior to 1991 on its website. We use their current data to update our original series (which starts in 1980:1) using a linear forward projection. As a robustness check, we also used five other commonly used aggregate indexes (from Commodity Research Bureau-BLS, Reuters/Jeffries, Moody's, Dow Jones-AIG, and Goldman Sachs); all are obtained from Global Financial Data.

- Dow Jones-UBS Commodity 3-month forward Index (DJUBSF3T) and "spot" index (DJUBSTR) are used in Figure V. We note that these indices are total return indices, and are not the conceptual forward and spot indices we need (see http://www.djindexes.com/commodity/)[5]

As in CRR (2010), all data are logged and we denote first-differences with a Δ.

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

2.1. In-Sample Granger-Causality (GC) Tests. As in Section 3 of CRR (2010), the first three sets of tables report in-sample Granger Causality test results. We first test the null hypothesis that $\beta_0 = \beta_1 = 0$ in the regression:

$$E_t \Delta cp^i_{t+1} = \beta_0 + \beta_1 \Delta s^i_t + \beta_2 \Delta cp^i_t \tag{1}$$

where i indicates each of the five commodity currency countries. In addition, we test for the marginal effect of the exchange rate only; that is, we test for $H_0 : \beta_1 = 0$. To account for potential parameter instabilities, we test for structural breaks, using Andrews (1993) QLR test, for the bivariate Granger-causality regressions. We then test for the joint null hypothesis that $\beta_{0t} = \beta_0 = 0$ and $\beta_{1t} = \beta_1 = 0$ by using Rossi's (2005) $Exp - W^*$ test, in the following regression setup:

$$E_t \Delta cp^i_{t+1} = \beta_{0t} + \beta_{1t} \Delta s^i_t + \beta_2 \Delta cp^i_t \tag{2}$$

As discussed in CRR (2010), $Exp - W^*$ simultaneously tests for the null hypothesis of no time variation and no Granger causality. When the null is rejected, it indicates that there is evidence for

[5] While there are alternatives such as the S&P GSCI indices, their heavy emphasis on fuel prices make them less suitable for the currencies we are examining. The ones we use here are the updated version of the Dow Jones-AIG indices used in CRR (2010).

Granger causality in at least part of the sample. Here again we also consider the marginal effect of the exchange rate in each case, e.g. test only $H_0 : \beta_{1t} = \beta_1 = 0$.

For each of the above, we investigate the reverse direction as well to see if commodity prices Granger-cause the exchange rate, as in:

$$E_t \Delta s^i_{t+1} = \beta_0 + \beta_1 \Delta cp^i_t + \beta_2 \Delta s^i_t \tag{3}$$

The Tables I-III report the p-values from the above tests for the five exchange rates and their corresponding commodity price indices.[6] A number below 0.10 implies evidence in favor of Granger-causality at the 10% level. We see clearly evidence of exchange rate Granger-causing world commodity prices, especially after structural break is taken into account. The only exception is Canada. There is also evidence of structural break around the time of the financial crisis for some of the countries. As in CRR (2010), we see much weaker evidence for commodity prices Granger-causing exchange rate movements in Panels B's an D's of Tables I-III.

INSERT TABLES I, II AND III HERE

2.2. Out-of-Sample Forecasts. We adopt a rolling forecast scheme to evaluate out-of-sample forecasting ability of the exchange rate models.[7] We estimate the exchange-rate based model and test for forecast encompassing relative to three statistical benchmarks:

1. an autoregressive (AR) model of order one: $E_t \Delta cp^i_{t+1} = \gamma_{0t} + \gamma_t \Delta cp^i_t$

[6] The estimations are heteroskedasticity and serial correlation-consistent. Results are based on the Newey and West (1987) procedure with bandwidth $T^{1/3}$ (where T is the sample size.)

[7] Note that there was a typo in CRR(2010), where the results were based on a recursive, rather than rolling, forecasting procedure. We also corrected the formula for constructing the test statistic in this update. This issue, of course, is not relevant to any of the in-sample statistics or the causality tests.

2. a random walk (RW) benchmark: $E_t \Delta cp^i_{t+1} = 0$.

3. a random walk with drift (RWWD) comparison, $E_t \Delta cp^i_{t+1} = \gamma_{0t}$.

In each case, the exchange rate model is the benchmark plus a $\beta \Delta s^i_t$ term (and a constant term in the case of RW comparison), as specified in Table IV. We use a rolling window of the same size as in CRR (2010) to estimate the model parameters and generate one-quarter ahead forecasts recursively.[8] Again, we conduct the parallel exercise for exchange rate forecasting using commodity prices.

Table IV provides the following information on the forecast comparisons, as in CRR (2010):

- the numbers reported are the differences between the mean square forecast errors (MSFE) of the model and the MSFE of the benchmark, both re-scaled by a measure of their variability. A negative number indicates that the model outperforms the benchmark;

- using Clark and McCracken's (2001) "ENCNEW" test of equal MSFEs to compare these nested models, we indicate with asterisks when the additional regressor contains out-of-sample forecasting power for the dependent variable, relative to the benchmark specification.

For forecasting country-specific commodity price index, we see from the row A of each panel in Table IV that the results are somewhat mixed. The Canadian dollar and the South African rand show the worst performance, and do not forecast any better than the benchmarks. On the other hand, the Australian dollar and the New Zealand dollar continue to have robust forecasting power that out-performs the benchmarks, delivering smaller MSFEs that are also statistically significant

[8] As is well-known in the forecasting literature, the choice of window size would affect the forecast outcome. One can look for the optimal window size when conducting these out-of-sample forecasts, but that is beyond the scope of this exercise.

under the Clark and McCracken test. These mixed results in out-of-sample predictive ability were already recognized in CRR (2010) and echo the empirical findings in Groen and Pesenti (2011).[9] In the next section, we will see much stronger forecasting performance of the exchange rate-based models in forecasting the aggregate world commodity price series.

As for forecasting in the reverse direction, we see that there is essentially no evidence that the country-specific commodity prices can help forecast their respective exchange rates better than the benchmarks.

INSERT TABLE IV HERE

2.3. Can Exchange Rates Predict Aggregate World Commodity Price Movements?. We next look at predicting the aggregate world commodity price index using multiple commodity currencies. Despite the mixed results above with forecasting country-specific commodity prices, this section presents strong evidence that commodity currencies together can predict aggregate world commodity price movements. Following CRR(2010), we first look at the aggregate index from the IMF (cp^W). We test for in-sample predictability and consider multivariate Granger-causality regressions using two, three, or four exchange rate series. For instance, the four-exchange rate regression used in the in-sample analysis is as follows, and the other specifications include the currencies specified in the headings of Table V(a).

$$E_t \Delta cp_{t+1}^W = \beta_0 + \beta_{11} \Delta s_t^{AUS} + \beta_{12} \Delta s_t^{NZ} + \beta_{13} \Delta s_t^{CAN} + \beta_{13} \Delta s_t^{CHI} + \beta_2 \Delta cp_t^W \qquad (4)$$

Panels A through C in Table V(a), testing the null hypothesis of $\beta_0 = \beta_{1i} = 0$, show results

[9] Burgess and Rohde (2013) and Ignacio Arbués and Ledo (2013) are additional examples of recent papers finding that the the out-of-sample forecasting power is fragile.

consistent with our earlier findings. Here, the evidence for in-sample Granger causality is strong and robust, even without explicitly accounting for parameter instability. (As we will show in Table IV(b) Panel D later, the same is true when one tests for $\beta_{1i} = 0$ only.)

For out-of-sample forecasting, we compare multi-exchange rate models against the three benchmarks discussed above.[10] In addition, we consider forecast combination, where forecasts from individual currencies, as below, are aggregated using equal weighting and then compared to the benchmarks:

$$E_t \Delta cp^W_{t+1} = \beta_{0,i} + \beta_{1,i} \Delta s^i_t + \beta_2 \Delta cp^W_t \text{ where } i = AUS, NZ, CAN, CHI$$

To judge the significance of forecast combinations, we use critical values based on Diebold and Mariano (1995). All forecasts are conducted using the rolling procedure described above.

From Panel D, we see the multi-exchange rate specifications outperform the three benchmarks consistently, whether we used two, three, or four commodity exchange rates. We see smaller MSFEs, and the improvements over the benchmarks are also of statistical significance under the Clark and McCracken (2001) test. On the other hand, Panel E shows that when the information from the currencies are aggregated using forecast combination, the improvements over the benchmarks are no longer statistically significant, even though we still see uniformly smaller MSFEs compared to the benchmarks. This pattern is exactly the same regardless of the number of currencies used; it is also consistent with what we pointed out in CRR (2010) regarding the fragility of out-of-sample results to alternative specifications.[11]

[10] The regression specification used for out-of-sample forecasting is the same as discussed in the previous section, except that now we include several exchange rates in the same regression, not just one.

