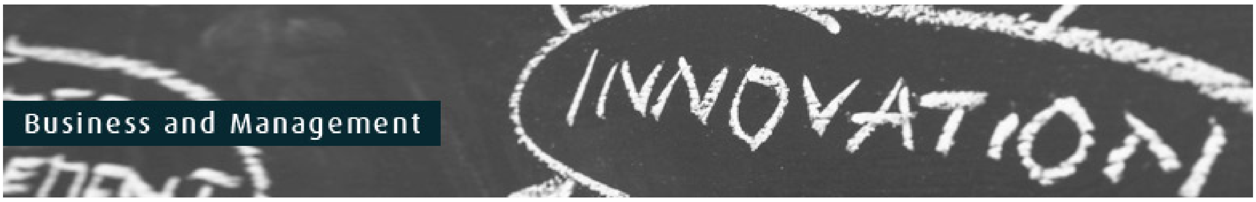

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Do Exchange Rates Really Help Forecasting Commodity Prices?

By

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Tuesday, July 29, 2014

Abstract

Chen et al. (2010) report that for ‘commodity currencies’, the exchange rate predicts the country’s commodity index but not vice versa. The commodity currency hypothesis is consistent with the Engel andWest (2005) exchange rate model if the fundamental is chosen to be the country’s key export prices and if the latter are exogenous to the exchange rate dynamics. In our view, however, commodity prices are essentially financial asset prices that are set in a forward-looking way, exactly like exchange rates. If both the exchange rate and the commodity prices are based on discounted future expectations, one should mostly observe contemporaneous correlations, not one-directional cross-predictability from one variable toward the other.

Using three different data sets and various econometric techniques, we do find the contemporaneous correlations as predicted by the financial asset view of commodity prices. Cross-predictability, in contrast, seems to be only minor at best, not robust to plausible variations in the test design, and bi-directional rather than one-directional. The difference between Chen et al’s empirical findings and ours is to a large extent traceable to the presence of time-averaged prices in the commodity index data that they use. Price averaging induces spurious autocorrelation and predictability that disappears if one uses e.g. month’s-end prices. Some slip-ups in their test design seem to play an additional role too.

Keywords: Commodity prices, exchange rate
JEL classification: C22, C52, C53, F31, F47

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Introduction

In a recent article, Chen et al. (2010) (henceforth CRR) investigate the relation between the exchange rates of Australia, Canada, Chile, New Zealand and South Africa, and the price of the commodity bundles produced by these countries. These exchange rates, CRR point out, are commodity currencies; i.e. *floating currencies that co-move with the world prices of primary commodity products, due to these countries' heavy dependency on commodity exports* (p. 1149). CRR's Commodity Currency Hypothesis (CCH) states that these exchange rates should predict the prices of the commodities exported by these countries but not vice versa. From their empirical work they conclude that the hypothesis is upheld.

The CCH refers to the work of Engel and West (2005) who, based on Campbell and Shiller (1987), take the view that exchange rates can be modeled as any other asset price in the sense that their present value corresponds to the discounted value of their expected future fundamentals. This modelling approach is not only fully consistent with some familiar monetary models developed earlier, e.g. Frenkel (1976), Mussa (1976) and Bilson (1978), but it also implies that exchange rates embed information about the expected value of future fundamentals. As a consequence, exchange rates should help predicting their fundamentals. Fundamentals, in contrast, should remain uninformative about future exchange rate values. As noted by CRR, a reverse predictability can arise only indirectly, notably if movements in commodity prices have the ability to predict their own future values which, in turn, are a future exchange rate fundamental.

While the CCH is an appealing hypothesis, it runs counter to a long literature that regards commodities as, essentially, assets whose prices are set efficiently by financial markets. Below, we refer to this paradigm as the financial-asset hypothesis (FAH) of commodity prices. The FAH starts from the observation that spot prices move in close tandem with futures prices – e.g. Fama and French (1988), Chinn and Coibion (2013) – and commodity futures in turn are undoubtedly financial contracts. The time series of futures prices for a given delivery date should be almost unpredictable, and the same holds if many series of consecutive returns per contract are stacked into one longer vector.[1] Any predictability in commodity prices should be in the day's term structure of futures prices for different expiry dates, not in the longitudinal changes of the prices per contract. Spot prices, moving in an almost exact one-to-one fashion with nearby futures, should then display an almost unpredictable

[1]This holds of course provided that one does not compute a 'return' between the first price of a new contract and the last price of the old one, as this return cannot be realized by an investor.

behavior as well.

This does not mean that the exchange rate and commodity prices should be fully disconnected. If spot commodity prices anticipate future scarcities or gluts, any news about the distribution of future availabilities is immediately translated into spot commodity prices. In this logic, the current spot-price change becomes an excellent reflection of the update in the expectations and risks about future spot prices that, in the commodity-currency logic, should also drive the exchange rate. For that reason the Engel-West model would predict mostly contemporaneous correlations. The one-directional forecasting power would be expected only if the fundamental (commodity prices) were not a financial price.

In this article we accordingly re-assess the empirical validity of the CCH. We do find contemporaneous correlation, but no clear evidence of one-sided predictive ability between exchange rates and commodity prices. The divergence between our and CRR's empirical findings is largely due to a problem with some of the commodity price indices they use. CRR's findings rely on indices that are based on time-averaged spot prices, like the month's mean price, instead of end-of-period observations. For the purpose of displaying broad trends about a country's export package this practice is fine, but in the context of testing the CCH it seems less appropriate, for it induces a spurious autoregressive pattern that should be (and actually is) absent in end-of-period data.

In the remainder of this introduction we expound our thoughts regarding the CCH itself and then about the way in which CRR test it. We close with a review of the additional tests we provide.

CCH versus FAH

Consider the theory, first. Being a speculative price, the exchange rate must be based on probability distributions of future values. These in turn must be mapped from distributions of the underlying fundamentals. Nominal exchange rates, then, must reflect conditional distributions of the fundamentals. To simplify the argument, CRR assume that the exchange rate fundamental (the price of commodities) behaves like a random walk to the untrained eye, but is nevertheless perfectly predictable to the market participants. This allows CRR to collapse the entire distribution of the fundamental to just a single point at each future date: the realized value. Thus, the exchange rate can be traced to subsequent realizations in the fundamentals, and in that sense it 'predicts' its fundamentals. In contrast, past changes in fundamentals can at best predict the future spot rate in an indirect way only, notably if they have the ability to predict their own future values. This possibility is assumed away by CRR however, for the sequence behaves like a random walk.

If the above holds, there must be something that stops these agents from trading on their insights in the commodity markets themselves. For instance, there are no futures markets; or spot markets are disconnected from futures markets because the good is completely non-storable so that intertemporal arbitrage in spot makers is impossible. There is a factual issue here: in reality, commodity prices themselves have financial-asset-like characteristics too. As soon as the good is storable, even at a cost, it can be kept out of the market by a producer, or acquired by an individual not just for immediate use but also for storage, see Kaldor (1939). In other cases, inventories can be reduced. For non-agricultural goods, one can increase or decrease the rate of extraction. So markets for commodity prices are definitely not sequences of separate 'sessions', each having an exogenously determined supply and demand. Since both buyers and sellers can carry over goods to later or earlier periods, pricing becomes an intertemporal equilibrium issue, just like in pure financial markets.

In the tradition of the 'theory of storage' (Kaldor (1939), Working (1948, 1949), Brennan (1958)), the future income flow that underpins the good's spot value is the net convenience yield, the premium in spot prices relative to futures after correcting for cost of carry and time value.[2] As predicted by this theory, a large body of evidence indeed uncovers a negative relationship between inventory levels and the convenience yield; see e.g. Working (1948, 1949), Brennan (1958), Telser (1958), Thompson (1986), Fama and French (1987), Yoon and Brorsen (2002), Carter and Giha (2007), Gorton et al. (2013), Carbonez et al. (2012). The convenience yield in turn is the variable that underpins spot prices: Pindyck (1993) and Carbonez et al. (2012), show that a commodity's spot price corresponds to the present value of all future expected convenience yields, in the same way as a share price reflects the discounted value of the future expected dividends.[3] Being a present value of future pay-offs, the spot price should immediately reflect any information that changes the conditional distribution of future scarcity. Thus, commodity prices should themselves be priced in a forward-looking way, very much in the same way as stock prices and exchange rates. This means that past data cannot be very useful to predict future nominal commodity spot price changes because these are the result of future changes in expectations, and the latter are in principle unpredictable.

If the FAH of commodity prices holds, the CCH as formulated before is likely to be wide off

[2] If demand for raw materials at time T is temporarily high relative to inventories, one observes a spike in the time-T spot price relative to futures prices (which, in turn, reflect expected subsequent spot prices adjusted for risk). Specifically, there is a premium when the cash price, augmented with the costs of storage and financing, exceeds the futures price. That premium for cash goods (called the net convenience yield at T) reflects a gain that the holder of a cash position can reap and that is not available to the holder of a futures position, like being able to continue business activities that would be costly to suspend. See Kaldor (1939) and Working (1948, 1949).

[3] See also Gorton and Rouwenhorst (2006), Baumeister and Kilian (2011). In private mail, Michael Brennan mentioned an unpublished note by Steve Ross as the likely first appearance.

the mark. For example, imagine that a large importing country announces that, next summer, it will start building a substantial strategic reserve of pig iron. If it were impossible to increase or deplete inventories or to postpone or speed-up production, such an announcement would entail a rise in next summer's spot price as well as in the current futures prices for delivery next summer, but without affecting spot prices today. Realistically though, producers, speculators and users are perfectly able to store iron, and miners and smelters can and will delay production. As a consequence, spot commodity prices today will immediately react to such an announcement. In the end, the expected return between the moment right after the announcement and the next summer would not be much affected, as the price adjustment took place right at the time of the announcement. Most of the ex post realized subsequent price change, between today and the next summer, must therefore reflect unexpected news that became available during that very same period; and these, almost tautologically, are unpredictable, otherwise that information would not be news.

All this implies that if commodity markets are efficient and the FAH holds, then i) most of the impact from commodity prices on exchange rates should be contemporaneous; and ii) any predictability that one might find must be based on something else than just the updating of expectations about commodity prices, as implied by the CCH. Future changes in spot prices could be partly predictable, as long as their link with expectations involves a risk premium, pure time value, and the convenience yield. All three factors could be partially non-random, but all in all one does not expect the resulting predictability to amount to much. Below, we review the arguments.

The variable that should behave randomly in an efficient market is the sequence of changes in the expectation about a future spot price for a given date. But expectations are not observable; all we have is sequences of forward or futures prices per contract, which are certainty equivalents for the future spot price. The difference between the expectation and a futures price for a given delivery date is the risk premium. The empirical evidence regarding the existence of commodity price risk premiums is mixed, but if they do exist they seem to be neither constants nor martingales, see Fama and French (1987, 1988), Moosa and Al-Loughani (1994), Chernenko et al. (2004), Wu and McCallum (2005), Pagano and Pisani (2009), Alquist and Kilian (2010), Hamilton and Wu (2014). So mean-reverting risk premiums may induce a modicum of predictability in changes of futures prices for a given date, just like in stock markets.

If we then go from futures to spot prices, two more variables intervene: the net convenience yield and pure time value. Each of them could again be partly predictable. For instance, if current inventories are extremely low and production cannot rise fast, an expected gradual increase in supply in the future cannot trigger an anticipatory liquidation of 'speculative' inventories right now. So instead there would be predictability in convenience yields, which would be expected to slowly fall until the scarcity is resolved. Also stock prices should be weakly predictable, for essentially the same reasons: risk premiums, risk-free rates, and dividend yields are neither constants nor martingales. In practice, though, there is not much of a pattern to be seen in stock returns. CRR implicitly take a different view in their article: either commodities are not assets, or they are priced in a relatively inefficient way, or they have pronounced patterns in risk and convenience that are captured by currency markets. As a result of this, in CRR' view: i) currency data can be used to predict commodity prices and ii) the predictability is empirically and economically significant.

Reviewing and complementing CRR's tests of the CCH

Let us now review CRR's approach to test the CCH. CRR use data from various sources, including the IMF (IFS), the Reserve Bank of Australia, the Bank of Canada and others. These sources tend to publish commodity price data that is time-averaged rather than sampled at the end of each period.[4] As a result, some of the return series used by CRR is highly autocorrelated and, as the authors note themselves, self-predictability in commodity price changes causes problems with the interpretation of the Granger causality (GC) test in the context of the CCH. This problem is then compounded by some unfortunate slip-ups in their implementation of the Granger and Clark-McCracken tests (see Tables (3) and (4) and Table (28), respectively).

In order to re-assess the validity of the CCH, we compile a dataset of 18 commodity prices and 6 exchange rates sampled at the end of every month. Because our data is considerably less autocorrelated than CRR's data, our results do not suffer from that particular problem. When testing the CCH, we essentially use data that are similar to CRR's, namely commodity prices of country export baskets, and we apply the same testing methodology. Our results indicate a generalized lack of support of the CCH. One possible explanation for this finding could be a lack of power, and maybe other ways to arrange the data could work better. The estimated coefficient in a regression model in which the dependent variable is a basket composed of N commodities, corresponds to the weighted average of the coefficient estimates of the N regression models where the dependent variable are the individual

[4] In the next section we provide a more detailed description of the way in which these sources compute their commodity price data before publishing it. We thank Yu-Chin Chen for providing us a detailed description about the way in which they construct their data set.

commodity prices.[5] As a result, if the CCH holds for baskets it must also hold for the component goods. Of course a price index is less noisy than the underlying variables, which in itself boosts the power of the test. But if the weights are pre-set on the basis of export patterns – that is, considerations that are not related to fit – the basket variable will probably not be the most informative one. As a first alternative way of arranging the data we extract the first principal component for each country's main export goods, and we let the exchange rate of the corresponding country predict this common factor. Familiarly, the weights in a first component are set so as to pick up most of the variability in the underlying data. While this approach still is not explicitly maximizing power, it looks for a maximally informative portfolio. We still obtain no clear support for the CCH, though.

As a second alternative, we use the individual commodity data. Each such individual regression is more noisy and, therefore, less powerful than a basket-based test, but the upside is that we can rely on many more series than just one. The evidence in favor of the CCH however remains as scant as before.

Finally, we perform a forecast combination exercise in order to uncover any potential predictability of commodity prices. We produce a large number of individual forecasting models and we combine them using a Bayesian Information Criterion in order to produce a weighted forecast, with continuous updating of the weights. This approach is more robust to structural breaks in predictors than standard univariate models, and is often found to offer good empirical performance over individual model forecasts. Again our conclusions remain unchanged.