[11] We note, of course, that one can further consider alternative or optimal weighting schemes in carrying out the forecat combination exercise. We used equal weighting, and our point is to demonstrate the fragility of the results.

We next consider forecasting five alternative aggregate commodity price indexes commonly quoted in the markets. We conduct the same analyses as in Table V(a) but use only the Australian, Canadian, and New Zealand exchange rates to predict movements in these price indexes. Table V(b) shows in-sample and out-of-sample results that are virtually the same as what we saw in Table V(a) for the IMF index. This is perhaps not surprising since these indexes, while weighing specific commodity products differentially, all aim to capture movements in the overall market of primary commodities. Overall, we see exchange rates consistently granger cause these commodity price indexes, and they out-perform all three statistical benchmarks in multivariate forecasting comparisons.

Figures I and II illustrate the performance of the three-exchange rate model in forecasting the IMF index. They plot the forecasted global commodity price from the exchange-rate models 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 forecasts track the actual world price series relatively well, though there are periods of large deviations.

INSERT TABLE V(a), V(b) AND FIGURES I and II HERE

We next look at whether each individual exchange rate by itself can predict the IMF world market commodity price index, and vice versa, in Table VI. The first lines (e.g. labeled "s_t GC cp^W_{t+1}") in Table VI(a) report Granger-causality results for each country-specific exchange rates, where the null hypothesis considered is $\beta_0 = \beta_1 = 0$ for the equation below.

$$E_t \Delta cp^W_{t+1} = \beta_0 + \beta_1 \Delta s^i_t + \beta_2 \Delta cp^W_t \text{ where } i = AUS, NZ, CAN, CHI, SA \tag{5}$$

In Table VI (b), the parallel results for the null hypothesis $\beta_1 = 0$ only are reported. Results for regressions in the reversed directions are reported with labels: "cp_t^W GC s_{t+1}". Panel D of Table VI(a) shows out-of-sample forecast performance of each individual currency against the three statistical benchmarks. Panel D of Table VI(b) reports the results for testing the null hypothesis that $\beta_{11} = \beta_{12} = \beta_{13} = 0$ in the multivariate Granger-causality regression below:

$$E_t \Delta cp_{t+1}^W = \beta_0 + \beta_{11} \Delta s_t^{AUS} + \beta_{12} \Delta s_t^{CAN} + \beta_{13} \Delta s_t^{NZ} + \beta_2 \Delta cp_t^W.$$

These results provide clear evidence that commodity currencies individually, and together, can predict the aggregate commodity index. The in-sample results are especially strong for Australia, New Zealand, and Chile, though they are also positive for Canada. We also see that the in-sample test results are strong when we exclude the intercept term and consider only the coefficient on the explanatory variable in our tests ($H_0 : \beta_{1i} = 0$ in eq.(5)). Multivariate Granger-causality testing that excludes the constant term produces results that corroborate findings in Table V.

The out-of-sample forecast performance also supports findings in Table V using multiple currencies. Against the AR(1) benchmark, we see four out of the five currencies delivering superior MSFEs and three of them being statistically better according to the Clark-McCracken statistics. Against the random walk benchmark, all five currencies beat the benchmark, with four of them being statistically significant. Last but not least, we see the strongest forecast performance from the individual commodity currencies against the random walk with drift benchmark: all five commodity currencies significantly out-perform the benchmark.

For prediction in the reverse direction, the second row in Panel C of Table VI(a) shows some evidence of the aggregate commodity index Granger-causing individual exchange rate movements. However, by comparing the results with the ones in Panel C of Table VI(b), we see that the positive results mostly come from the intercept term. While there is some evidence that the IMF aggregate index can forecast the Canadian exchange rate out-of-sample, the overall pattern shows much stronger predictive power from the various exchange rates to commodity prices.

INSERT TABLE VI(a) & VI(b)

3. **Robustness Analyses**

3.1. Alternative Benchmark Currencies. As in CRR(2010), we re-do the analyses in Tables I-V using each country's nominal effective exchange rates and bilateral rates against the British pound instead of the U.S. dollar. We first look at the country-specific commodity price indexes, before turning to the aggregate IMF index. Tables VII(a) and VII(b) report in-sample Granger causality results, as well as out-of-sample forecasting performance against all three benchmarks discussed in Section 2.2. Compared to results based on pre-financial crisis data, we see that the results weakened somewhat, in particular when the pound is used as the numeraire currency. This is no doubt related to the dramatic behavior of the British pound over the financial crisis period. As an additional robustness check, Table VII(c) reports results using the Japanese Yen as the numeraire currency. We see that the in-sample Granger causality results from each currencies to its corresponding commodity prices are again very strong, even for the Canadian dollar. Table VII(d) complements the results above and tests if the slope coefficient alone is zero for NEER and Yen exchange rates. We see that some of the Granger-causality results indeed come from the level term, but there is still evidence for the exchange rate alone Granger-causing commodity prices.[12]

Regarding the out-of-sample forecasting of country-specific commodity price index, all three alternative measures of the exchange rate show much less forecasting power compared to the results

[12] We do not report results based on the British pounds as they, again, are extremely weak.

based on U.S. dollar exchange rates. However, the Australian and New Zealand dollars still show evidence of out-performing the two random walk benchmarks significantly. This serves as another reminder for the difficulty in finding a robust forecasting model; sample period and benchmark currencies clearly both play a role.[13] As further evidence, Table VII(e) shows that even when the commodity currencies are measured relative to pound, yen, or a basket of currencies (NEER), their ability to forecast world aggregate price index remains robust. We see strong evidence of in-sample predictability, and significantly better out-of-sample forecast performance than the benchmarks using multi-variate model. As in Table V, equal-weighted forecast combination does no produce superior forecasts.

INSERT TABLE VII(a)-(e) HERE

3.2. Long-Horizon Predictability, Commodity Derivatives, and Financial Crisis. Here we repeat three additional robustness results in CRR (2010) using the updated data.[14] First, we consider an alternative specification and look at longer-horizon predictive regressions. We model the regressors as highly persistent and use tests statistics based on local-to-unity asymptotics (see CRR (2010) Appendix C for details). The confidence intervals in Table VIII show that the in-sample predictive regressions work well in both directions for horizons up to two years, as none of the confidence intervals contain zero. This is the same pattern as observed in CRR (2010).

INSERT TABLE VIII HERE

[13] In addition, as mentioned earlier, the size of the window used to conduct pseudo out-of-sample rolling forecasts can also make a difference in terms of model performance. It is possible that for these alternative currencies, a different window size would improve the model's forecast performance. We do not explore the issue of optimizing the window size in this paper.

[14] Due to data access limitation, we are not able to update all robustness results in CRR(2010) at this point. We also choose to omit some of the tables as they are not as relevant to our central messages.

Next, we look at forecasting the Dow Jones-UBS aggregate commodity index, and compare our exchange rate model against the 3-month forward version of the same index. The idea is to see whether the commodity currencies offer information that is superior to what is contained in the forward market. We compare the exchange rate model:

$$E_t \Delta cp_{t+1}^{DJ-UBS} = \beta_0 + \beta_{11} \Delta s_t^{AUS} + \beta_{12} \Delta s_t^{NZ} + \beta_{13} \Delta s_t^{CAN}$$

with prediction based on the forward premium concept:[15]

$$E_t \Delta cp_{t+1}^{DJ-UBS} = f_{t+1}^{DJ-UBS} - cp_t^{DJ-UBS}.$$

Figure III shows that the prediction based on futures prices is way off, compared to the exchange rate-based predictions.

INSERT FIGURE III HERE

Lastly, we recursively compare the models' forecasting performance against the three statistical benchmarks over a range of dates. This exercise mimics how a forecaster would have evaluated the models' forecasting performance in real time. We consider Australia, Canada, New Zealand, and Chile here, and look at how the individual exchange rate forecasts both its own corresponding country-specific commodity price index, and also the IMF aggregate price index. Note that, again, we do not consider the issue of choosing the optimal window size but focus on the broader patterns, using the window size defined earlier. Figures IV and V plot the Clark and McCracken (2001) test statistics calculated at different points in time, as specified on the x-axis, when we compare the

[15] Again, we note that these are total return indices, so they are not very clean measures of the theoretical conepts of forward premium, or forward and spot rates.

performance of the exchange rate models relative to the three statistical benchmarks described in Section 2.2 above. The evidence is favorable to the exchange rate model when the line is above the 10% critical value line. For forecasting each country's own commodity price index (Figure IV), we see that the predictability is fairly robust for Australia overall, and for New Zealand especially post-2009, while the evidence for Canada is uniformly weak. This is consistent with the full-sample results we reported in Table IV. These figures again illustrate the fragility in out-of-sample forecasting. Figure V, A-C, graphs the corresponding test statistics when individual exchange rate forecasts the IMF aggregate index. Again, consistent with earlier reports, we see overall very strong evidence that the exchange rate models out-perform the benchmark, except in the case of Chile in which case the results depend on the sub-sample period.

INSERT FIGURES IV A-C and V A-C HERE

4. **Conclusion**

Five years after the crisis that wracked havoc on the international financial markets, we provide this update to see whether commodity currencies can still predict world commodity prices. We find that the original messages in CRR (2010) continue to hold, though they are perhaps more nuanced than we initially recognized. First, we continue to find strong in-sample Granger causality from exchange rates to commodity prices overall, though the country-specific patterns have change somewhat. In addition, we also find evidence of out-of-sample superior forecasts against the three standard statistical benchmarks we considered, especially when we combine several exchange rates to forecast the aggregate world price index. Obtaining a uniformly best model that out-performs all statistical benchmarks consistently is not an easy task (nor is it our goal). Here we show that numeraire currencies, sample periods, as well as the benchmark used for comparisons all make a difference, and perhaps more so than we found earlier using pre-crisis data. We view these results as evidence that the long-term theoretical relationship we identify is important, and that one will need to rely on more detailed analyses and sophisticated methodology to address the elusive real-time forecasting power.

5. References

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6. Tables and Figures

Table I. Bivariate Granger-Causality Tests

	AUS	NZ	CA	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***	0.070*	0.275	0.062*	0.128
B. P-values of $H_0 : \beta_0 = \beta_1 = 0$ in $\Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta s_t$					
	0.802	0.812	0.150	0.463	0.031**
C: P-values of $H_0 : \beta_1 = 0$ in $\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$					
	0.0345**	0.0566*	0.9301	0.0300**	0.2584
D: P-values of $H_0 : \beta_1 = 0$ in $\Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta s_t$					
	0.5354	0.7226	0.0522*	0.5209	0.0955*

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

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

	AUS	NZ	CA	CHI	SA
A. P-values of stability of (β_{0t}, β_{1t}) in: $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \beta_2 \Delta cp_t$					
	0.039**	0***	0.697	0.768	0.017***
	(2003:1)	(1993:2)			(1997:1)
B. P-values of stability of (β_{0t}, β_{1t}) in: $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t + \beta_2 \Delta s_t$					
	0.076*	0.367	0.312	0.174	0.072*
	(2001:2)				(2001:2)
C. P-values of stability of β_{1t} in: $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \beta_2 \Delta cp_t$					
	0.0216**	0***	0.7247	0.3502	0.0929*
	(2003:1)	(1993:2)			(1997:1)
D. P-values of stability of β_{1t} in: $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t + \beta_2 \Delta s_t$					
	0.6938	0.4158	0.0714*	0.7821	0.0475**
			(2001:4)		(2001:2)

Note: The table reports p-values for Andrew's (1993) QLR test of parameter stability. Asterisks 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-dates are reported in the parentheses below.

Table III. Granger-Causality Test Robust to Instabilities, Rossi (2005)

	AUS	NZ	CA	CHI	SA
A. P-values for $\text{H}_0: \beta_t = \beta = 0$ in: $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \gamma_2 \Delta cp_t$					
	0***	0.058*	0.199	0***	0***
B. P-values for $\text{H}_0: \beta_t = \beta = 0$ in: $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t + \gamma_2 \Delta s_t$					
	0.332	0.895	0.286	0.014**	0.043**
C. P-values for $\text{H}_0: \beta_{1t} = \beta_1 = 0$ in: $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \gamma_2 \Delta cp_t$					
	0***	0.0335**	1	0.0298**	0.0420**
D. P-values for $\text{H}_0: \beta_{1t} = \beta_1 = 0$ in: $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t + \gamma_2 \Delta s_t$					
	0.8243	1.0000	0.0339**	1.0000	0.2010

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

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

	AUS	NZ	CAN	CHI	SA
Panel A: Autoregressive Benchmark					
A. MSFE Differences. Model: $\mathrm{E}_t\Delta cp^i_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp^i_t + \beta_{2t}\Delta s^i_t$ vs. AR(1): $\mathrm{E}_t\Delta cp^i_{t+1} = \gamma_{0t} + \gamma_{1t}\Delta cp^i_t$					
	-0.643***	-0.370**	1.247	-0.260	0.998
B. MSFE Differences. Model: $\mathrm{E}_t\Delta s^i_{t+1} = \beta_{0t} + \beta_{1t}\Delta s^i_t + \beta_{2t}\Delta cp^i_t$ vs. AR(1): $\mathrm{E}_t\Delta s^i_{t+1} = \gamma_{0t} + \gamma_{1t}\Delta s^i_t$					
	0.861	1.173	0.151	1.240	0.687
Panel B: Random walk benchmark					
A. MSFE Differences. Model: $\mathrm{E}_t\Delta cp^i_{t+1} = \beta_{0t} + \beta_{1t}\Delta s^i_t$ vs. Random walk: $\mathrm{E}_t\Delta cp^i_{t+1} = 0$					
	-1.865***	-1.015***	0.980	0.526	0.051*
B. MSFE Differences. Model: $\mathrm{E}_t\Delta s^i_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp^i_t$ vs. Random walk: $\mathrm{E}_t\Delta s^i_{t+1} = 0$					
	1.346	1.139	-0.348**	1.677	1.111
Panel C: Random walk with drift benchmark					
A. MSFE Differences. Model: $\mathrm{E}_t\Delta cp^i_{t+1} = \beta_{0t} + \beta_{1t}\Delta s^i_t$ vs. Random walk: $\mathrm{E}_t\Delta cp^i_{t+1} = \gamma_{0t}$					
	-1.536***	-0.914***	1.798	0.083*	0.807
B. MSFE Differences. Model: $\mathrm{E}_t\Delta s^i_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp^i_t$ vs. Random walk: $\mathrm{E}_t\Delta s^i_{t+1} = \gamma_{0t}$					
	1.024	0.959	-0.410	1.421	0.626

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

Table V(a). Exchange Rates and the Aggregate Global Commodity Price Index

	AUS-NZ	AUS-NZ-CAN	AUS-NZ-CAN-CHI
Panel A: Multivariate Granger-causality Test			
	0***	0***	0***
Panel B: Andrews' (1993) QLR Test for Instabilities			
	0.4225	0.280	0.0672*
			(2003:2)
Panel C: Multivariate Granger-causality Tests Robust to Instabilities (Rossi, 2005)			
	0***	0***	0***
Panel D: Out-of-Sample Forecasting Ability			
AR(1) Benchmark	-0.8076***	-0.4583**	-0.9693***
RW Benchmark	-0.9251***	-0.7139***	-1.1453***
RWWD Benchmark	-0.9814***	-0.8308***	-1.1449***
Panel E: Forecast Combination			
AR(1) Benchmark	-1.0887	-0.6215	-1.0620
RW Benchmark	-0.3	-0.0611	-0.2092
RWWD Benchmark	-0.4011	-0.1848	-0.2951

Notes: The table reports results using the exchange rates of the countries listed in the second row to jointly predict the IMF aggregate global commodity price index (cp^W). Panels A-C report the p-values from in-sample test results, and Panels D and E report the MSFE differences between the model-based forecasts and the RW and AR forecasts, as well as the levels of statistical significance based on the Clark and McCracken and Diebol-Mariano test statistics, respectively. Asterisks indicate 1% (***), 5% (**), and 10% (*) significance levels. See Section 2.3 for exact specifications.