The remaining sections of the paper are organized as follows. Section (1) describes the CRR paper in detail. In section (2) we perform a new set of GC tests using end-of-period data only. In section (3) we analyze the ability of exchange rates to predict commodity prices, and vice versa, again using only end-of-period data and as a robustness comparison, also monthly averaged data. Section (4) shows the results of the forecast combination exercise. Finally, section (5) concludes.

1 The Commodity Currency Hypothesis revisited

In this section we critically review the main ingredients of the commodity currency hypothesis, both theoretical and empirical.

[5]This of course holds as long as the basket is computed in the form of a weighted arithmetic mean of individual commodity prices. CRR compute the basket as a weighted geometric mean instead, in which case this no longer holds by necessity.

1.1 An Engel-West Model when fundamentals are speculative prices

Underlying the CCH is the Engel-West present value equation,

$$s_t = \gamma \sum_{i=0}^{\infty} \psi^i \mathbb{E}_t[f_{t+i}]. \tag{1}$$

In the above equation s_t is the nominal exchange rate, $\mathbb{E}_t[f_{t+i}]$ is the expected value of the fundamental based on information available up to time t. The parameters γ and ψ are derived from the corresponding structural model. Writing equation (1) in first differences and specifying the fundamental f_t to be the commodity prices cp_t, CRR obtain their test equation

$$\Delta s_{t+1} = \gamma \sum_{i=0}^{\infty} \psi^i (\mathbb{E}_{t+1}[cp_{t+1+i}] - \mathbb{E}_t[cp_{t+i}]) + z_{t+1}, \tag{2}$$

where z_{t+1} are additional exchange rate determinants that are assumed to be independent of commodity prices.

Since expectations about commodity prices (and fundamentals in general) are non-observable, CRR replace them by realized figures. A radically different approach becomes available when one starts from the FAH-based presumption that commodity prices anticipate future scarcity or abundance. To formally flesh out the argument, note that almost tautologically the expectation of the future spot price can be written as the current price plus the expected subsequent change, like $\mathbb{E}_t[cp_{t+i}] = cp_t + \mathbb{E}_t[cp_{t+i} - cp_t]$ and similarly for its update one period later. So we can write the change in the expectations for a particular horizon i as

$$\mathbb{E}_{t+1}[cp_{t+1+i}] - \mathbb{E}_t[cp_{t+i}] = [cp_{t+1} - cp_t] + \mathbb{E}_{t+1}[cp_{t+1+i} - cp_{t+1}] - \mathbb{E}_t[cp_{t+i} - cp_t] \tag{3}$$

That is, for any horizon of i months, the change in the expectation over a month can be decomposed into, first, the concurrent change in the spot price (the first square-bracketed term, above), and second, changes in the further price adjustments anticipated over the subsequent i months. If the fundamental were a really exogenous variable, say sunspot activity, the above decomposition would be pointless. But if we have in mind a financial price, then standard finance-theory insights can be invoked for the last two terms, which relate to expected returns. Specifically, imagine for a moment that risk-free rates, risks, and convenience yields are all constant. Then any three-month expected future return would be a constant too, which means that the last two square-bracketed terms in Equation (3) would be virtually identical. The conclusion would be that the change in expectations about the future price would be almost fully reflected in the current price change, with little adjustment left for later. Stated differently, one would need very strong term-structure shifts in the risk-free rate, risk premium and/or convenience yield to make the concurrent price change a poor proxy for the change in expectations.[6]

The upshot then is that, to evaluate the Engel-West model in a setup where fundamentals are financial-asset-like prices, contemporaneous correlations with the changes in the fundamentals should be the prime acid test, not predictability. Only if the fundamental is not a market-set price, or if future market sessions are intertemporally totally unrelated to the sessions before, would there be no immediate translation of the future event into the current spot-price change. In that case the CRR approach of substituting observations for expectations and looking for predictability would be one way out.

CRR do recognize that actual price change has an unexpected part too. The resulting errors-in-the-regressor problem attenuates the regression coefficient towards zero, but does not alter its sign as long as there is some 'signal' left underneath the noise. CRR accordingly construct commodity price baskets for Australia, Canada, Chile, New Zealand and South Africa and test whether these countries' nominal exchange rate Granger cause the dynamics of the respective commodity prices and vice versa. In a first stage, they perform the GC test using full sample parameter estimates. Due to the potential presence of structural breaks in the data as a result of policy and market changes, in a second stage they perform the GC test using an alternative approach, the Rossi (2005) test, which is robust to structural breaks. Finally, CRR use the exchange rate data in order to produce series of one period ahead out-of-sample forecasts. The forecasting accuracy of their model is tested using the Clark and McCracken (2001) test of equal forecasting power for nested models.

Motivated by the misgivings voiced thus far, in the next sections we proceed sequentially in order to test the CCH. In a first stage, we use the same data as CRR as well as an alternative dataset to deal with the following two questions: i) do commodity prices have the ability to predict their own future? and ii) do exchange rates Granger cause commodity prices while a GC relationship in opposite direction is rejected?[7] In later sections of the paper we produce a series of out-of-sample forecasts of commodity prices using exchange rate data and we evaluate these forecasts against those obtained from standard benchmark models.

[6]To be more precise, (i) the current nearest month will have disappeared from the forecasting horizon, (ii) a new month will be added at the far end, and (iii) there are updates for all in-between months. For the latter part there can be no predictability, because this is an update in expectations. So the predictable part, if any, is from the difference between the nearest month that will disappear and the one that will be added. For example, in an inverted term structure the current first month is high-yield but we may expect that the new 1-month forward rate in 12 months added will be lower-yield.

[7]In Chen et al. (2010) CRR address only the second question.

Table 1: AR(1) coefficient 1st differences CRR data

	sample period	Basket	*p*-val	Ex. Rate	*p*-val
Australia	1984Q2 - 2008Q1	0.4221	**0.0003**	0.0284	0.7481
Canada	1973Q2 - 2008Q1	0.1090	0.2197	0.0978	0.2821
Chile	1989Q4 - 2008Q1	0.2039	**0.0567**	0.1318	0.1648
New Zealand	1987Q2 - 2008Q1	0.3687	**0.0011**	0.1360	0.2783
South Africa	1994Q2 - 2008Q1	0.1492	0.3637	0.1385	0.2362

Note: AR(1) coefficient and *p*-values of the first difference of the commodity basket (ComB) and exchange rate (ExR) data used by CRR. The reported *p-values* are based on the Newey and West (1987) procedure with bandwidth $T^{1/3}$, which produces heteroscedasticity and serial correlation consistent estimates of the parameters' covariance matrix.

1.2 Do commodity prices have the ability to predict their own future? The role of averaging

In order to address this question, we estimate the first order autocorrelation coefficient of the first difference of the data. Any finding of autocorrelation would reject the martingale property for commodity prices. Table (1) reports the AR(1) coefficients of the changes in the commodity price and exchange rate data used by CRR.[8] The reported values correspond to the OLS estimates of the parameter ρ in the regression model $\Delta X_t = \rho \Delta X_{t-1} + \varepsilon_t$, where X is equal to the commodity price basket or the exchange rate of every country and ε_t is a noise process. The table shows that the commodity index data displays a high degree of autocorrelation. This finding is particularly strong for the cases of Australia and New Zealand where the AR(1) estimates reach values in the order of 0.35 or higher. On the contrary, the exchange rate data displays a considerably lower degree of autocorrelation, in line with the evidence reported by Engel and West (2005) and others. It worth noting that of the three exchange rates with ρs of about 0.13, at least two were dirty floaters during at least part of the period.[9]

[8] We thank the Yu-chin Chen for providing us their data set and also for providing us additional information about the way in which their data set was constructed.

[9] One of the requirements for the CCH to hold is that the exchange rate in question is freely floating. This condition might not entirely apply to the cases of Chile and South Africa. Between August 1984 and September 1999 Chile had a managed floating exchange rate regime that in practice was applied through a crawling band. Officially, Chile begun with a pure floating regime in September of 1999 after it unified its dual rate system. Reinhart and Rogoff (2004) indicate however that it was only in 2001 that the country effectively let its exchange rate float. See also Morandé and Tapia (2002), De Gregorio and Tokman (2004), Frankel and Rapetti (2010). During that period, the exchange rate was allowed to freely float within a band set by the central bank. Whenever the exchange rate came 'too' close to the band the central bank intervened in the FOREX market so as to keep the parity of the CLP with respect to the USD. Foreign exchange interventions occurred all along this period.

In the second half of the 1990s, South-Africa still restricted the number of transactions that residents could take, and practiced 'active intervention', e.g. van der Merwe (2003). Mtonga (2011) describes the regime until January 2000 as a managed float, part of it two-tier.

One factor that can help explain the autocorrelation pattern that we report in Table (1) is the aggregation process applied by the data sources themselves. In their paper, CRR use commodity price data from the following sources: the Reserve Bank of Australia, the Bank of Canada, the ANZ Bank, the IMF and the Global Financial Database. Several of these sources publish data that corresponds to monthly averages instead of end-of-period observations.[10]

To see why price averaging induces spurious autocorrelation in the first differences, it suffices to consider the simplest possible variant of the current set-up, one in which the price average is computed just over two prices – for instance, a daily price is computed as the average of the noon and close prices, P_t^n and P_t^c. When the change in the average price is calculated, the weight of the day's afternoon price change has been halved, while half of yesterday's afternoon price move now appears instead:

$$\frac{P_t^n + P_t^c}{2} - \frac{P_{t-1}^n + P_{t-1}^c}{2} = \frac{P_t^c - P_t^n}{2} + (P_t^n - P_{t-1}^c) + \frac{P_{t-1}^c - P_{t-1}^n}{2}. \tag{4}$$

A first implication is that the two returns that enter into an autocovariance will share a common term, related to yesterday afternoon's price change, $(P_{t-1}^c - P_{t-1}^n)/2$. So the autocovariance will equal $\mathrm{var}(P^c - P^n)/4$ even if the process is a pure martingale. Second, if a one-day-lagged covariate $X_{t-1}^c - X_{t-2}^c$ is tried out which in reality is just contemporaneously related to the price changes, then the covariance will pick up the yesterday-afternoon contemporaneous covariance, which will be mistaken for a lagged reaction. Thus, averaging induces a spurious autocorrelation and predictability.[11] When testing for GC in the context of the CCH, one should therefore work with end-of-period observations. When we do that, there are no economically meaningful autocorrelations as can be seen from Table (2): the average autocorrelation is 0.006 for instance, in monthly data, and 0.0175 in quarterly data instead of the 0.10-0.40 figures we saw for the average-price-based indices used by CRR. Notice also from the table that the autoregressive coefficients of the commodity price data appear to be lower than the autocorrelation coefficients of the exchange rate data — the opposite of what appears to be the case with CRR's data.

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[10]As Yu-chin Chen has confirmed to us, they only use individual commodity price data for the cases of Chile and South Africa. For the cases of Australia, Canada and New Zealand they construct the commodity price indices by computing the weighted geometric mean of the sub-indices provided by the Reserve Bank of Australia, the Reserve Bank of Canada and the ANZ Bank directly. The use of time-averaged prices has been confirmed to us by the the Bank of Canada, the Reserve Bank of Australia, the ANZ Bank and also by the IMF. Also the World Bank publishes a commodity price index based on monthly averages instead of end-of-period observations.

[11]Working (1960) was the first one to note that time averaging leads to spurious autocorrelation patterns; he generalises the noon-close example to averages containing N terms. It is possible to show that the same effect holds, although in different magnitude, when quarterly changes are computed from e.g. monthly averages of daily prices, as CRR do.

Table 2: AR(1) coefficient of log-changes in monthly and quarterly commodity prices using end-of-period data

AR(1) coefficient log-changes monthly and quarterly commodity price data										
	Monthly					Quarterly				
	AR1	p-val	AR1 JK	p-val JK	Begin	AR1	p-val	AR1-JK	p-val JK	Begin
Aluminium	-0.0617	0.5876	-0.0791	0.4695	1975M2	0.1973	**0.0168**	0.1948	**0.0202**	1970Q2
Copper	0.0886	0.1928	0.0923	0.1751	1976M2	0.0481	0.4858	0.0792	0.2700	1976Q2
Corn	0.0453	0.5044	0.0344	0.6118	1979M2	0.0639	0.2566	0.0557	0.3267	1979Q2
Cotton	-0.0512	0.5103	-0.0504	0.5195	1986M2	0.0776	0.5156	0.0944	0.4317	1980Q2
Crude Oil	0.1575	**0.0828**	0.1576	**0.0817**	1983M2	-0.0769	0.3475	-0.0737	0.3820	1983Q2
Fish	0.0516	0.5651	0.0213	0.8142	2000M2	-0.0862	0.4185	-0.1009	0.3738	2000Q2
Gold	0.0073	0.9072	0.0467	0.4458	1970M2	0.0990	0.2787	0.1348	0.1526	1970Q2
Hogs	-0.0376	0.3562	-0.0416	0.3111	1976M2	-0.1447	**0.0091**	-0.1304	**0.0201**	1976Q2
Lead	0.0452	0.3672	0.0354	0.4818	1976M2	0.0108	0.8970	0.0038	0.9640	1976Q2
Lumber	-0.1170	**0.0260**	-0.1170	**0.0264**	1979M2	-0.1984	**0.0014**	-0.1998	**0.0014**	1979Q2
Nat. Gas	-0.1722	**0.0479**	-0.1955	**0.0220**	1997M5	-0.1870	0.1597	-0.1997	0.1305	1990Q3
Nickel	0.0463	0.4902	0.0649	0.3330	1993M8	0.1532	0.1548	0.1661	0.1296	1993Q4
Platinum	-0.0338	0.6681	-0.0759	0.3473	1976M2	0.0709	0.3747	0.0642	0.4248	1976Q2
Silver	-0.0094	0.8369	0.0075	0.8642	1970M2	-0.0161	0.8752	-0.0097	0.9295	1970Q2
Sugar	0.0837	**0.0773**	0.0692	0.1436	1983M2	-0.1374	0.1696	-0.1705	**0.0772**	1983Q2
Wheat	-0.0104	0.8477	-0.0421	0.4314	1979M2	0.0620	0.3323	0.0764	0.2355	1979Q2
Wool	0.1258	**0.0135**	0.1477	**0.0042**	1985M8	0.2025	**0.0512**	0.2400	**0.0230**	1985Q4
Zinc	0.0447	0.3780	0.0327	0.5191	1975M2	0.1041	0.1023	0.0908	0.1565	1970Q2
Mean	0.0113		0.0060			0.0135		0.0175		
Median	0.0260		0.0270			0.0550		0.0599		
AR(1) coefficient log-changes monthly and quarterly exchange rate data										
	Monthly					Quarterly				
	AR1	p-val	AR1 JK	p-val JK	Begin	AR1	p-val	AR1-JK	p-val JK	Begin
AUD/USD	0.0312	0.6083	0.0396	0.5159	1971M2	0.0603	0.3773	0.0776	0.2557	1971Q2
CAD/USD	-0.0670	0.2688	-0.0742	0.2182	1971M2	0.1549	**0.0516**	0.1786	**0.0204**	1971Q2
CLP/USD	0.1366	**0.0335**	0.1095	**0.0874**	1988M2	-0.0143	0.8446	-0.0016	0.9833	1988Q2
NZD/USD	0.0245	0.5936	0.0286	0.5427	1971M2	0.1140	0.1606	0.1210	0.1323	1971Q2
ZAR/USD	0.0352	0.4059	0.0349	0.4108	1971M2	0.1063	0.1770	0.1071	0.1775	1971Q2
NOK/USD	0.0036	0.9738	0.0130	0.9050	1994M1	0.0852	0.4134	0.0934	0.3670	1994Q1
Mean	0.0273		0.0252			0.0844		0.0960		
Median	0.0278		0.0317			0.0958		0.1002		

Note: The columns labeled AR1 report the OLS estimates of the autoregressive coefficient while the columns labeled AR1 JK report the estimates obtained when the jackknife method is applied to the original OLS estimates; see Chambers (2013). The reported p-values are based on the Newey and West (1987) procedure with bandwidth $T^{1/3}$, which produces heteroscedasticity and serial correlation consistent estimates of the parameters' covariance matrix. All the sample periods end in September 2013.