Table V(b). Alternative Aggregate Global Commodity Price Indexes

$$E_t \Delta cp^{Wi}_{t+1} = \beta_0 + \beta_{11}\Delta s^{AUS}_t + \beta_{12}\Delta s^{NZ}_t + \beta_{13}\Delta s^{CAN}_t + \beta_2 \Delta cp^{Wi}_t$$

	CRB/BLS	Reuters/Jeffries	Goldman Sachs	Moody's	Dow Jones-AIG
Panel A: Multivariate Granger-causality Test					
	0***	0***	0.0141**	0***	0.0295**
Panel B: Andrews' (1993) QLR Test for Instabilities					
	0.0233**	0.0785*	0***	0.8024	0.0742*
	(1980:3)	(1980:3)	(1998:4)		(1980:3)
Panel C: Multivariate Granger-causality Tests Robust to Instabilities (Rossi, 2005)					
	0***	0***	0***	0.0380**	0***
Panel D: Out-of-Sample Forecasting Ability					
vs. AR(1)	0.3384***	0.0547**	-0.1678**	0.7350	-0.4705**
vs. RW	0.6406***	1.1454*	0.5860*	-0.1986***	0.3308**
vs. RWWD	0.2500***	0.7998**	0.4948*	0.1473**	-0.0491**
Panel E: Forecast Combination					
vs. AR(1)	-0.9055	-0.6480	-0.6564	-0.4002	-1.2558
vs. RW	0.2496	1.6071	1.1268	0.0334	1.4338
vs. RWWD	0.0140	1.5475	1.2053	0.2036	1.2426

Notes: The table reports results using the exchange rates of AUS, NZ, and CAN (vs. USD) to jointly predict different aggregate global commodity price indexes (cp^{Wi}) where i is as listed in the third row. Panels A-C report the p-values from in-sample test results, and Panels D and E report the MSFE differences between the model-based forecasts and the RW and AR forecasts, and the levels of statistical significance based on the Clark and McCracken and Diebol-Mariano test statistics, respectively. Asterisks indicate 1% (***), 5% (**), and 10% (*) significance levels.

Table VI(a). Aggregate Global Commodity Price Index and Individual Exchange Rates

Granger Causality and Out-of-Sample Forecasts

		AUS	NZ	CAN	CHI	SA
Panel A: Granger-causality Tests						
s_t GC cp^W_{t+1}		0***	0***	0.0352**	0***	0.1085
cp^W_t GC s_{t+1}		0.1218	0.1695	0.1204	0.0349**	0.2057
Panel B: Andrews' (1993) QLR Test for Instabilities						
s_t GC cp^W_{t+1}		0.2594	0.6332	0.5347	0.0666**	0.5865
					(1988:1)	
cp^W_t GC s_{t+1}		0.3599	0.0398**	0.1086	0***	0.6675
					(1985:2)	
Panel C: Granger-Causality Test Robust to Instabilities, Rossi (2005)						
s_t GC cp^W_{t+1}		0***	0***	0.0824*	0***	0.5275
cp^W_t GC s_{t+1}		0.0787*	0.0390**	0.1066	0***	0.0429**
Panel D: Out-of-Sample Forecasting Ability						
AR(1) benchmark:	$s_t \Rightarrow cp^W_{t+1}$	-1.115***	-0.675***	0.855	-1.226***	-0.701
	$cp^W_t \Rightarrow s_{t+1}$	-0.129	0.974	-0.347**	0.426	1.595
RW benchmark:	$s_t \Rightarrow cp^W_{t+1}$	-1.045***	-1.100***	0.381*	-1.781***	-1.044
	$cp^W_t \Rightarrow s_{t+1}$	-1.475	0.908	-0.124**	0.892	1.827
RWWD benchmark:	$s_t \Rightarrow cp^W_{t+1}$	-1.083***	-1.160***	-0.002**	-1.787***	-1.708*
	$cp^W_t \Rightarrow s_{t+1}$	-0.015	-0.152*	-0.965***	0.652	1.373

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 forecasts versus the AR and RW forecasts, where the model is $E_t \Delta y_{t+1} = \beta_0 + \beta_1 \Delta x_t$ (labeled $x \Rightarrow y$) and includes $\beta_2 \Delta y_t$.in the AR(1) case. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively.

Table VI(b). Aggregate Global Commodity Price Index and Exchange Rates

Granger Causality: Slope Coefficients Only

	AUS	NZ	CAN	CHI	SA
			Panel A: Granger-causality Tests		
s_t GC cp^W_{t+1}	0.0010***	0.0003***	0.0422**	0.0000***	0.0543*
cp^W_t GC s_{t+1}	0.0489**	0.0717*	0.0572*	0.1073	0.3074
			Panel B: Andrews' (1993) QLR Test for Instabilities		
s_t GC cp^W_{t+1}	0.0681*	0.5654	0.3402	0.0254**	0.8695
	(2001:3)			(2001:1)	(2003:1)
cp^W_t GC s_{t+1}	0.5990	0.1143	0.0433**	0.0272**	0.8271
			(2005:4)	(1999:4)	
			Panel C: Granger-Causality Test Robust to Instabilities, Rossi (2005)		
s_t GC cp^W_{t+1}	0***	0***	0.0472**	0***	0.4093
cp^W_t GC s_{t+1}	0.1215	0.2180	0.0439	0.1873	1
			Panel D: Joint Tests		
Granger-causality Tests				0***	
Andrews' (1993) QLR Test for Instabilities				0.1100	
Granger-Causality Test Robust to Instabilities, Rossi (2005)				0***	

Note. Panels A-C report p-values for tests for $\beta_1 = 0$ 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 results for testing $\beta_{11} = \beta_{12} = \beta_{13} = 0$ in the multivariate regression below:

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

Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively.

Table VII(a). Nominal Effective Exchange Rate

		AUS	NZ	CAN	CHI	SA
		Panel A. Multivariate Granger-Causality Tests				
s_t GC cp_{t+1}		0.065*	0.406	0.320	0.361	0.055*
cp_t GC s_{t+1}		1	0.307	0.060*	0.427	0.010**
		Panel B. Andrews' (1993) QLR Test for Instabilities				
s_t GC cp_{t+1}		0***	0.059	0.830	0.117	0.043**
		(1999:1)				(1999:1)
cp_t GC s_{t+1}		0.274	0.013**	0.706	0.067*	0.115
			(2008:4)		(1995:1)	
		Panel C. Granger-Causality Tests Robust to Instabilities, Rossi (2005)				
s_t GC cp_{t+1}		0***	0.499	0.047**	0***	0.061**
cp_t GC s_{t+1}		0.554	0***	0.403	0.343	0.018**
		Panel D. Out-of-Sample Forecasting Ability				
AR(1) benchmark:	$s_t \Rightarrow cp_{t+1}$	-0.356**	1.057	1.641	0.016	0.687
	$cp_t \Rightarrow s_{t+1}$	0.394*	0.960	0.692	1.893	0.207*
RW benchmark:	$s_t \Rightarrow cp_{t+1}$	-1.303***	-0.522**	1.056	0.843	0.001**
	$cp_t \Rightarrow s_{t+1}$	1.489	0.262	-0.705***	1.689	0.131*
RW with drift	$s_t \Rightarrow cp_{t+1}$	-1.461***	-0.353*	1.533	0.356	0.453
benchmark:	$cp_t \Rightarrow s_{t+1}$	1.081	0.341*	-0.745***	1.153	0.181*

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

Table VII(b). U.K. Pound as the Numeraire Currency

		AUS	NZ	CAN	CHI	SA
Panel A: Multivariate Granger-Causality Tests						
s_t GC cp_{t+1}		0.2621	0.5634	0.2227	0.3502	0.1265
cp_t GC s_{t+1}		1	0.3682	0.1107	0.0254**	0.3092
Panel B: Andrews' (1993) QLR Test for Instabilities						
s_t GC cp_{t+1}		0.1835	0.1666	0.6813	0.0267**	0.0372**
					(2009:1)	(1999:1)
cp_t GC s_{t+1}		0.6722	0.5284	1	0.1098	0.5630
Panel C: Granger-Causality Test Robust to Instabilities, Rossi (2005)						
s_t GC cp_{t+1}		0.4525	0.3895	0***	0***	0***
cp_t GC s_{t+1}		1	0.3577	0.7649	0***	0***
Panel D: Out-of-Sample Forecasting Ability						
AR(1) benchmark:	$s_t \Rightarrow cp_{t+1}$	0.132*	1.139	1.486	0.362	0.975
	$cp_t \Rightarrow s_{t+1}$	1.459	1.025	0.684	-0.639***	1.639
RW benchmark:	$s_t \Rightarrow cp_{t+1}$	-0.279**	-0.006	0.824	0.702	-0.015*
	$cp_t \Rightarrow s_{t+1}$	1.535	0.735	0.767	-0.163***	1.828
RWWD benchmark:	$s_t \Rightarrow cp_{t+1}$	-0.324*	0.991	1.485	0.455	0.567
	$cp_t \Rightarrow s_{t+1}$	1.357	0.866	0.657	-0.628***	1.679

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

Table VII(c). Yen as the Numeraire Currency

		AUS	NZ	CAN	CHI	SA
Panel A: Multivariate Granger-Causality Tests						
s_t GC cp_{t+1}		0.052*	0.467	0.034**	0.629	0.054*
cp_t GC s_{t+1}		0.432	0.909	0.117	0.109	0.064*
Panel B: Andrews' (1993) QLR Test for Instabilities						
s_t GC cp_{t+1}		0.074*	0***	0.095*	0***	0***
		(1999:1)	(1992:1)	(2001:4)	(2008:2)	(1999:1)
cp_t GC s_{t+1}		0***	0.622	0.082*	0***	0.354
		(2001:2)		(1979:4)	(1994:1)	
Panel C: Granger-Causality Test Robust to Instabilities, Rossi (2005)						
s_t GC cp_{t+1}		0***	0***	0.039**	0.026**	0.025**
cp_t GC s_{t+1}		0***	1	0.033**	0***	0.2216
Panel D: Out-of-Sample Forecasting Ability						
AR(1) benchmark:	$s_t \Rightarrow cp_{t+1}$	0.101	-0.035	-0.693*	0.729	1.124
	$cp_t \Rightarrow s_{t+1}$	-0.105*	1.548	1.353	1.548	0.542
RW benchmark:	$s_t \Rightarrow cp_{t+1}$	-0.334**	-0.837***	0.168	0.856	0.112*
	$cp_t \Rightarrow s_{t+1}$	0.345	1.502	1.244	1.388	1.005
RWWD benchmark:	$s_t \Rightarrow cp_{t+1}$	-0.346**	-0.808**	-0.023	0.558	1.201
	$cp_t \Rightarrow s_{t+1}$	-0.049*	1.580	1.380	1.537	0.518

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

Table VII(d). Granger-Causality and Instabilities Tests

Random Walk with Drift Benchmark for NEER & Yen Crossrates

		AUS	NZ	CAN	CHI	SA
NEER	**Panel A: Granger-Causality Tests**					
	s_t GC cp_{t+1}	0.1040	0.5056	0.8190	0.2473	0.1244
	cp_t GC s_{t+1}	0.9282	0.1590	0.0202**	0.3308	0.0726*
	Panel B: Andrews' (1993) QLR Test for Instabilities					
	s_t GC cp_{t+1}	0***	0.0321**	1.0000	0.0353**	0.7695
	cp_t GC s_{t+1}	0.3664	0.8610	1.0000	0.3074	0.0472**
	Panel C: Granger-Causality Test Robust to Instabilities, Rossi (2005)					
	s_t GC cp_{t+1}	0***	0.2383	0.6589	0.2093	0.2105
	cp_t GC s_{t+1}	0.6816	0.5096	0.1355	0.7039	0.1630
YEN	**Panel A: Granger-Causality Tests**					
	s_t GC cp_{t+1}	0.1409	0.5186	0.1852	0.5317	0.6614
	cp_t GC s_{t+1}	0.3644	0.6826	0.0906*	0.0862*	0.1070
	Panel B: Andrews' (1993) QLR Test for Instabilities					
	s_t GC cp_{t+1}	0.1203	0***	0.0216**	0***	0.3880
	cp_t GC s_{t+1}	0***	1	0***	0.1299	0.1380
	Panel C: Granger-Causality Test Robust to Instabilities, Rossi (2005)					
	s_t GC cp_{t+1}	0.0475**	0***	0.2020	0.0254**	0.8179
	cp_t GC s_{t+1}	0.0172**	1	0	0.2591	0.1678

Note. Here we report p-values for tests for $\beta_1 = 0$ based on two the following regressions: (i) $\Delta cp_{t+1}^i = \beta_0 + \beta_1 \Delta s_t^i + \beta_2 \Delta cp_t^i$ (labeled s_t GC cp_{t+1}) and (ii) $\Delta s_{t+1}^i = \beta_0 + \beta_1 \Delta cp_t^i + \beta_2 \Delta s_t^i$ (labeled cp_t GC s_{t+1}). Asterisks indicate 1% (***), 5% (**), and 10% (*) significance levels. (To conserve space, break dates are not reported)

Table VII(e) Aggregate Global Commodity Price Index and Alternative Exchange Rates

$$E_t \Delta cp_{t+1}^W = \beta_0 + \beta_{11}\Delta s_t^{AUS} + \beta_{12}\Delta s_t^{NZ} + \beta_{13}\Delta s_t^{CAN} + \beta_2 \Delta cp_t^W$$

	NEER	U.K. Pound	Yen
Panel A: Multivariate Granger-causality Test			
	0.2110	0.0146**	0.028**
Panel B: Andrews' (1993) QLR Test for Instabilities			
	0.0702*	0.0223**	0.000***
	(1985:2)	(1992:4)	(1986:1)
Panel C: Multivariate Granger-causality Tests Robust to Instabilities (Rossi, 2005)			
	0***	0***	0***
Panel D: Out-of-Sample Forecasting Ability			
AR(1) Benchmark	0.5962	-0.7060**	-0.6141**
RW Benchmark	0.2952**	-0.4075**	-0.5143**
RWWD Benchmark	0.1468**	-0.6696**	-0.7208***
Panel E: Forecast Combination			
AR(1) Benchmark	0.4130	-0.6568	0.9540
RW Benchmark	0.3498	0.1027	0.5093
RWWD Benchmark	0.2431	-0.1099	0.3972

Notes: The table reports results using NEER and exchange rates measured against the pound and the yen to jointly predict the IMF aggregate global commodity price index (cp^W). Panels A-C report the p-values from in-sample test results, and Panels D and E report the MSFE differences between the model-based forecasts and the RW and AR forecasts, and the levels of statistical significance based on the Clark and McCracken and Diebol-Mariano test statistics, respectively. Asterisks indicate 1% (***), 5% (**), and 10% (*) significance levels.

Table VIII. Short- and Long-Horizon Predictive Regressions

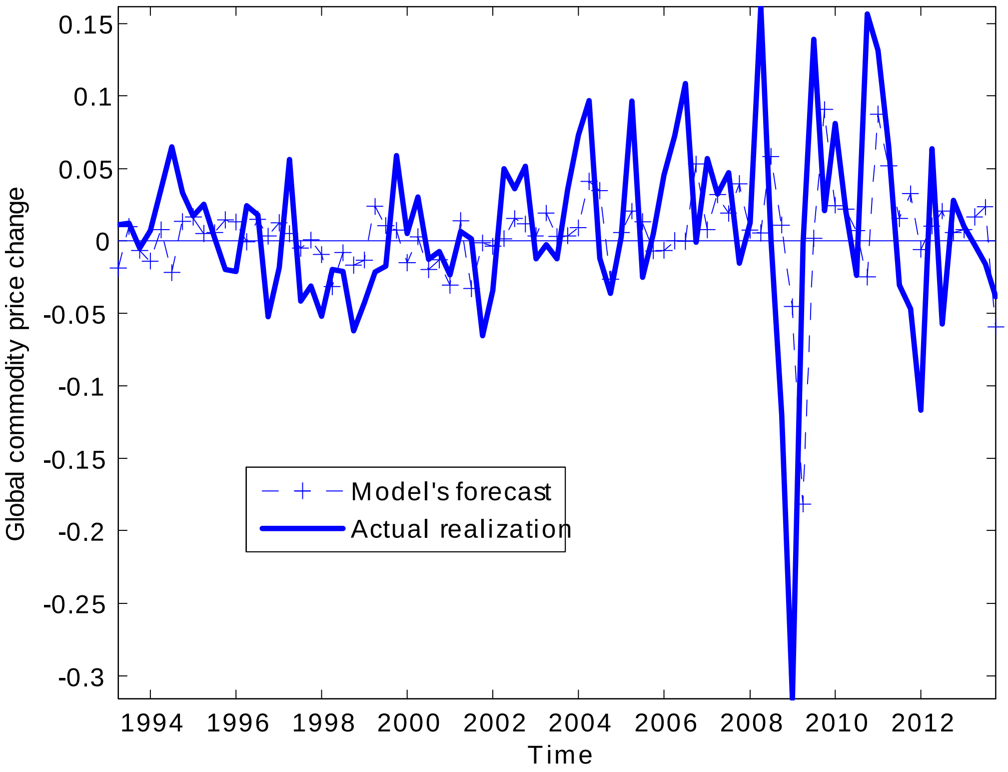
(Robust to Highly Persistent Regressors)