The above analysis means that in order to test the null of no Granger causality one should use end-of-period observations instead of data that has been time-averaged. Because time-averaged data are autocorrelated by construction, such data violates the condition necessary to render the Granger causality tests meaningful in the context of the CCH; namely, that commodity prices (the fundamental variable) must not have the capacity to predict their own future.

Table 3: Granger causality test - full sample

	$\Delta cp_t = \beta_0 + \beta_1\,\Delta cp_{t-1} + \beta_2\,\Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1\,\Delta s_{t-1} + \beta_2\,\Delta cp_{t-1}$					
	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	Single	Joint	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	Single	Joint	Begin
Australia	0.007	0.424	0.003	0.005	3.344	0.001	-0.016	-0.147	1.636	1.757	1984Q2
p-value	**0.073**	**0.000**	0.945	0.945	0.188	0.925	0.861	0.204	0.201	0.415	
Canada	0.011	0.104	-0.045	0.111	4.907	0.000	0.089	-0.016	0.138	0.154	1973Q2
p-value	**0.030**	0.237	0.739	0.739	**0.086**	0.867	0.318	0.711	0.710	0.926	
Chile	0.019	0.130	-0.622	4.177	4.366	0.004	0.129	-0.003	0.005	0.688	1989Q4
p-value	0.1601	0.248	**0.045**	**0.041**	0.113	0.459	0.262	0.943	0.942	0.709	
New Zealand	0.005	0.335	-0.102	2.395	4.608	-0.002	0.109	-0.131	1.067	1.591	1987Q2
p-value	0.194	**0.001**	0.126	0.122	**0.100**	0.740	0.359	0.305	0.302	0.451	
South Africa	0.021	0.108	-0.118	1.121	8.536	0.014	0.122	-0.082	0.102	1.816	1994Q2
p-value	**0.006**	0.515	0.295	0.290	**0.014**	0.184	0.314	0.750	0.749	0.403	

Note: The columns $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$ report the coefficient estimates of the full sample OLS regressions and their corresponding *p*-values. The column CRR reports the results GC test when the joint hypothesis: $\beta_0 = \beta_1 = 0$ is tested, while the column Single reports the results of the GC test when the single hypothesis: $\beta_1 = 0$ is tested. All the reported *p*-values are based on the Newey and West (1987) procedure with bandwidth $T^{1/3}$, which produces heteroscedasticity and serial correlation consistent estimates of the parameters' covariance matrix. Notice that we obtain slightly different *p*-values than CRR when we replicate their joint hypothesis GC test. The reason for this small difference is that CRR compute the values of the χ^2 cumulative distribution function themselves following an interpolation procedure, while our values are obtained directly from the Matlab function *chi2cdf*. The reported *p*-values in the CRR paper are as follows: Australia (0.17 and 0.41), Canada (0.06 and 0.92), Chile (0.10 and 0.70), New Zealand (0.11 and 0.45) and South Africa (0.01 and 0.40).

1.3 Do exchange rates Granger cause commodity prices while a Granger causality in opposite direction is rejected?

Table (3) reports the results of the GC test obtained when we use exactly the same data set as CRR over the full sample period. For each country we report the individual parameter estimates of the regression model $\Delta y_{t+1} = \beta_0 + \beta_1 \Delta y_t + \beta_2 \Delta x_t$, and their corresponding p-values. The t-test on β_2, whose p-value is shown in the table below the parameter estimate, finds evidence of GC just once (Chile), and the Wald test on β_2, shown in the column 'Single', tells us the same. The support of the asymmetric predictability hypothesis is weak, in short; self-prediction by commodity prices actually does a better job, with two significant β_1 estimates. CRR proceed differently: their GC test is for the joint hypothesis that $\hat{\beta}_0 = \hat{\beta}_2 = 0$. But GC has nothing to do with the intercept, so including β_0 into the test hypothesis may, and apparently does, invalidate the conclusions.

CRR correctly argue that the lack of support of the asymmetric predictability hypothesis could be in part explained by the presence of structural breaks. For this reason they test for GC applying the Rossi (2005) test, which is note robust to parameter instabilities. But also here they test the hypothesis that both the intercept and the slope are jointly equal to 0 instead of testing the single hypothesis that only the slope is equal to 0. This is shown in Table (4), which has been again produced using their

Table 4: p-values of the Rossi (2005) GC test

	ER→CP		CP→ER		
	Joint	Single	Joint	Single	Sample Period
Australia	**0.0212**	0.8358	**0.0000**	**0.0716**	1984Q2 - 2008Q1
Canada	**0.0569**	1.0000	0.3605	1.0000	1973Q2 - 2008Q1
Chile	0.2242	0.2950	**0.0000**	1.0000	1989Q4 - 2008Q1
New Zealand	**0.0716**	0.1459	**0.0994**	**0.0603**	1987Q2 - 2008Q1
South Africa	**0.0000**	**0.0000**	**0.0000**	0.3238	1994Q2 - 2008Q1

Note: The table reports the p-values of the Rossi (2005) GC test, which is robust to parameter instabilities. This table has been produced using the same dataset as CRR. ER→CP stands for 'exchange rate Granger causes commodity prices', while under CP→ER causality runs in the opposite direction. The column Joint displays the results when the test is applied in the same way as in the CRR paper, i.e. testing the joint hypothesis that $\beta_{0,t} = \beta_0 = 0$ and $\beta_{1t} = \beta_1 = 0$. The column Single shows the results obtained when the intercept is excluded from the null, i.e. when we test that $\beta_{1t} = \beta_1 = 0$. Bold numbers indicate a rejection of the null of no GC.

dataset. Notice that the regression model is now adjusted to allow the parameters to change over time, in exactly the same way as in CRR, in order to account for the potential existence of structural breaks: $\Delta y_{t+1} = \beta_{0,t} + \beta_{1,t}\Delta y_t + \beta_{2,t}\Delta x_t$. We again report the 'Single' hypothesis test that $\beta_{2,t} = \beta_2 = 0$ next to CRR's 'Joint' one ($\beta_{2,t} = \beta_2 = 0 = \beta_{0,t} = \beta_0$). The Joint test suggests eight significant outcomes; four cases from the exchange rate towards commodity prices and four cases from commodity prices towards exchange rates. To the contrary, the Single test finds just one case in which GC runs from the exchange rate towards commodity prices and in addition, two instances where the GC runs in the opposite direction. This suggests that the support for the CCH is weak.

But as pointed out earlier, for the GC test to be meaningful it is necessary that the exchange rate fundamental does not have the ability to predict its own future. The evidence presented in Table (1) casts doubts about how suitable these data are to test the validity of the CCH.

2 Additional Granger Causality Tests

In this section we use an extended data set to test whether exchange rates data Granger cause commodity prices while a GC relationship in opposite direction is rejected. In order to avoid working with data that has been time-averaged, we download Datastream's month's-end prices for the five countries' main export goods of the CRR paper, and we add Norway for completeness. Our dataset differs from

CRRs in two ways. First, we now work with monthly data.[12] This way the number of observations is considerably larger than with CRR's quarterly observations, which should lead to higher power. Second, our data set is less comprehensive than the one reported by CRR in the sense that not all goods comprised in their indices are available individually on Datastream. Also, some of the noise diversified away in indices remains present in individual series. On the upside, though, we can now test the CCH in 42 different cases rather than five, and from those data we can (and do) also compute alternative, and potentially more powerful, price indices.

Specifically, besides using predetermined export-based weights in order to construct a CRR-like basket of commodities, we also construct an alternative basket using principal components. Because we have an unbalanced panel of commodities we apply the EM algorithm to solve the optimization problem required to obtain the principal components iteratively.[13] Given the size of our cross section we extract only the first principal component from commodity prices and use it in exactly the same way as a commodity basket.

Table (10) in the Appendix I displays the correlation coefficient between the five commodity price baskets (computed using the same export-based weights as CRR do) and the corresponding factors, with all series expressed in units of USD. Both series co-move strongly.[14] Table (11) in the same appendix reports the variance decomposition of the factor and commodity price basket for each country.[15] The table shows that in each country the factor explains a higher proportion of the variation in individual commodity prices than the commodity baskets. This is not surprising given that the method of principal components is designed to achieve this specific goal, even though, unlike the basket, the principal component is constructed using no economic information.

Table (5) reports the contemporaneous correlation analysis. The table shows the contemporaneous correlation coefficient between each exchange rate series and the corresponding commodity price bas-

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[12]We have performed the same GC analysis using end-of-period data sampled at quarterly frequency. Our results, available upon request, differ only marginally with respect to the results that we report below.

[13]This approach has been widely used to extract common factors of macroeconomic variables and other data, e.g. Stock and Watson (2002a,b). The details of the EM algorithm can be found in Tipping and Bishop (1999) and Stock and Watson (2002b). Using the EM algorithm allows us to obtain a longer factor series than it would be possible otherwise. As a robustness test, we compare the variance decompositions of the factor extracted using the EM algorithm and the variance decomposition of another factor, which was extracted by standard PCA but over a shorter sample period in which the panel is balanced. The variance decomposition analysis shows that both factors are nearly identical. Not surprisingly, when we plot both factors, they coincide almost perfectly. We therefore conclude that the results reported below cannot be attributed to the fact that we extract the factor using the EM algorithm.

[14]This is also confirmed when we plot the basket and factor of each country. The plots are available upon request.

[15]We do not consider the case of Chile, which in the CRR paper is reported to export only one commodity.

Table 5: Contemporaneous correlation analysis - full sample.

	Basket		Factor	
	Corr	p-val	Corr	p-val
Australia	0.4607	**0.0000**	0.5913	**0.0000**
Canada	0.3650	**0.0000**	0.4875	**0.0000**
Chile	0.3918	**0.0000**	0.3918	**0.0000**
New Zealand	0.3327	**0.0000**	0.4276	**0.0000**
Norway	0.4413	**0.0000**	0.5936	**0.0000**
South Africa	0.2326	**0.0003**	0.2531	**0.0001**

All samples end in 2013M9. For Australia, the beginning of the sample period is 1984M3 (aluminium, copper, gold, lead, sugar, wheat, zinc, basket and factor), 1985M8 (wool), 1986M2 (cotton) and 19993M8 (nickel). For Canada, the beginning of the sample period is 1980M3 (aluminium, copper, corn, gold, hogs, lumber, silver, wheat, zinc, basket and factor), 1983M2, (crude oil), 1993M8 (nickel) and 1997M2 (natural gas). Chile's sample starts in 1991M3, New Zealand's in 1987M2, for Norway's in 2001M4, and South Africa's in 1994M3.

ket and the first principal component respectively. The table also displays the corresponding p-values. Two important conclusions can be drown from the results. First, there is strong evidence of contemporaneous correlation between the nominal exchange rate and the common component of the commodities exported by these countries. This is the well documented commodity currency phenomenon, which says that currencies from commodity exporting countries strongly co-move with the price of the commodities exported by them. Second, the contemporaneous correlation is always stronger with the factor than with the commodity price basket.[16] This indicates that the factor captures the common component of commodity price fluctuations better than the basket does. Moreover, the exchange rate appears to be more strongly related to this common component than to other measures of commodity price fluctuations. Unreported results indicate indeed that the correlation coefficient between the exchange rate and the individual changes in commodity prices is always lower than the correlation with the factor.

We now proceed with the GC tests of cross-correlation rather than contemporaneous correlation. Table (6) reports the p-values of the GC test for the six countries, based on full sample parameter estimates. The GC tests are performed in the standard way: given the regression model $\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$ we test the null hypothesis that the estimated coefficient $\hat{\beta}_1$ is equal to 0, not the null that both $\hat{\beta}_0$ and $\hat{\beta}_1$ are jointly equal to 0.

The evidence is not much more in favor of the asymmetric predictability hypothesis than what we

[16]For the case of Chile only one commodity enters into the basket, copper. As such, the Chilean commodity price basket and factor are not entirely comparable to the baskets and the factors of the other countries.

Table 6: Granger causality test individual commodities - full sample.

Australia	ER → CP	CP → ER
Aluminium	**0.001**	0.689
Copper	0.642	0.443
Cotton	0.113	0.858
Gold	0.508	0.450
Lead	**0.063**	0.612
Nickel	0.168	0.764
Sugar	0.847	0.587
Wheat	0.433	0.727
Wool	0.749	0.898
Zinc	0.399	0.372
Basket	**0.078**	0.963
Factor	**0.061**	0.996

Canada	ER → CP	CP → ER
Aluminium	**0.060**	0.187
Copper	0.989	**0.084**
Corn	0.677	0.764
Crude Oil	0.681	0.368
Gold	0.429	0.643
Hogs	0.601	0.124
Lumber	0.258	0.425
Nat. Gas	0.443	0.233
Nickel	0.630	0.239
Silver	0.227	0.416
Wheat	0.748	0.786
Zinc	0.845	0.628
Basket	0.750	0.328
Factor	0.612	0.344

Chile	ER → CP	CP → ER
Copper	**0.022**	0.433

New Zealand	ER → CP	CP → ER
Aluminium	**0.002**	0.250
Wool	0.491	**0.084**
Basket	**0.004**	0.202
Factor	0.025	**0.092**

Norway	ER → CP	CP → ER
Aluminium	0.488	0.219
Crude Oil	0.486	0.721
Fish	0.564	0.873
Nat. Gas	0.542	0.937
Nickel	0.498	0.514
Basket	0.486	0.680
Factor	0.679	0.675

South Africa	ER → CP	CP → ER
Gold	**0.028**	0.409
Platinum	0.244	0.274
Basket	0.168	0.632
Factor	0.102	0.713

Overview	ER → CP	CP → ER
# significant individual commodities	6/32	2/32
# significant basket	2/5	0/5
# significant factor	1/5	1/5

Note: The table reports the *p*-values of the Granger causality test. All the *p*-values are based on the Newey and West (1987) procedure with bandwidth $T^{1/3}$, which produces heteroscedasticity and serial correlation consistent estimates of the covariance matrix. All samples end in 2013M9. For Australia, the beginning of the sample period is 1984M3 (aluminium, copper, gold, lead, sugar, wheat, zinc, basket and factor), 1985M8 (wool), 1986M2 (cotton) and 19993M8 (nickel). For Canada, the beginning of the sample period is 1980M3 (aluminium, copper, corn, gold, hogs, lumber, silver, wheat, zinc, basket and factor), 1983M2, (crude oil), 1993M8 (nickel) and 1997M2 (natural gas). Chile's sample starts in 1991M3, New Zealand's in 1987M2, for Norway's in 2001M4, and South Africa's in 1994M3.

obtained earlier from the indices. The exchange rate appears to help predicting individual goods in six out of 32 cases, two of which are Australian. For the baskets, there is a significant cross correlation in two out of five cases (Australia and New Zealand), and for the first principal components there is just one case (Australia). Again, Australia comes up as the most convincing example of a commodity currency. This is odd in the sense that Australia's index seemed particularly hard to predict when we were using the CRR data, and the same holds when the Rossi (2005) GC test is applied to the same data as here (see below, section 4 and especially Table 18). Robustness is not impressive, in short. The

Table 7: Rossi 2005 Granger causality test robust to parmeter instabilities.

Australia

	ER → CP	CP → ER
Aluminium	**0.0314**	1.0000
Copper	0.5678	0.8291
Cotton	0.4468	1.0000
Gold	0.3471	1.0000
Lead	0.1834	1.0000
Nickel	0.1269	1.0000
Sugar	1.0000	1.0000
Wheat	1.0000	0.4371
Wool	1.0000	0.1905
Zinc	1.0000	1.0000
Basket	0.6060	0.8342
Factor	0.3192	1.0000

Canada

	ER → CP	CP → ER
Aluminium	0.2252	0.1051
Copper	1.0000	0.4380
Corn	1.0000	1.0000
Crude Oil	0.5808	0.1854
Gold	0.6734	0.8977
Hogs	1.0000	0.2533
Lumber	0.1715	0.8395
Nat. Gas	1.0000	**0.0184**
Nickel	0.7192	0.5540
Silver	0.7664	1.0000
Wheat	1.0000	1.0000
Zinc	0.8595	0.7213
Basket	0.5801	0.2106
Factor	0.3187	1.0000

Chile

	ER → CP	CP → ER
Copper	0.1350	0.8925

Norway

	ER → CP	CP → ER
Aluminium	0.7786	0.4168
Crude Oil	**0.0823**	0.7255
Fish	1.0000	0.2804
Nat. Gas	1.0000	0.5212
Nickel	0.1166	**0.0367**
Basket	**0.0911**	**0.0489**
Factor	0.2267	0.2817

New Zealand

	ER → CP	CP → ER
Aluminium	**0.0000**	0.7986
Wool	0.8289	0.4233
Basket	**0.0000**	0.6603
Factor	**0.0000**	0.4618

South Africa

	ER → CP	CP → ER
Gold	**0.0000**	0.8525
Platinum	0.7008	0.7083
Basket	0.2266	0.8973
Factor	**0.0890**	1.0000

Overview

	ER → CP	CP → ER
# significant individual commodities	4/32	2/32
# significant basket	2/5	1/5
# significant factor	2/5	0/5

Note: The tables below report the p-values of the Rossi (2005) version of the Granger causality test, which is robust to parameter instabilities. The test is applied excluding the intercept from the null, i.e. we test that $\beta_{1t} = \beta_1 = 0$ in the model $y_t = \beta_{0,t} + \beta_{1,t}\, x_t + \beta_{2,t}\, y_{t-1} + e_t$. All samples end in 2013M9. For Australia, the beginning of the sample period is 1984M3 (aluminium, copper, gold, lead, sugar, wheat, zinc, basket and factor), 1985M8 (wool), 1986M2 (cotton) and 19993M8 (nickel). For Canada, the beginning of the sample period is 1980M3 (aluminium, copper, corn, gold, hogs, lumber, silver, wheat, zinc, basket and factor), 1983M2, (crude oil), 1993M8 (nickel) and 1997M2 (natural gas). Chile's sample starts in 1991M3, New Zealand's in 1987M2, for Norway's in 2001M4, and South Africa's in 1994M3.

only bright spot, from the CCH point of view, is that in these data the evidence of reverse predictability is even weaker.

The lack of evidence in favor of GC just presented could of course be the result of structural breaks altering the relationship between commodity prices and the exchange rate data, as CRR correctly point out. For this reason we also perform the Rossi (2005) test, which allows testing for GC in the presence of structural breaks. The results are shown in Table (7). The number of CCH successes is now five out of 32, down from six, and Australia is no longer a star example. New Zealand appears to do better, with significant CCH-like results for both the index and the factor. Notice also that in the case Chile the evidence of GC disappears when the Rossi (2005) test is applied, as is the case of Canada with aluminium and Australia with the basket and the factor.

The fact that the static and the updated Rossi (2005) sets of GC results do not strongly differ suggest that structural breaks are not the main source behind the scant evidence of GC when full sample estimates are considered. Overall, our results indicate again a general lack of robust and systematic evidence in favor of a GC relationship in either direction. This is particularly striking for Australia, Canada and Norway, where we were able to collect a relatively rich cross-section of spot commodity prices.

To summarize our findings thus far, the evidence does not seem to consistently and robustly favor the CCH. In some cases it even flatly contradicts it. For the CCH to stand we would have expected to observe a clear pattern of GC running from the exchange rate towards commodity prices. Such evidence seems just not to be present in the data, regardless of the testing approach that we use. Instead, these results are the ones that one would expect to obtain if the FAH holds. According to the FAH, past exchange rate data should not be of much help to predict future commodity prices, in the same way that past commodity prices should be of not much help to predict future exchange rates. Moreover, the fact that we sometimes find weak evidence of GC in both directions simultaneously suggests also that there are common factors jointly driving spot nominal exchange rates and spot commodity prices. This again, is a prediction that stands in contradiction with the CCH, not so with the FAH.

3 Do exchange rates really help forecasting commodity prices out of sample?

In this section we analyze the out-of-sample forecasting power of the exchange rate over commodities prices and vice versa, using two different data sets. The first data set consists of the same end-of-period monthly observations that we used in the preceding section. The second dataset consists of monthly observations published by the IMF, the World Bank and Statistics Canada.[17] In the preceding section

[17]The IMF data is compiled by the Commodities Team of the Research Department. The World Bank is obtained from the *Pink Sheet* and the data of Statistics Canada corresponds to the CANSIM table 330-0007. All data is monthly and in the cases of the IMF as well as the World Bank the data published correspond to period averages. As in the previous GC analysis, also here we perform the entire analysis using end-of-quarter data. Our results differ again only marginally with respect to the results obtained using end-of-month data, which we report here. The results using end-of-quarter information are available upon request from the authors.

we performed the analysis exclusively using end-of-period data. Remember that the results presented in Table (2) indicate that these data do not appear to have the ability to predict their own future, which is crucial for the interpretability of the results of the GC results. The alternative time series are admittedly autocorrelated, but this enables us to collect a wider range of commodity prices, so that we can analyze whether our unpromising out of sample findings can be attributed to the lack of data.

3.1 End of period data

We follow CRR by splitting our sample of T observations into two and using a rolling regression approach to produce a series of one-period-ahead forecasts for the periods $T/2+1$ until T and comparing their accuracy against the true realizations over the same period. This is perhaps the simplest way to take into account the presence of potential structural breaks in the relationship between commodity prices and the exchange rate, as it allows the estimated parameters to adjust over time.[18] Tables (12) - (17) shown in the Appendix II report the results of the out-of-sample exercise with month's-end data. Table (8) provides a summary of the key findings.

In Table (8) we provide a summary of the relative forecasting performance of the CRR model against two benchmark models; the AR(1) and RW model respectively. Specifically, for the $N = 32$ individual commodities or the combined $N = 10$ baskets and factors, we report the number of times that the mean squared forecasting errors of the CRR model relative to the particular benchmark model is less than unity in the column $RSFE < 1$. The statistical significance of $RSFE < 1$ is based on the one-sided Clark and West (2007) test of equal predictive power in nested models, and in the column CW we report the number of times that $RSFE < 1$ is significant at 10%. We also compute a Relative Success Ratio (RSR), that is, the success ratio (SR) of a benchmark model divided by that of CRR, where a SR is the proportion of times that a particular model predicted the correct sign of change of the dependent variable. Like for the RFSE metric, an RSR number less than unity implies that the CRR model does well; here, it predicts the correct sign more often than the corresponding benchmark model. We report how often RSR is below or above unity, and in the column sig we compute the number of times that the RSR is significantly different from unity at a 10% significance level.[19]

[18] We have also produced an equivalent set of results enlarging the estimation window by one observation after every iteration, instead of keeping the length of the estimation window constant. We do not report the results here, as they are qualitatively equivalent to the ones shown in the tables. These additional results are available upon request from the authors.

[19] While the Pesaran and Timmerman (1992) test of directional accuracy is useful in comparing a forecast model to a zero-drift random walk model, this test is, however, not very useful for other benchmarks, such as the AR(1) model or a random walk with drift. Consequently, to assess the statistical difference between the success ratios of two competing models, we

Table 8: **Forecasting performance of CCH model, end-of-month data: summary**

		N	RSFE < 1	CW	RSR < 1	sig	RSR ≥ 1	sig
			ER → CP					
CRR/AR(1)	individual commodities	32	7	3	16	1	16	2
	basket and factor	10	4	2	7	1	3	0
CRR/RW	individual commodities	32	3	3	13	0	19	4
	basket and factor	10	2	2	2	0	8	2
			CP → ER					
		N	RSFE < 1	CW	RSR < 1	sig	RSR ≥ 1	sig
CRR/AR(1)	individual commodities	32	6	1	17	1	15	3
	basket and factor	10	2	0	6	1	4	1
CRR/RW	individual commodities	32	2	0	15	3	17	3
	basket and factor	10	0	0	1	0	9	5

Note: In the top half of the table, the CCH forecasting model that predicts cp using s is being compared to either an AR(1) or a RW model, for either 32 individual commodity/country pairs or ten country baskets or factors. In the lower half, the two variables switch roles. The statistics we consider are: (i) the relative sum of squared forecasting errors (RSFE) of the CRR model against the corresponding benchmark model (AR(1) or RW): the number of ratios below 1; (ii) the p-values of the Clark and West (2007) test of equal predictive power in nested models: number of p-values below 0.1; (iii) the relative success ratio (RSR): ratio between fraction of times that the alternative model correctly predicted the direction of change over the fraction of times that the CRR model correctly predicted the direction of change; (iv) the number of RSRs significantly below 1 (columns 'sig'); and (v-vi) the couterparts for RSR$>$ 1.

The tables indicate that in most cases the exchange rate helps predict neither the spot price of the individual commodities, nor the basket, nor the first principal component. More often than not, the CCH model does worse than its benchmark forecast in terms of RSFE, and the number of significant successes (5 out of 32, using the Clark and West test) is hardly above what one expects on the basis of pure chance (3.2 out of 32). The success ratio is likewise typically well below one-half, and among the significant SRs more have the wrong sign than the right sign. All this suggests a model of no out-of-sample forecasting ability — worse than a toss of a coin, in fact. Lastly, as shown in the Appendix II, the same message is conveyed by the correlations between the forecasting errors obtained form the CRR and the benchmark models: in light of values that usually exceed 0.98, one must conclude that the two models do an equally poor job at predicting commodity prices. Furthermore, some evidence directly contradicts the CCH. In particular, the reverse model, where exchange rates are predicted using

propose a simple Newey-West t-test. Specifically, denote by $i_{m,t}$ the indicator variable taking the value 1 for each demeaned prediction of model m that has the correct sign. When we compare the CRR model to an AR(1) benchmark model ($m = AR1$ and $m = CRR$), we compute the t-statistic $(\hat{\alpha} - \alpha_0)/s.e.(\hat{\alpha})$ from the regression $i_{AR1,t} - i_{CRR,t} = \alpha + \varepsilon_t$. As $\hat{\alpha}$ estimates the difference of the two probabilities of success, we test the null hypothesis of $\alpha_0 = 0$. When the comparison is made against the RW model ($m = RW$ and $m = CRR$), the population benchmark SR is known to be 0.5 and needs no estimation; so in this case we regress $i_{CRR} = \alpha + \varepsilon_t$ and compute the t-statistic with $\alpha_0 = 0.5$. All standard errors are based on the Newey and West (1987) procedure.

commodity price data, does about as well: the RSFEs are somewhat worse, but the SRs are less dismal. Looking at the tables in the Appendix II, we observe once more that the correlations between the forecasting errors are almost unity, that is, the errors are essentially the same.