	A. Confidence Interval for β_h in: $\mathrm{E}_t \sum_{j=1}^{h} \Delta cp_{t+j} = \beta_h \Delta s_t + \gamma \Delta cp_t$		
k=	1	4	8
AUS	$(0.01; 0.03)$	$(0.05; 0.12)$	$(0.08; 0.26)$
NZ	$(-0.01; -0.00)$	$(-0.06; -0.03)$	$(-0.11; -0.07)$
CAN	$(-0.01; -0.003)$	$(-0.04; -0.01)$	$(-0.08; -0.03)$
CHI	$(0.13; 0.15)$	$(0.48; 0.64)$	$(0.89; 0.42)$
SA	$(0.03; 0.04)$	$(0.12; 0.17)$	$(0.24; 0.40)$
	B. Confidence Interval for β_h in: $\mathrm{E}_t \sum_{j=1}^{h} \Delta s_{t+j} = \beta_h \Delta cp_t + \gamma \Delta s_t$		
AUS	$(-0.003; -0.001)$	$(-0.013; -0.006)$	$(-0.026; -0.014)$
NZ	$(0.009; 0.011)$	$(0.026; 0.045)$	$(0.036; 0.086)$
CAN	$(-0.003; -0.001)$	$(-0.013; -0.007)$	$(-0.025; -0.015)$
CHI	$(-0.002; -0.001)$	$(-0.006; -0.004)$	$(-0.008; -0.009)$
SA	$(0.003; 0.004)$	$(0.008; 0.017)$	$(0.010; 0.033)$

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

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

$$\text{Model}: E_t\Delta cp_{t+1}^{W} = \beta_0 + \beta_{11}\Delta s_t^{AUS} + \beta_{12}\Delta s_t^{CAN} + \beta_{13}\Delta s_t^{NZ} + \beta_2\Delta cp_t^{W}$$

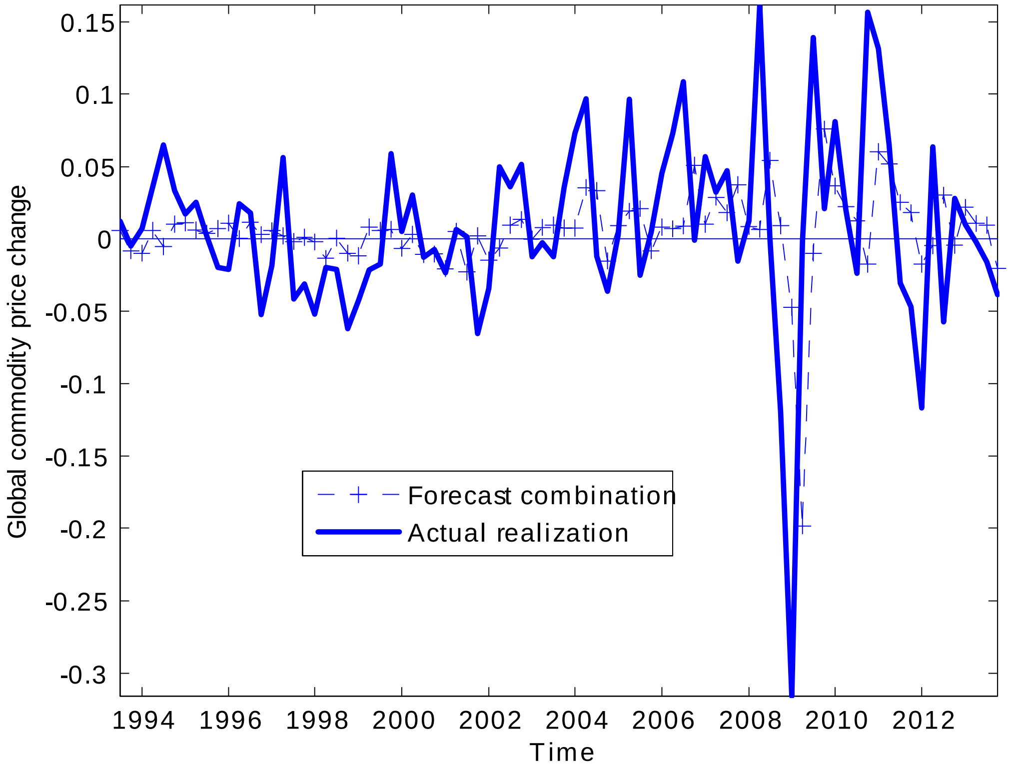


Note. The figure plots the realized change in the global commodity price level (labeled "Actual realization") and their exchange rate-based forecasts (labeled "Model's forecast")

Figure II. Forecasting Aggregate Global Commodity Price Using Forecast Combinations

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

where $E_t \Delta cp_{t+1}^{W,i} = \beta_{0,i} + \beta_{1,i} \Delta s_t^i + \beta_{2,i} \Delta cp_t^W$, $i = AUS, CAN, NZ$

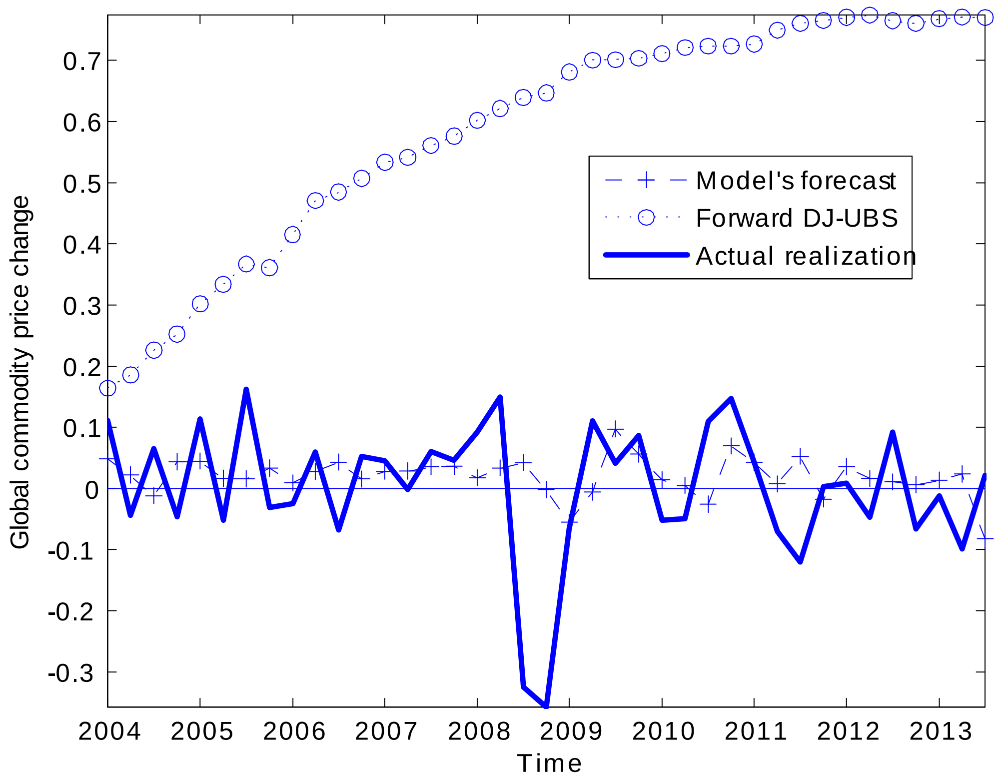


Note. The figure plots the realized change in the global commodity price level (labeled "Actual realization") and their forecasts based on the three exchange rates (labeled "Forecast combination")

Figure III. Forecasting the DJ-UBS Spot Commodity Price Index: Forward Index vs. Exchange Rates

$$\text{Model}: E_t \Delta cp_{t+1}^{DJ-UBS} = \beta_0 + \beta_{11}\Delta s_t^{AUS} + \beta_{12}\Delta s_t^{CAN} + \beta_{13}\Delta s_t^{NZ};$$

$$\text{Forward}: E_t \Delta cp_{t+1}^{DJ-UBS} = f_{t+1}^{DJ-UBS} - cp_t^{DJ-UBS}$$

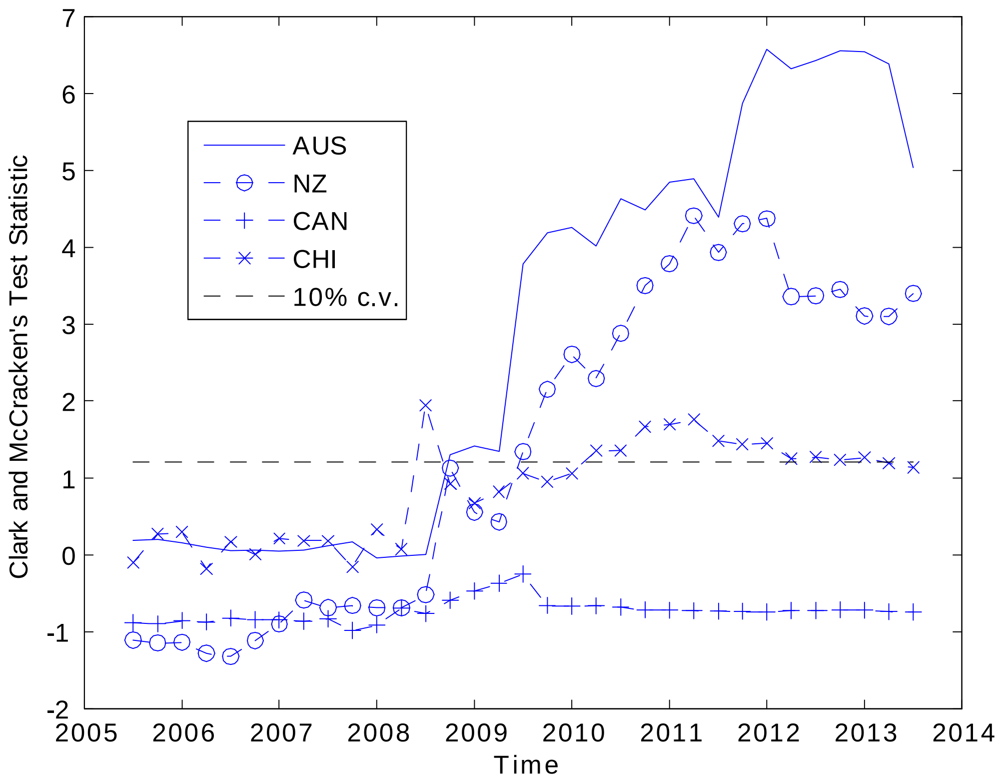


Note. The figure plots the realized change in the DJ-UBS global commodity price spot index (labeled "Actual realization"), the exchange rate-based forecast (labeled "Model's forecast"), and the prediction based on the DJ-UBS 3-month forward index (labeled "Forward DJ-UBS").

Figure IV: Out-of-Sample Forecast Performance Over Time

A. Exchange Rate Model vs. AR(1)

Model: $E_t \Delta cp^i_{t+1} = \beta_{0,i} + \beta_{1,i} \Delta s^i_t + \beta_2 \Delta cp^i_t$ where $i = AUS, NZ, CAN, CHI$

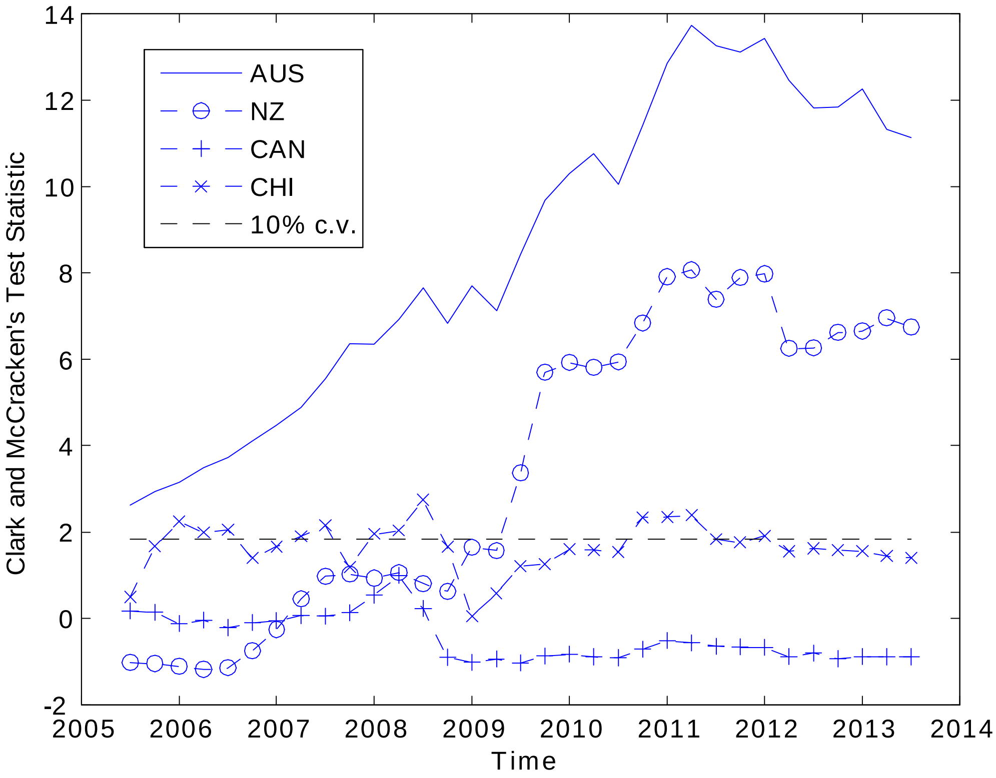


Note. The figure plots the Clark and McCracken's test statistics for the Model vs. the AR(1) benchmark calculated at different points in time (labeled on the x-axis) using the rolling windows discussed in the main paper.

Figure IV: Out-of-Sample Forecast Performance Over Time

B. Exchange Rate Model vs. RW

Model: $E_t \Delta cp^i_{t+1} = \beta_{0,i} + \beta_{1,i} \Delta s^i_t + \beta_2 \Delta cp^i_t$ where $i = AUS, NZ, CAN, CHI$

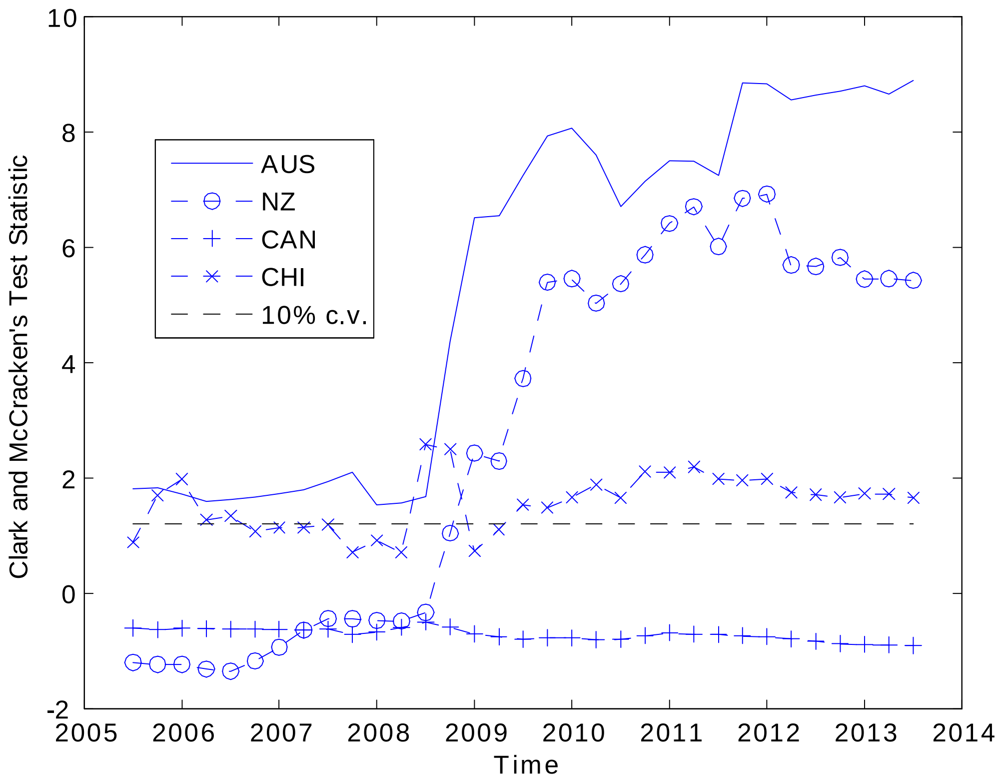


Note. The figure plots the Clark and McCracken's test statistics for the Model vs. the RW benchmark calculated at different points in time (labeled on the x-axis) using the rolling windows discussed in the main paper.