That last observation is illustrated more visually in the Appendix III, where we plot the forecasting errors of the CRR model (AR1(X) and X) and the benchmark model (AR(1) and RW) for the cases of aluminium and the commodity price basket when the AUD is used as predictor. The figures reveal that the forecasting errors not only co-move in a one-to-one fashion, but also that they overlap nearly perfectly over the entire forecasting period. That is, even in the periods in which the CRR model delivers smaller forecasting errors than the corresponding benchmark model (indicated by the grey areas) the distance between the two forecasting errors is barely distinguishable. This suggests that even if the two series of forecasting errors are significantly different from one another – as suggested by the Clark and West test – from an economic viewpoint the relevance of such difference seems minor, at best. In short, out-of-sample, there is no evidence whatsoever of predictability.

3.2 Monthly average data

In this subsection we perform the same analysis as in the preceding one, but instead we use commodity price data published by the IMF, the World Bank and Statistics Canada by way of robustness check. Notice that because the first difference of the commodity price data has now a significant degree of spurious autocorrelation, the benchmark model should be an AR(1) model rather than the RW model. So if would report that with time-averaged commodity price data, the exchange rate beats the RW forecasts more often than the AR(1) one, that would tell us nothing valid.

The results provide almost the same picture as it was the case with the end-of-period data. That is, only in a small number of cases does the exchange rate appear to improve upon the forecasts obtained with the benchmark model. Australia is again the case in which the evidence most favors the CCH. This time however, the SRs indicate that the AUD is good at predicting prices in fewer instances than the inverse, *i.e.* the AUD being predicted by the prices. This is exactly the opposite of what should happen under CRR's CCH. This last finding repeats itself in the cases of Canada, New Zealand and Norway. Lastly, also when we use time-average data, the correlation between the forecasting errors obtained with the CRR model and the AR(1) remains extremely high. This suggests again that even in the cases in which the exchange rate seems to improve the forecasts of the benchmark model, its contribution as a predictor is negligible from an economic point of view.

4 Out-of-sample Forecasting performance using forecast combinations

Many commodities are produced in multiple locations, so their price should act as a fundamental for more than one currency. Of course, that price is just one of the many fundamentals underlying a related currency, and this may create a power issue: in a finite sample, the impact from the anticipated future evolution of, say, the aluminium market on currency k may be hard to detect. Creating country price indices, as CRR do, is one sensible way out: by grouping many commodities that share relevance to country k into a country-specific index, the combined link may be easier to detect. In this section we seek extra power by going in the other direction. If aluminium is relevant for many currencies, then maybe these currencies can be grouped into a currency basket whose link with that commodity is relatively stronger than each of the links with the separate currencies. Regressing Δcp_t on a set of past $\Delta s_{k,t-1}$ for various currencies k is one way to achieve that aim: the squared correlation with the total fitted value (i.e. the total R^2) should be better than the squared pairwise correlations.

But one can do more than just one multiple regression. If the good is produced by, say, three countries, then one might consider seven conceivable models: three that use one currency as regressor, three more models that rely on two regressors, and finally one model with three currencies on the right hand side. That is, there would be seven possible models $i = 1, \cdots, 7$ instead of the the single three-regressor model considered in a straightforward regression. If there are already many possible combinations of regressors rather than just one regressor alone, one can additionally also try different lag lengths of the regressors. If the maximum number of lags being considered is equal to three, for instance, then one could still choose models with 1, 2, or 3 lagged observations per currency. We can also include lagged observations of the commodity price changes, which would then further increase the number of possible combinations of regressors.

To generalize, let there be m competing regressor combinations for the forecast horizon h. We distill a single forecast out of these, in three steps. First, for every combination i and horizon h we estimate all m models with different lag lengths. Specifically, each i^{th} model takes the form

$$\hat{y}_{i,t+h|t} = \hat{\beta}_{0,i} + \hat{\beta}_{1,i}(L)' x_t + \hat{\beta}_{2,i}\,(L)\,y_t, \tag{5}$$

where the (exogenous) predictors in x_t are a subset of all exogenous regressors collected in X_t, $\hat{\beta}_i\,(L)$ is a lag polynomial of order p_x ($\hat{\beta}_{1,0} + \hat{\beta}_{1,1}L + ... + \hat{\beta}_{1,p_x}L^{p_x}$), and $\hat{\beta}_{2i}\,(L)$ is of order p_y ($\hat{\beta}_{2,0} + \hat{\beta}_{2,1}L + ... + \hat{\beta}_{2,p_y}L^{p_y}$). At each time t, the optimum lag structure of equation (5) is selected by the Schwartz information criterion (SIC).[20] In Step Two, for each of the m selected models we then produce a separate forecast. Finally, the m individual forecasts $\hat{y}_{i,t+h|t}$ are combined in order to produce a weighted forecast, $\hat{y}^{(c)}_{t+h|t}$ according to the scheme

$$\hat{y}^{(c)}_{t+h|t} = \sum_{i=1}^{m} \hat{\omega}_{i,t+h|t} \ \hat{y}_{i,t+h|t}, \tag{6}$$

where h is the forecast horizon, m is the total number of individual forecasts, $\hat{\omega}_{i,t+h|t}$ is the time-t weight assigned to forecast i and $\hat{y}_{i,t+h|t}$ is the forecast obtained from model i. See Bates and Granger (1969) for an early contribution and Timmermann (2006) for a recent review.

Regarding the weights, we consider three popular weighting schemes; see e.g. Stock and Watson (1998) and Timmermann (2006). The first one is based on the Schwartz information criterion (SIC), which can also be viewed as Bayesian model averaging. The second scheme is based on the past mean square forecasting error (MSFE) performance, and the third one is based on past discounted MSFE performance. The three weighting schemes can be summarized as:

$$\hat{\omega}_{i,t+h|t} = \left\{ \begin{array}{l} \exp\left\{-\Delta SIC_{i,t|t-h}/2\right\} / \sum_{j=1}^{m} \exp\left\{-\Delta SIC_{j,t|t-h}/2\right\}, \\ MSFE^{-1}_{i,t|t-h} / \sum_{j=1}^{m} MSFE^{-1}_{j,t|t-h}, \\ DMSFE^{-1}_{i,t|t-h} / \sum_{j=1}^{m} DMSFE^{-1}_{j,t|t-h}, \end{array} \right\} \tag{7}$$

where $\Delta SIC_{i,t|t-h}$ refers to the difference between the SIC criterion for the i^{th} model at time t minus the time-t best model according to the SIC. The variable $MSFE_{i,t|t-h}$ is in turn calculated over a window of the preceding v periods:

$$MSFE_{i,t|t-h} = \frac{1}{v} \sum_{\tau=t-v}^{t} \left(y_{i,\tau} - \hat{y}_{i,\tau|\tau-h}\right)^2, \tag{8}$$

while $DMSFE_{i,t|t-h}$ refers to a 'discounted' MSFE that works with exponentially falling weights 0.9^{τ}. In the last two weighting schemes, if the MSFE of a given model has been high during the past v periods, the forecast of that model receives a relatively low weight and vice versa.

In our application, $\hat{y}_{i,t+h|t}$ is either equal to $\Delta cp_{i,t+h|t}$ or to $\Delta s_{i,t+h|t}$ depending on whether we use exchange rates as predictors of commodity prices or vice versa. Given that we are testing the empirical

[20] Specifically, we choose the lowest SIC value from a $(p_y + 1) \times p_x$ matrix, where the columns represent an increasing number of lags of x_t, i.e. $\{x_t\}, \{x_t, Lx_t\}, ..., \{x_t, .., L^{p_x} x_t\}$. Note that x_t always enters. In addition, we allow the lagged dependent variable, y_t, to be absent, such that the rows of the matrix are $\{\varnothing\}, \{y_t\}, \{y_t, y_{t-1}\}, ..., \{y_t, y_{t-1}, ..., L^{p_y} y_t\}$, where $\varnothing$ denotes the absense of y_t. In order to limit the computational time, we allow the dimension of x_t to be at most 4 while p_x and p_y is at most 1 and 2, respectively.

Table 9: **Forecasting performance of CCH model, end-of-month data: summary**

Out-of-sample predictions using the forecast combination approach: Significant RSFEs

		$h = 1$		$h = 3$		$h = 6$		$h = 12$		
	N	RSFE < 1	RSFE > 1	RSFE < 1	RSFE > 1	RSFE < 1	RSFE > 1	RSFE < 1	RSFE > 1	Total N
					ER $\rightarrow$ CP					
End-of-period	18	1	3	0	0	0	0	0	0	72
Monthly-averaged	27	0	2	0	0	0	0	0	0	108
					CP $\rightarrow$ ER					
End-of-period	6	0	0	0	0	0	0	0	0	24
Monthly-averaged	6	0	2	0	0	0	0	0	0	24

Out-of-sample predictions using the forecast combination approach: Significant RSRs

		$h = 1$		$h = 3$		$h = 6$		$h = 12$		
	N	RSR < 1	RSR > 1	RSR < 1	RSR > 1	RSR < 1	RSR > 1	RSR < 1	RSR > 1	Total N
					ER $\rightarrow$ CP					
End-of-period	18	0	1	1	2	3	0	3	0	72
Monthly-averaged	27	1	3	2	2	3	3	5	1	108
					CP $\rightarrow$ ER					
End-of-period	6	1	0	1	0	0	0	0	0	24
Monthly-averaged	6	0	0	0	1	0	0	0	0	24

Note: We predict the 18 end-of-period and 27 monthly-averaged commodity prices, as well as six exchange rates using a forecast combination approach. We compare these forecasts to the ones obtained by an AR(L) benchmark model, where L is determined by the SIC criterion. Only currencies of countries that produce the particular commodity are included as regressors in the forecast combination, e.g. for aluminium we include AUD, CAD, NZD, CLP, NOK and ZAR and combinations of these variables. As in CRR, each forecast from the i-th candidate model, $\hat{y}_{i,t+h|t}$, is based on a rolling estimation window. This implies that the weight $\hat{\omega}_{i,t+h|t}$ is zero if, at time t, the sample is of insufficient length. The same principle applies when we use exchange rates data to predict commodity prices. Each cell in the upper panel of the table shows the number of times in which the RSFE was statistically larger/smaller than one, according to the Diebold-Mariano test statistic. The lower panel displays the number of times in which the RSR was statistically smaller/larger than 1 according to the Pesaran and Timmerman (1992) test statistic.

validity of the CCH we ensure that at least one of the exchange rates related to that good enters the i^{th} commodity price forecasting model.

Any prediction of the forecast combination is then compared to those from a benchmark model, which is an AR(L) reset at every t on the basis of the SIC. As before, we compare the competing models in terms of the mean square forecast error and the success ratio.

In Tables (24) to (27) in Appendix V we provide more details on the performance of the forecast combinations using end-of-period and monthly averaged data, respectively. In the main text we discuss the summary provided in Table (9), where for each of forecast horizon h and data type we show the number of series in which the predictions from the forecast combinations typically beat, or are beaten by, the benchmark model.

To summarize the discussion that follows, we are in general not able to uncover any noteworthy commodity price predictability nor any exchange rate predictability using forecast combinations. Let us focus first on the commodity price predictability taking the end-of-period and monthly averaged data together. Based on the RSFE, in only one case out of 180 do we find that the exchange rate is a significantly useful predictor; actually this predictor does significantly worse in five cases. Based on the relative success ratios (RSR), we find 18 cases out of 180 where the exchange rate predicts the correct sign of the commodity price change relatively better than the benchmark model, but also 12 cases where it does significantly worse than the benchmark model. Furthermore, this very modest performance relative to the benchmark model is mainly driven by longer horizon predictions, i.e. for $h = 12$. Overall, this suggests again that the contribution of the exchange rate as a predictor is only marginal, at best.

For the reverse tests, where commodity data are used to produce predictions on currency movements, we do not expect the choice of month-end versus monthly-average prices to be very decisive.[21] In fact, there is little difference across data types in the forecasting performances of the two models. To sum up, we cannot uncover any consistent pattern of commodity price or exchange rate predictability evaluated by means of the RSFE and RSR.

5 Conclusion

We question the validity of the Commodity Currency Hypothesis (CCH), at least in the version that says that exchange rates help predicting commodity markets. On the theoretical flank we have argued that both exchange rates and commodity prices can be viewed as asset prices, implying they both should be priced in a forward-looking way. This is not a critique to the Engel-West model as a whole, or the more general class of models that applies the present-value approach to exchange rates. Those theories retain their strong economic appeal. What we question is whether spot exchange-rate changes should always be able to consistently and robustly predict future movements in the fundamental. Specifically, when the fundamental in question is a price set in forward-looking markets, most of the shifts in expectations about its future level are immediately reflected in the current price. This should then lead to mostly contemporaneous relations between exchange rate and fundamentals, leaving as little room for cross-predictability between the two-series as for autocorrelation within each series.

Our results confirm indeed the familiar lack of exchange rate predictability, which is consistent with the asset price view of exchange rates. But in our view the asset price paradigm should apply to commodity prices as well. There is a long literature in commodity price forecasting sustaining this view, which we labeled the Financial Asset Hypothesis (FAH) of commodity prices. The FAH predicts that past exchange rates should not be very informative predictors of commodity prices; instead, the

[21] This is because the exchange-rate data on the left-hand side contain little autocorrelation, so that inducing spurious autocorrelation on the right-hand side will not help. Rather, if there is any forecasting ability at all, then inducing errors in the regressors should harm the model.

FAH largely confines the links to contemporaneous co-movements between commodity prices and the exchange rates of commodity producing countries.

The empirical evidence seems to be in line with our hunch. First, we perform two different versions of the Granger Causality (GC) test, one based on full-sample constant-parameter estimates and the second one based on the Rossi (2005) test, which continuously updates the model to attenuate any structural breaks. Overall, our results provide only scant evidence that exchange rates Granger cause commodity prices. These results hold when we perform the GC tests using the same dataset as CRR and also when we use an alternative dataset, which consists of end-of-period monthly observations; in fact, the rare cases of *prima-facie* forecasting ability are non-robust to changes in the data or methodology. Second, we have evaluated the ability of exchange rates to predict future commodity prices out-of-sample, again using two different data sets (end-of-period observations and monthly time-averaged observations) and now also using model averaging with many variables and lags next to the simple one-lag, one-regressor models. Our forecasting exercises are fully in line with our GC-test findings: exchange rates are as poor predictors of future commodity prices as commodity prices are for exchange rates.

Appendix I Factor analysis

Table 10: Correlation between the estimated factor and the commodity basket

	Australia	Canada	New Zealand	South Africa	Norway
corr.	0.814	0.740	0.911	0.996	0.817
p-val	0.000	0.000	0.000	0.000	0.000

Note: Chile is not included on the table, as its basket is composed of copper only.

Table 11: Variance decomposition

Australia	Factor	Basket	WCRR	Canada	Factor	Basket	WCRR
Aluminium	45.0	49.6	8.1	Aluminium	33.9	41.3	5.0
Copper	63.0	41.4	2.8	Copper	57.2	37.7	2.0
Cotton	12.7	2.6	2.8	Corn	12.5	2.8	0.5
Gold	19.1	11.1	9.4	Crude Oil	15.3	3.7	21.4
Lead	42.5	16.9	0.7	Gold	41.0	7.7	2.3
Nickel	49.4	89.9	2.6	Hogs	3.5	0.5	1.8
Sugar	4.7	0.5	2.5	Lumber	5.6	8.1	13.6
Wheat	7.6	2.2	8.3	Nat. Gas	2.1	1.3	10.7
Wool	28.6	14.8	4.1	Nickel	43.3	91.0	2.4
Zinc	54.4	24.3	1.5	Silver	51.4	12.2	0.3
				Wheat	14.6	3.0	3.4
				Zinc	42.6	25.5	2.3

New Zealand	Factor	Basket	WCRR	South Africa	Factor	Basket	WCRR
Aluminium	63.0	94.0	8.3	Gold	77.7	71.4	48.0
Wool	63.0	22.8	7.7	Platinum	77.7	82.9	30.0

Norway	Factor	Basket	W
Aluminium	55.0	41.0	2.6
Crude Oil	57.1	16.9	39.5
Fish	25.6	5.0	2.8
Nat. Gas	16.2	3.5	29.7
Nickel	51.3	96.2	1.0

Note: The columns Factor and Basket display the % of the variance explained by the factor and the commodity basket respectively. The column WCRR display the weights applied to construct the commodity baskets. These are the same weights reported used by CRR.

Appendix II Out-of-sample forecasting performance using end-of-period data

The tables in this section report the relative sum of squared forecasting errors (RSFE) of the CRR model (AR1X or X) against the corresponding benchmark (AR1 or RW). The column p-CW displays the p-value of the Clark and West (2007) test of equal predictive power in nested models. The column RSR reports the relative success ratios, i.e. the ratio between the proportion of times that the alternative model and the proportion of time that the CRR model correctly predicted the sign of the dependent variable. The column p-RSR reports the p-values of the intercept in the regression model . Finally, the column corr. displays the correlation coefficient between the forecasting errors obtained with the CRR model and those obtained with the corresponding benchmark model.

Table 12: Australia

		$\Delta cp_t = \beta_0 + \beta_1 \Delta cp_{t-1} + \beta_2 \Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1 \Delta s_{t-1} + \beta_2 \Delta cp_{t-1}$				
	Benchmark	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Aluminium	AR1X/AR1	0.970	**0.029**	1.122	0.270	0.981	1.011	0.981	1.035	0.417	1.000
	X/RW	0.987	**0.074**	1.060	0.497	0.983	1.021	0.967	1.187	**0.018**	0.998
Copper	AR1X/AR1	1.008	0.589	1.072	0.321	0.997	1.011	0.835	1.072	0.115	0.999
	X/RW	1.002	0.149	1.085	0.305	0.990	1.014	0.651	1.060	0.455	0.996
Cotton	AR1X/AR1	0.995	0.115	0.920	0.355	0.989	1.008	0.792	1.025	0.610	0.999
	X/RW	1.000	0.197	0.949	0.444	0.992	1.019	0.943	1.006	0.943	0.998
Gold	AR1X/AR1	1.010	0.606	0.968	0.436	0.997	1.010	0.759	1.047	0.321	0.999
	X/RW	1.010	0.378	0.927	0.300	0.992	1.022	0.931	1.023	0.742	0.998
Lead	AR1X/AR1	0.958	**0.005**	0.853	**0.023**	0.988	1.008	0.822	1.047	0.336	0.999
	X/RW	0.972	**0.015**	0.918	0.249	0.986	1.022	0.994	1.085	0.304	0.999
Nickel	AR1X/AR1	1.008	0.310	0.945	0.537	0.990	1.011	0.985	1.083	**0.025**	1.000
	X/RW	1.018	0.264	1.089	0.376	0.984	1.030	0.914	1.070	0.478	0.997
Sugar	AR1X/AR1	1.014	0.906	1.051	0.256	0.998	1.004	0.637	1.011	0.705	0.999
	X/RW	1.021	0.983	1.060	0.462	0.998	1.013	0.895	1.085	0.281	0.998
Wheat	AR1X/AR1	1.013	0.757	0.989	0.876	0.998	1.012	0.669	1.127	**0.062**	0.997
	X/RW	1.024	0.943	1.060	0.442	0.998	1.026	0.822	1.141	**0.056**	0.995
Wool	AR1X/AR1	1.021	0.791	0.990	0.851	0.996	1.006	0.490	0.914	0.160	0.997
	X/RW	1.017	0.405	0.934	0.345	0.989	1.018	0.740	0.934	0.389	0.996
Zinc	AR1X/AR1	1.006	0.565	0.975	0.670	0.998	1.002	0.401	0.967	0.442	0.998
	X/RW	1.018	0.746	1.156	**0.060**	0.996	1.019	0.944	0.978	0.794	0.998
Basket	AR1X/AR1	0.983	**0.040**	0.907	0.273	0.993	1.007	0.978	1.060	**0.076**	1.000
	X/RW	0.986	**0.047**	1.127	0.175	0.988	1.018	0.915	1.127	**0.097**	0.998
Factor	AR1X/AR1	0.986	**0.039**	0.935	0.481	0.995	1.011	0.977	0.975	0.727	1.000
	X/RW	0.991	**0.071**	1.000	1.000	0.990	1.023	0.988	1.589	**0.000**	0.998

Note: The beginning of the sample period is 1984M3 (aluminium, copper, gold, lead, sugar, wheat, zinc, basket and factor), 1985M8 (wool), 1986M2 (cotton) and 19993M8 (nickel). All samples end in 2013M9.

Table 13: Canada

		$\Delta cp_t = \beta_0 + \beta_1 \Delta cp_{t-1} + \beta_2 \Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1 \Delta s_{t-1} + \beta_2 \Delta cp_{t-1}$				
	Benchmark	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Aluminium	AR1X/AR1	1.022	0.352	0.989	0.864	0.985	1.003	0.473	1.081	0.249	0.998
	X/RW	1.036	0.583	1.063	0.292	0.985	1.011	0.677	1.052	0.398	0.997
Copper	AR1X/AR1	1.009	0.992	1.030	0.377	1.000	0.993	0.181	1.009	0.851	0.996
	X/RW	1.007	0.525	1.020	0.798	0.998	1.009	0.462	0.990	0.900	0.995
Corn	AR1X/AR1	1.010	0.774	1.000	1.000	0.998	1.011	0.880	1.081	**0.036**	0.999
	X/RW	1.016	0.877	0.981	0.778	0.998	1.014	0.845	0.962	0.586	0.999
Crude Oil	AR1X/AR1	1.044	0.943	1.080	0.221	0.995	0.995	0.226	0.895	0.128	0.997
	X/RW	1.054	0.928	1.088	0.331	0.993	1.012	0.559	0.925	0.271	0.996
Gold	AR1X/AR1	1.012	0.724	1.068	0.191	0.997	1.010	0.869	0.955	0.381	0.999
	X/RW	1.005	0.330	0.990	0.884	0.994	1.008	0.600	0.878	**0.067**	0.997
Hogs	AR1X/AR1	1.017	0.899	1.089	0.247	0.998	0.993	0.116	0.955	0.360	0.998
	X/RW	1.024	0.966	1.161	**0.044**	0.998	0.998	0.220	0.918	0.206	0.998
Lumber	AR1X/AR1	1.010	0.732	1.038	0.397	0.998	1.005	0.721	0.982	0.646	0.999
	X/RW	1.016	0.943	1.074	0.239	0.998	1.009	0.796	0.871	**0.022**	0.999
Nat.Gas	AR1X/AR1	1.007	0.499	0.978	0.644	0.996	1.002	0.436	0.982	0.783	0.998
	X/RW	1.017	0.530	1.100	0.423	0.993	1.009	0.388	0.952	0.568	0.997
Nickel	AR1X/AR1	1.028	0.583	0.867	0.109	0.990	0.995	0.220	1.038	0.616	0.996
	X/RW	1.050	0.799	0.953	0.590	0.993	1.025	0.634	1.245	**0.024**	0.995
Silver	AR1X/AR1	1.009	0.949	1.000	1.000	0.999	1.004	0.551	1.019	0.729	0.998
	X/RW	1.013	0.709	0.962	0.583	0.997	1.003	0.397	0.910	0.127	0.997
Wheat	AR1X/AR1	1.016	0.968	1.090	**0.059**	0.999	1.014	0.666	0.947	0.343	0.997
	X/RW	1.019	0.949	1.074	0.302	0.999	1.019	0.699	0.863	**0.044**	0.996
Zinc	AR1X/AR1	1.020	0.898	0.879	0.154	0.997	1.004	0.655	1.039	0.404	0.999
	X/RW	1.025	0.924	1.000	1.000	0.996	1.010	0.820	0.962	0.585	0.999
Basket	AR1X/AR1	1.012	0.536	0.856	**0.039**	0.995	1.012	0.742	1.081	0.194	0.998
	X/RW	1.021	0.632	0.944	0.371	0.996	1.023	0.928	1.000	1.000	0.997
Factor	AR1X/AR1	1.014	0.598	0.939	0.414	0.994	1.008	0.684	1.032	0.683	0.998
	X/RW	1.026	0.969	1.161	**0.050**	0.996	1.022	0.973	1.384	**0.000**	0.998

Note: The beginning of the sample period is 1980M3 (aluminium, copper, corn, gold, hogs, lumber, silver, wheat, zinc, basket and factor), 1983M2, (crude oil), 1993M8 (nickel) and 1997M2 (natural gas). All samples end in 2013M9.

Table 14: Chile

		$\Delta cp_t = \beta_0 + \beta_1 \Delta cp_{t-1} + \beta_2 \Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1 \Delta s_{t-1} + \beta_2 \Delta cp_{t-1}$				
	Benchmark	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Copper	AR1X/AR1	0.987	**0.096**	1.046	0.527	0.989	1.025	0.606	0.910	**0.042**	0.992
	X/RW	0.972	**0.020**	1.030	0.716	0.974	1.037	0.439	0.958	0.577	0.979

Note: The sample period is 1991M3 - 2013M9.

Table 15: New Zealand

		$\Delta cp_t = \beta_0 + \beta_1 \Delta cp_{t-1} + \beta_2 \Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1 \Delta s_{t-1} + \beta_2 \Delta cp_{t-1}$				
	Benchmark	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Aluminium	AR1X/AR1	0.999	0.129	0.963	0.654	0.978	1.008	0.638	0.988	0.817	0.998
	X/RW	1.007	0.144	0.947	0.485	0.977	1.012	0.630	1.073	0.346	0.996
Wool	AR1X/AR1	1.015	0.513	1.000	1.000	0.993	0.981	**0.063**	0.919	0.105	0.996
	X/RW	1.019	0.378	0.925	0.334	0.988	0.996	0.205	0.982	0.801	0.993
Basket	AR1X/AR1	1.007	0.160	1.012	0.893	0.977	0.998	0.263	1.000	1.000	0.997
	X/RW	1.007	0.132	1.019	0.824	0.974	1.005	0.368	1.059	0.410	0.994
Factor	AR1X/AR1	1.004	0.156	0.930	0.337	0.982	0.995	0.175	0.950	0.347	0.997
	X/RW	1.004	0.139	0.947	0.375	0.979	1.006	0.432	1.220	**0.030**	0.996

Note: The sample period is 1987M2 - 2013M9.

Table 16: Norway

		$\Delta cp_t = \beta_0 + \beta_1 \Delta cp_{t-1} + \beta_2 \Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1 \Delta s_{t-1} + \beta_2 \Delta cp_{t-1}$				
	Benchmark	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Aluminium	AR1X/AR1	1.006	0.428	0.974	0.404	0.995	0.995	0.132	0.850	0.214	0.986
	X/RW	1.042	0.406	0.987	0.890	0.974	1.053	0.415	0.987	0.904	0.971
Crude Oil	AR1X/AR1	1.010	0.329	0.950	0.643	0.982	1.007	0.596	0.971	0.791	0.998
	X/RW	1.042	0.186	0.938	0.596	0.946	1.056	0.873	1.103	0.401	0.991
Fish	AR1X/AR1	1.053	0.944	1.259	**0.011**	0.992	1.019	0.914	1.000	1.000	0.998
	X/RW	1.048	0.974	1.250	**0.054**	0.997	1.046	0.858	1.210	0.143	0.992
Nat. Gas	AR1X/AR1	0.996	0.183	0.923	0.315	0.990	1.004	0.562	0.944	0.573	0.999
	X/RW	1.010	0.420	0.938	0.594	0.993	1.038	0.888	1.071	0.549	0.996
Nickel	AR1X/AR1	0.988	0.188	1.077	0.495	0.979	1.041	0.790	0.944	0.524	0.993
	X/RW	1.065	0.392	1.250	**0.079**	0.959	1.087	0.852	1.071	0.561	0.988
Basket	AR1X/AR1	0.981	0.176	0.931	0.472	0.981	1.041	0.790	0.919	0.390	0.992
	X/RW	1.060	0.320	1.172	0.205	0.952	1.097	0.874	1.136	0.290	0.987
Factor	AR1X/AR1	0.975	0.171	0.906	0.443	0.986	1.038	0.721	0.811	0.171	0.991
	X/RW	1.030	0.277	1.136	0.305	0.961	1.124	0.969	1.172	0.113	0.985

Note: The sample period is 2001M5 - 2013M9.