Figure IV: Out-of-Sample Forecast Performance Over Time

C. Exchange Rate Model vs. RWWD

Model: $E_t \Delta cp^i_{t+1} = \beta_{0,i} + \beta_{1,i} \Delta s^i_t + \beta_2 \Delta cp^i_t$ where $i = AUS, NZ, CAN, CHI$

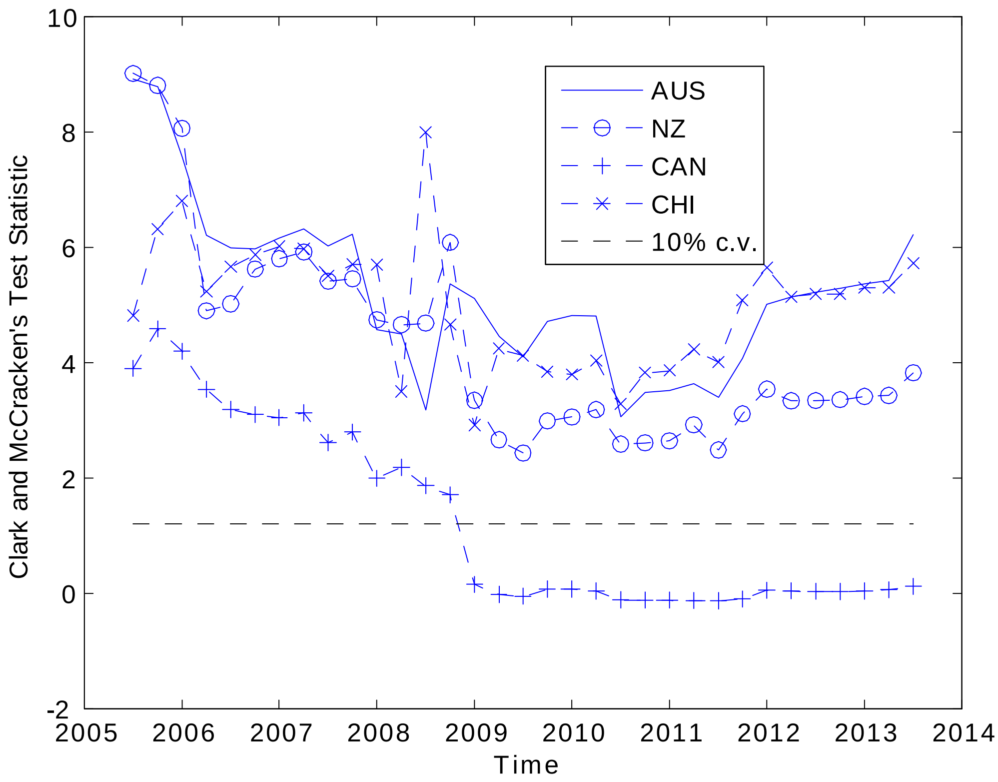


Note. The figure plots the Clark and McCracken's test statistics for the Model vs. the RWWD benchmark calculated at different points in time (labeled on the x-axis) using the rolling windows discussed in the main paper.

Figure V: Forecasting Aggregate World Commodity Price Index Over Time

A. Exchange Rate Model vs. AR(1)

Model: $E_t \Delta cp^W_{t+1} = \beta_{0,i} + \beta_{1,i} \Delta s^i_t + \beta_2 \Delta cp^W_t$ where $i = AUS, NZ, CAN, CHI$

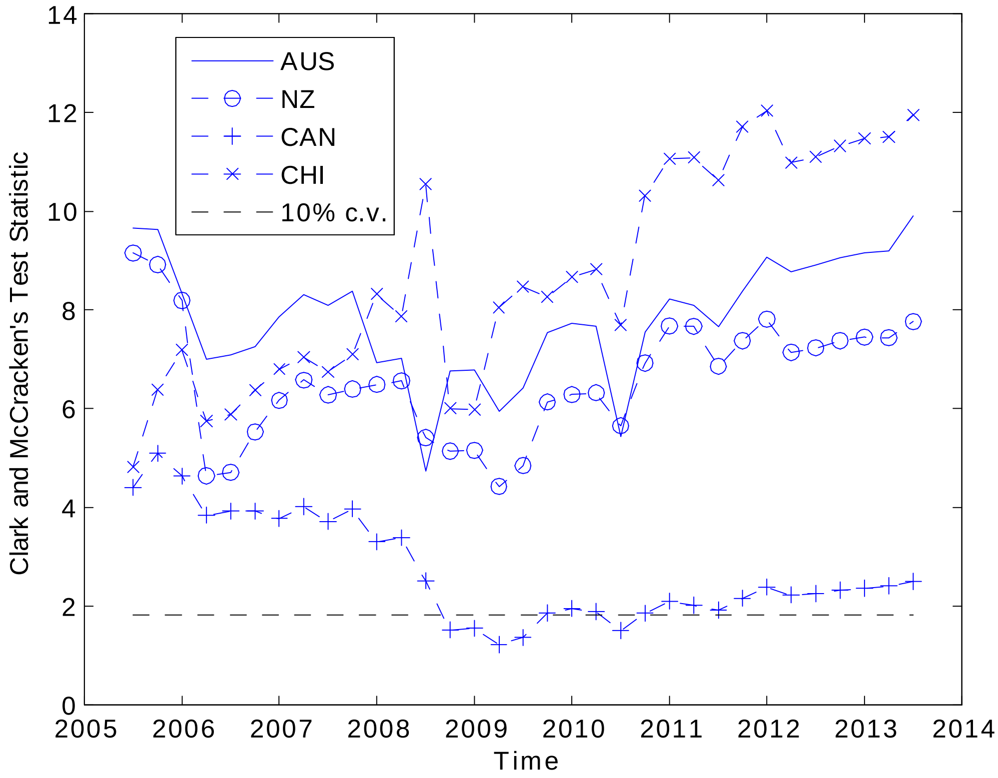


Note. The figure plots the Clark and McCracken's test statistics for the Model vs. the AR(1) benchmark calculated at different points in time (labeled on the x-axis) using the rolling windows discussed in the main paper.

Figure V: Forecasting Aggregate World Commodity Price Index Over Time

B. Exchange Rate Model vs. RW

Model: $E_t \Delta cp^W_{t+1} = \beta_{0,i} + \beta_{1,i} \Delta s^i_t + \beta_2 \Delta cp^W_t$ where $i = AUS, NZ, CAN, CHI$

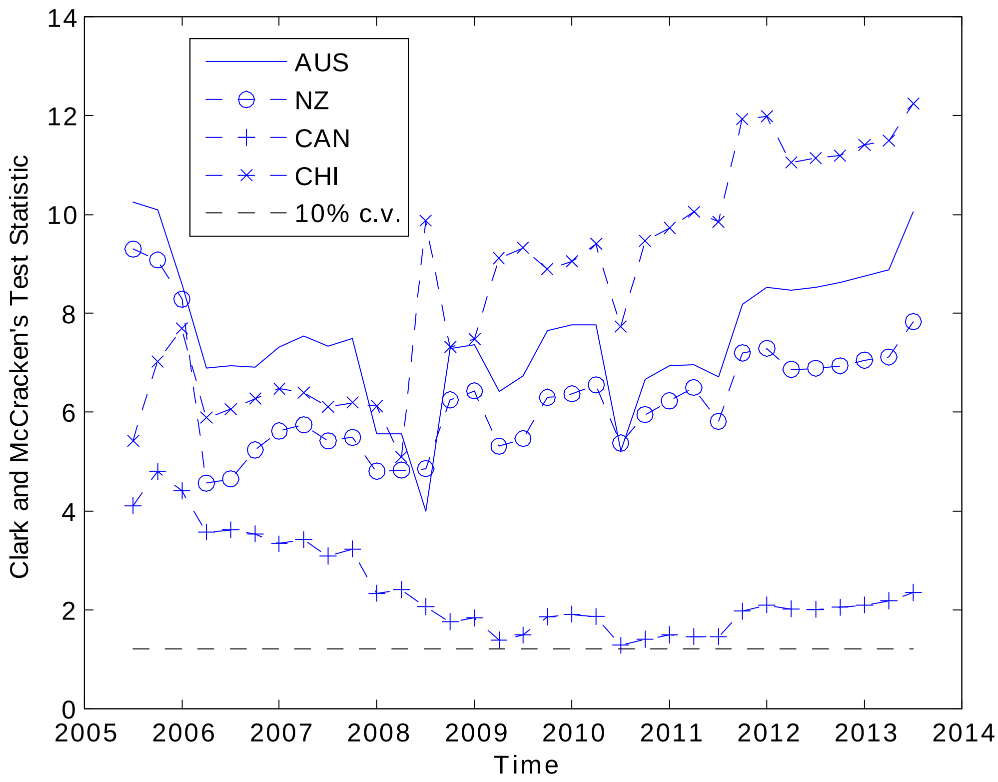


Note. The figure plots the Clark and McCracken's test statistics for the Model vs. the RW benchmark calculated at different points in time (labeled on the x-axis) using the rolling windows discussed in the main paper.

Figure V: Forecasting Aggregate World Commodity Price Index Over Time

C. Exchange Rate Model vs. RWWD

Model: $E_t\Delta cp^W_{t+1} = \beta_{0,i} + \beta_{1,i}\Delta s^i_t + \beta_2\Delta cp^W_t$ where $i = AUS, NZ, CAN, CHI$



Note. The figure plots the Clark and McCracken's test statistics for the Model vs. the RWWD benchmark calculated at different points in time (labeled on the x-axis) using the rolling windows discussed in the main paper.