Table 17: South Africa

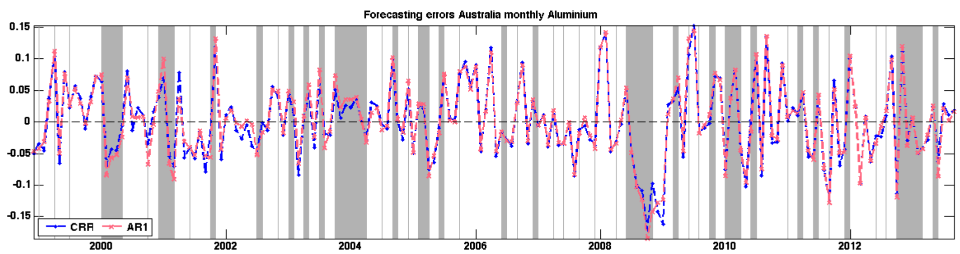
		$\Delta cp_t = \beta_0 + \beta_1 \Delta cp_{t-1} + \beta_2 \Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1 \Delta s_{t-1} + \beta_2 \Delta cp_{t-1}$				
	Benchmark	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Gold	AR1X/AR1	1.015	0.498	1.073	0.383	0.993	1.024	0.512	0.944	0.617	0.989
	X/RW	1.019	0.275	1.113	0.302	0.991	1.038	0.672	1.135	0.247	0.989
Platinum	AR1X/AR1	1.011	0.776	0.967	0.575	0.999	1.026	0.634	0.962	0.713	0.991
	X/RW	1.009	0.363	1.054	0.567	0.997	1.039	0.746	1.113	0.229	0.990
Basket	AR1X/AR1	1.016	0.785	1.036	0.562	0.998	1.044	0.977	0.895	0.152	0.997
	X/RW	1.011	0.275	1.135	0.115	0.996	1.058	0.991	1.054	0.562	0.995
Factor	AR1X/AR1	1.018	0.720	1.160	0.117	0.997	1.049	0.982	1.043	0.704	0.997
	X/RW	1.032	0.898	1.204	**0.032**	0.996	1.070	0.997	1.341	**0.007**	0.997

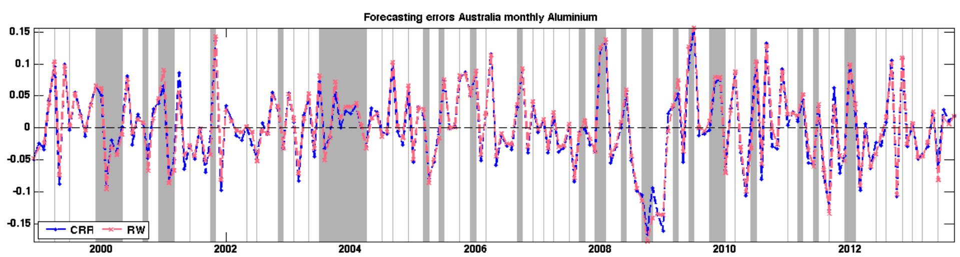
Note: The sample period is 1994M3 - 2013M9.

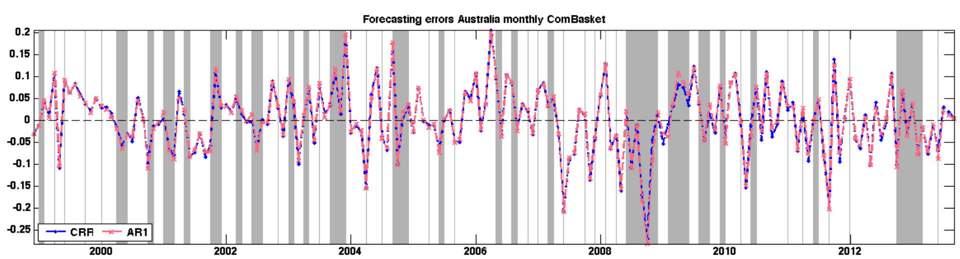
Appendix III

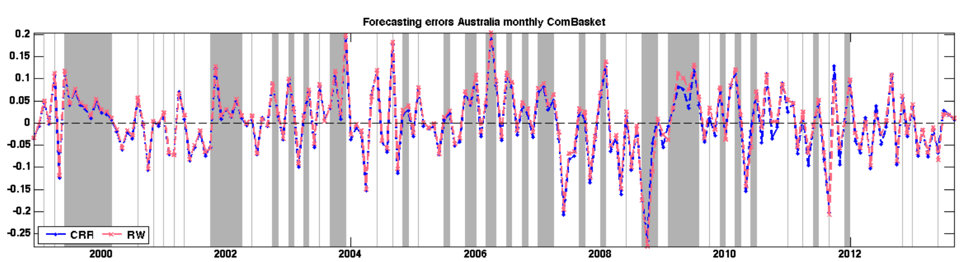
Out-of-sample forecasting performance. CRR forecasts vs benchmark.

The figures display the forecasting errors of the CRR model and the corresponding benchmark models for the cases of lead and the commodity price basket. The areas in gray correspond to the periods in which the forecast error of the CRR model is smaller than that of the benchmark model.









Appendix IV Out-of-sample forecasting performance using monthly averaged data

The tables in this section report the relative sum of squared forecasting errors (RSFE) of the CRR model (AR1X or X) against the corresponding benchmark (AR1 or RW). The column p-CW displays the p-value of the Clark and West (2007) test of equal predictive power in nested models. The column SR reports the success ratios, i.e. the proportion of times that the CRR model correctly predicted the sign of the dependent variable. The column p-SR reports the p-values of the Pesaran and Timmerman (1992) test of direction accuracy. Finally, the column corr. displays the correlation coefficient between the forecasting errors obtained with the CRR model and those obtained with the corresponding benchmark model.

Table 18: Australia

	$\Delta cp_t = \beta_0 + \beta_1 \Delta cp_{t-1} + \beta_2 \Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1 \Delta s_{t-1} + \beta_2 \Delta cp_{t-1}$				
	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Aluminum	0.958	**0.001**	1.011	0.818	0.993	1.005	0.511	1.020	0.410	0.998
Barley	1.048	0.922	1.167	**0.003**	0.992	1.008	0.523	1.010	0.705	0.996
Beef	0.964	**0.076**	1.000	1.000	0.991	1.009	0.985	1.010	0.562	1.000
Canola	1.023	0.803	0.971	0.445	0.995	1.002	0.467	1.030	0.125	0.998
Coal Thermal	0.999	0.237	0.907	0.104	0.998	1.011	0.590	1.040	0.235	0.996
Copper	0.996	0.235	0.964	0.276	0.997	1.012	0.943	1.051	**0.077**	0.999
Cotton	0.971	**0.039**	1.000	1.000	0.988	1.006	0.751	1.030	0.209	0.999
Gold	0.993	**0.076**	0.989	0.805	0.998	1.010	0.969	1.030	0.169	0.999
Lead	0.981	**0.045**	1.000	1.000	0.994	1.006	0.547	1.030	0.169	0.997
LNG	0.937	**0.029**	0.797	**0.003**	0.971	1.014	0.947	1.013	0.678	0.999
Nickel	1.007	0.622	1.039	**0.034**	0.999	1.002	0.290	0.990	0.792	0.994
Rice	1.009	0.266	1.099	**0.015**	0.990	1.003	0.991	1.010	0.562	1.000
Sugar	1.035	0.945	1.059	**0.020**	0.996	1.016	0.658	1.010	0.786	0.996
Wheat	1.007	0.765	0.990	0.654	0.999	1.005	0.548	1.030	0.184	0.998
Wool	0.987	**0.082**	1.051	0.263	0.992	0.994	**0.087**	0.981	0.477	0.998
Zinc	1.006	0.656	1.010	0.619	0.999	1.008	0.747	1.010	0.735	0.998
Basket	1.001	0.442	1.010	0.562	0.998	1.005	0.395	1.010	0.815	0.996
Factor	0.991	**0.073**	1.010	0.734	0.998	1.011	0.753	1.010	0.634	0.998

Note: The beginning of the sample period is 1984M3 (aluminium, copper, gold, lead, sugar, wheat, zinc, basket and factor), 1985M8 (wool), 1986M2 (cotton) and 19993M8 (nickel). All samples end in 2013M9.

Table 19: Canada

	$\Delta cp_t = \beta_0 + \beta_1\,\Delta cp_{t-1} + \beta_2\,\Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1\,\Delta s_{t-1} + \beta_2\,\Delta cp_{t-1}$				
	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Aluminum	0.999	0.324	0.982	0.660	0.999	1.008	0.768	1.009	0.563	1.000
Beef	1.001	0.186	1.009	0.874	0.991	1.017	0.787	0.950	0.120	0.996
Canola	1.011	0.292	1.066	0.235	0.989	1.016	0.843	1.028	0.339	0.999
Coal Thermal	1.006	0.941	1.043	0.403	1.000	1.007	0.948	0.991	0.654	1.000
Copper	1.013	0.976	0.984	0.312	1.000	0.990	**0.098**	0.950	**0.081**	0.996
Corn	1.004	0.819	1.000	1.000	1.000	1.005	0.686	1.027	0.170	0.999
Crude Oil	1.005	0.407	0.942	0.117	0.996	1.003	0.428	0.955	0.114	0.998
Fish	1.026	0.956	1.000	1.000	0.998	1.003	0.256	0.966	0.317	0.993
Gold	1.002	0.398	1.067	**0.100**	0.998	1.008	0.691	0.983	0.494	0.998
Hogs	1.004	0.294	1.056	0.364	0.995	1.003	0.726	1.018	0.147	1.000
Lumber	1.010	0.411	0.938	0.304	0.993	1.004	0.942	1.009	0.763	1.000
Nat. Gas	1.015	0.221	1.145	0.158	0.986	1.008	0.764	1.026	0.438	0.999
Nickel	1.004	0.378	1.017	0.495	0.996	0.997	0.187	0.942	0.107	0.996
Pulp	0.998	0.215	1.021	**0.089**	0.997	1.002	0.576	1.010	0.654	1.000
Silver	1.006	0.616	0.991	0.864	0.998	1.016	0.912	1.027	0.170	0.999
Wheat	1.007	0.684	0.991	0.794	0.998	1.001	0.388	0.991	0.752	0.998
Zinc	1.011	0.658	0.958	0.213	0.997	1.005	0.660	0.991	0.798	0.999
Basket	1.005	0.389	0.958	0.149	0.996	0.998	0.180	0.926	**0.041**	0.994
Factor	1.007	0.732	0.975	0.375	0.998	0.998	0.191	0.975	0.431	0.996

Note: The beginning of the sample period is 1980M3 (aluminium, copper, corn, gold, hogs, lumber, silver, wheat, zinc, basket and factor), 1983M2, (crude oil), 1993M8 (nickel) and 1997M2 (natural gas). All samples end in 2013M9.

Table 20: Chile

	$\Delta cp_t = \beta_0 + \beta_1\,\Delta cp_{t-1} + \beta_2\,\Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1\,\Delta s_{t-1} + \beta_2\,\Delta cp_{t-1}$				
	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Copper	0.962	**0.019**	1.000	1.000	0.988	1.023	0.920	0.987	0.666	0.997

Note: The sample period is 1991M3 - 2013M9.

Table 21: New Zealand

	$\Delta cp_t = \beta_0 + \beta_1\,\Delta cp_{t-1} + \beta_2\,\Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1\,\Delta s_{t-1} + \beta_2\,\Delta cp_{t-1}$				
	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Aluminum	0.994	**0.088**	1.000	1.000	0.991	1.013	0.690	1.031	0.400	0.997
Beef	1.014	0.832	1.022	0.411	0.998	1.010	0.821	0.981	0.456	0.998
Lamb	1.002	0.299	0.990	0.777	0.995	1.008	0.761	1.010	0.561	0.999
Logs	1.034	0.899	1.014	0.835	0.995	1.014	0.967	1.000	1.000	0.999
Pulp	1.008	0.281	1.017	0.518	0.988	1.008	0.993	1.000	1.000	1.000
Wool	0.996	0.146	1.032	0.528	0.990	0.962	**0.003**	0.990	0.753	0.992
Basket	1.000	0.145	1.011	0.778	0.993	1.003	0.533	1.031	0.229	0.999
Factor	0.999	0.212	0.990	0.796	0.997	1.002	0.507	0.990	0.654	0.999

Note: The sample period is 1987M2 - 2013M9.

Table 22: Norway

	$\Delta cp_t = \beta_0 + \beta_1\,\Delta cp_{t-1} + \beta_2\,\Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1\,\Delta s_{t-1} + \beta_2\,\Delta cp_{t-1}$				
	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Aluminum	0.989	0.157	1.021	0.703	0.994	1.022	0.647	1.065	0.161	0.993
Crude Oil	0.910	**0.010**	1.200	0.104	0.967	1.037	0.953	1.021	0.468	0.998
Fish	1.048	0.895	0.973	0.739	0.993	1.018	0.705	0.980	0.683	0.996
Nat. Gas	0.998	0.159	1.054	0.602	0.990	1.001	0.343	0.942	0.243	0.996
Nickel	1.019	0.886	1.000	1.000	0.998	1.020	0.759	1.021	0.306	0.997
Basket	1.005	0.458	1.000	1.000	0.997	1.025	0.768	0.980	0.306	0.996
Factor	0.985	0.106	1.073	0.228	0.995	1.032	0.793	0.915	0.117	0.995

Note: The sample period is 2001M5 - 2013M9.

Table 23: South Africa

	$\Delta cp_t = \beta_0 + \beta_1\,\Delta cp_{t-1} + \beta_2\,\Delta s_{t-1}$					$\Delta s_t = \beta_0 + \beta_1\,\Delta s_{t-1} + \beta_2\,\Delta cp_{t-1}$				
	RSFE	p-CW	RSR	p-RSR	corr.	RSFE	p-CW	RSR	p-RSR	corr.
Coal Thermal	1.012	0.987	0.952	0.311	0.999	1.002	0.157	1.000	1.000	0.985
Gold	0.993	0.192	0.982	0.861	0.993	1.022	0.762	1.065	0.339	0.995
Platinum	0.992	0.119	0.943	0.350	0.996	1.084	0.948	1.065	0.290	0.989
Basket	0.988	0.109	0.957	0.511	0.995	1.071	0.985	1.031	0.477	0.995
Factor	0.991	0.153	1.000	1.000	0.994	1.075	0.979	1.034	0.533	0.995

Note: The sample period is 1994M3 - 2013M9.

Appendix V Out-of-sample forecasting performance using forecast combinations

Table 24: Individual commodities prices - end-of-period data

	Fcst. combi/	$h=1$		$h=3$		$h=6$		$h=12$	
	benchmark	RSFE	RSR	RSFE	RSR	RSFE	RSR	RSFE	RSR
Aluminium	FC/AR(SIC)	1.010	0.927	1.046	0.897	1.064	**0.796**	1.026	**0.570**
Copper	FC/AR(SIC)	1.006	1.057	0.994	0.902	1.002	0.927	1.038	0.910
Corn	FC/AR(SIC)	0.998	0.929	1.007	1.043	1.003	1.037	1.003	1.000
Cotton	FC/AR(SIC)	0.983	0.883	0.988	0.827	0.980	0.791	1.000	0.892
Crude Oil	FC/AR(SIC)	**1.179**	1.136	1.143	0.960	1.222	1.071	0.999	0.960
Fish	FC/AR(SIC)	1.003	1.222	1.011	**1.350**	1.014	1.107	1.007	1.167
Gold	FC/AR(SIC)	1.022	0.959	1.014	**1.066**	0.992	1.031	0.935	0.991
Hogs	FC/AR(SIC)	1.012	1.049	1.011	1.085	1.012	1.009	0.988	**0.644**
Lead	FC/AR(SIC)	**0.949**	0.894	0.977	**0.800**	0.973	**0.851**	1.007	1.027
Lumber	FC/AR(SIC)	1.014	1.123	1.027	1.107	1.017	1.032	1.016	1.044
Nat. Gas	FC/AR(SIC)	0.973	1.087	0.978	0.750	0.973	0.704	0.950	1.038
Nickel	FC/AR(SIC)	0.998	0.875	1.058	1.089	1.063	1.054	1.070	0.970
Platinum	FC/AR(SIC)	1.047	1.000	1.006	1.075	1.013	0.975	0.986	0.814
Silver	FC/AR(SIC)	1.011	1.065	1.004	1.050	0.998	0.954	1.017	1.019
Sugar	FC/AR(SIC)	**1.041**	1.084	1.019	0.843	0.986	**0.706**	1.029	0.836
Wheat	FC/AR(SIC)	1.011	1.012	1.020	0.865	1.003	0.825	1.003	1.072
Wool	FC/AR(SIC)	**1.040**	**1.188**	1.017	1.121	1.004	1.053	1.004	1.048
Zinc	FC/AR(SIC)	1.010	0.964	1.018	1.135	1.026	0.987	1.012	**0.714**
Mean(all)	FC/AR(SIC)	0.976	1.100	0.999	1.043	0.983	0.976	0.994	0.750

Notes: This table reports the ratio of mean squared forecast errors (RSFE) and relative success ratios (RSR) for forecast horizons $h = 1, 3, 6, 12$. In the second column "FC/AR(SIC)" denotes a comparison of forecast combination with SIC weights against an autoregressive model with the number of lags determined by the SIC information criteria. We predict the individual commodities listed in the first column as well as average measures (mean of all, IMF). Only currencies of countries that produce the particular currency are included as regressors in the forecast combination, so for e.g. aluminium we include AUD, CAD, NZD and NOK and combinations of these. As in CRR, each forecast from the i^{th} candidate model, $\hat{y}_{i,t+h|t}$, is based on a similar rolling estimation window. This implies that the weight $\hat{\omega}_{i,t+h|t}$ is zero if, at time t, the sample is of insufficient length to satisfy this rolling window approach. Accordingly, with aluminium and with CAD having the longest sample, CAD enters with a weight of one for the first $h = 1$ forecast of aluminium in 1996:12 until 1998:12 where AUD enters. In 2000:05 NZD and any combination with NZD attains a positive weight and so do NOK in 2007:07. Bold numbers represent significance at the 10% level. The p-value corresponding to the non-nested Diebold-Mariano test statistic is used to assess the significance of RSFE.

Table 25: Individual commodity prices - monthly averaged data

	Fcst. combi/	$h = 1$		$h = 3$		$h = 6$		$h = 12$	
	benchmark	RSFE	RSR	RSFE	RSR	RSFE	RSR	RSFE	RSR
Aluminium	FC/AR(SIC)	1.027	1.010	1.079	1.022	1.081	0.920	1.021	**0.651**
Barley	FC/AR(SIC)	1.037	1.037	0.981	1.046	0.999	1.101	1.020	1.164
Beef	FC/AR(SIC)	1.000	**1.117**	0.995	1.083	0.969	0.872	0.960	1.059
Canola	FC/AR(SIC)	0.995	1.010	1.000	0.978	1.034	**1.343**	1.029	**1.456**
Coal Thermal	FC/AR(SIC)	1.008	1.037	1.015	1.000	1.031	0.963	1.052	1.059
Copper	FC/AR(SIC)	0.989	1.028	0.998	1.031	0.998	1.000	1.034	1.062
Corn	FC/AR(SIC)	1.005	1.050	1.014	**1.140**	0.987	0.916	0.961	1.051
Cotton	FC/AR(SIC)	0.986	1.000	1.005	0.945	0.993	0.988	1.002	0.938
Crude Oil	FC/AR(SIC)	1.025	**1.381**	1.173	0.750	1.291	1.000	0.924	0.880
Fish	FC/AR(SIC)	1.041	1.000	0.960	1.294	0.979	1.032	0.984	0.920
Gold	FC/AR(SIC)	1.015	1.076	0.991	1.022	0.976	0.990	0.935	0.971
Hogs	FC/AR(SIC)	0.999	1.022	0.994	0.904	1.032	1.047	0.975	0.860
Lamb	FC/AR(SIC)	1.038	1.012	1.053	1.107	0.993	1.068	0.989	0.913
Lead	FC/AR(SIC)	0.991	0.990	0.986	1.113	1.014	1.071	1.019	1.075
LNG	FC/AR(SIC)	0.943	0.934	0.945	**0.778**	0.910	**0.702**	0.922	**0.727**
Logs	FC/AR(SIC)	1.027	1.061	1.059	1.141	1.055	1.067	0.987	0.905
Lumber	FC/AR(SIC)	1.008	0.912	1.003	0.987	1.003	**1.105**	1.013	1.021
Nat. Gas	FC/AR(SIC)	1.011	0.929	0.903	**0.667**	0.883	**0.500**	0.934	0.828
Nickel	FC/AR(SIC)	1.024	1.039	1.090	**1.170**	1.134	**1.234**	1.141	1.107
Platinum	FC/AR(SIC)	1.030	1.038	1.044	1.040	0.987	**0.804**	0.970	**0.711**
Pulp	FC/AR(SIC)	0.981	0.972	0.898	1.023	0.864	1.070	0.926	0.905
Rice	FC/AR(SIC)	1.025	1.033	0.985	1.055	0.998	0.900	0.980	**0.792**
Silver	FC/AR(SIC)	**1.040**	1.063	0.997	1.042	0.993	1.019	1.014	0.945
Sugar	FC/AR(SIC)	1.012	**1.057**	1.033	1.086	0.984	1.091	1.030	0.833
Wheat	FC/AR(SIC)	**1.016**	1.000	1.039	1.077	0.999	1.035	0.988	1.181
Wool	FC/AR(SIC)	0.997	1.051	1.051	1.101	0.976	0.951	1.040	1.175
Zinc	FC/AR(SIC)	1.008	**0.944**	1.049	1.011	1.053	0.976	1.054	**0.785**
IMF	FC/AR(SIC)	1.002	1.071	0.946	0.964	0.933	**0.793**	0.960	**0.688**

Notes: This table reports the ratio of mean squared forecast errors (RSFE) and relative success ratios (RSR) for forecast horizons $h = 1, 3, 6, 12$. In the second column "FC/AR(SIC)" denotes a comparison of forecast combination with SIC weights against an autoregressive model with the number of lags determined by the SIC information criteria. We predict the individual commodities listed in the first column as well as average measures (mean of all, IMF). Only currencies of countries that produce the particular currency are included as regressors in the forecast combination, so for e.g. aluminium we include AUD, CAD, NZD and NOK and combinations of these. As in CRR, each forecast from the i^{th} candidate model, $\hat{y}_{i,t+h|t}$, is based on a similar rolling estimation window. This implies that the weight $\hat{\omega}_{i,t+h|t}$ is zero if, at time t, the sample is of insufficient length to satisfy this rolling window approach. Accordingly, with aluminium and with CAD having the longest sample, CAD enters with a weight of one for the first $h = 1$ forecast of aluminium in 1996:12 until 1998:12 where AUD enters. In 2000:05 NZD and any combination with NZD attains a positive weight and so do NOK in 2007:07. Bold numbers represent significance at the 10% level. The p-value corresponding to the non-nested Diebold-Mariano test statistic is used to assess the significance of RSFE.

Table 26: Individual currencies - end-of-period data

	Fcst. combi/	$h=1$		$h=3$		$h=6$		$h=12$	
	benchmark	RSFE	RSR	RSFE	RSR	RSFE	RSR	RSFE	RSR
AUD	FC/AR(SIC)	1.019	1.086	1.002	0.928	1.003	1.015	0.980	0.956
CAD	FC/AR(SIC)	1.005	0.916	1.010	**0.878**	1.025	0.943	0.996	0.923
CLP	FC/AR(SIC)	1.001	**0.825**	1.032	1.021	1.033	1.000	1.004	0.957
NZD	FC/AR(SIC)	1.025	1.154	1.034	1.136	1.003	1.163	1.002	0.949
NOK	FC/AR(SIC)	0.950	1.083	0.943	1.174	0.974	1.091	1.040	0.914
ZAR	FC/AR(SIC)	0.981	1.189	0.956	0.894	0.966	0.977	1.074	1.200

Notes: This table reports the ratio of mean squared forecast errors (RSFE) and relative success ratios (RSR) for forecast horizons $h = 1, 3, 6, 12$. In the second column "FC/AR(SIC)" denotes a comparison of forecast combination with SIC weights against an autoregressive model with the number of lags determined by the SIC information criteria. For each currency, we only include commodities that are exported by that particular country as regressors in the forecast combination, so for e.g. AUD we include combinations of the commodities that Australia exports. As in CRR, each forecast from the i^{th} candidate model, $\hat{y}_{i,t+h|t}$, is based on a similar rolling estimation window. This implies that the weight $\hat{\omega}_{i,t+h|t}$ is zero if, at time t, the sample is of insufficient length to satisfy this rolling window approach. Bold numbers represent significance at the 10% level. The p-value corresponding to the non-nested Diebold-Mariano test statistic is used to assess the significance of RSFE.

Table 27: Individual currencies - monthly averaged data

	Fcst. combi/	$h=1$		$h=3$		$h=6$		$h=12$	
	benchmark	RSFE	RSR	RSFE	RSR	RSFE	RSR	RSFE	RSR
AUD	FC/AR(SIC)	1.017	1.047	1.019	0.987	0.993	0.944	1.005	1.000
CAD	FC/AR(SIC)	**1.021**	0.981	1.042	**1.109**	1.032	1.120	1.034	1.036
CLP	FC/AR(SIC)	**1.030**	0.984	1.040	1.057	1.072	1.159	1.004	1.073
NZD	FC/AR(SIC)	0.991	1.012	1.042	1.059	1.020	1.121	1.029	0.911
NOK	FC/AR(SIC)	1.033	1.067	1.048	1.071	1.013	0.963	1.086	1.033
ZAR	FC/AR(SIC)	1.059	1.040	0.994	1.200	0.974	0.935	1.070	1.108

Notes: This table reports the ratio of mean squared forecast errors (RSFE) and relative success ratios (RSR) for forecast horizons $h = 1, 3, 6, 12$. In the second column "FC/AR(SIC)" denotes a comparison of forecast combination with SIC weights against an autoregressive model with the number of lags determined by the SIC information criteria. We predict the individual currencies listed in the first column as well as average measures (mean of all). For each currency, we only include commodities that are exported by that particular country as regressors in the forecast combination, so for e.g. AUD we include combinations of the commodities that Australia exports. As in CRR, each forecast from the i^{th} candidate model, $\hat{y}_{i,t+h|t}$, is based on a similar rolling estimation window. This implies that the weight $\hat{\omega}_{i,t+h|t}$ is zero if, at time t, the sample is of insufficient length to satisfy this rolling window approach. Bold numbers represent significance at the 10% level. The p-value corresponding to the non-nested Diebold-Mariano test statistic is used to assess the significance of RSFE.

Table 28: Replication CRR Forecasting Excersice

		ER GC CP					CP GC ER				
	Benchmark	DSFE	RSFE	p-CW	p-CMCk CRR	p-CMCk corrected	DSFE	RSFE	p-CW	p-CMCk CRR	p-CMCk corrected
Australia	AR1X/AR1	1.813	1.027	0.956	**0.010**	1.000	0.241	1.011	0.395	1.000	1.000
	X/RW	-2.115	0.878	**0.002**	**0.010**	**0.050**	0.537	1.028	0.479	**0.100**	1.000
	X/RWWD	-0.142	0.996	0.239	**0.100**	1.000	0.064	1.003	0.328	1.000	1.000
Canada	AR1X/AR1	1.051	1.030	0.756	**0.050**	1.000	1.634	1.023	0.930	1.000	1.000
	X/RW	-0.010	1.000	0.275	1.000	1.000	0.594	1.012	0.566	1.000	1.000
	X/RWWD	1.047	1.026	0.737	1.000	1.000	1.794	1.024	0.945	**0.050**	1.000
Chile	AR1X/AR1	-0.163	0.992	0.289	**0.050**	1.000	1.188	1.042	0.754	**0.050**	1.000
	X/RW	-0.448	0.958	0.122	**0.010**	**0.100**	0.998	1.083	0.616	1.000	1.000
	X/RWWD	-0.431	0.972	0.168	**0.050**	1.000	0.906	1.044	0.623	1.000	1.000
NewZealand	AR1X/AR1	0.320	1.020	0.153	**0.010**	**0.100**	0.233	1.013	0.277	1.000	1.000
	X/RW	-1.613	0.857	**0.005**	**0.010**	**0.010**	0.232	1.017	0.149	**0.050**	1.000
	X/RWWD	-0.752	0.950	**0.022**	**0.010**	**0.050**	0.156	1.010	0.152	**0.050**	1.000
SouthAfrica	AR1X/AR1	1.346	1.123	0.913	**0.010**	1.000	1.571	1.142	0.881	1.000	1.000
	X/RW	-1.393	0.822	**0.018**	**0.010**	**0.050**	2.092	1.270	0.933	1.000	1.000
	X/RWWD	1.686	1.083	0.952	**0.010**	1.000	1.372	1.150	0.811	1.000	1.000

Note: The table replicates the main forecasting results of CRR's paper (Table IV: Tests for out-of-sample forecasting ability). We have identified a programing slip-up in the Clark-McCracken matlab routine of CRR. This slip-up leads to an overstatement in the significance levels of the their forecasting results. When we adjust their routine the resulting p-values of the Clark-McCracken test are in line with the findings in our paper and with the p-values obtained using the Clark-West test. Namely, exchange rates appear to be only poor predictors of commodity prices.
The column DSFE reports the Different in Mean Squared Forecasting Errors between the CRR and the corresponding benchmark model, while the column RSFE reports the Relative Mean Squared Forecasting Errors (a negative DSFE corresponds to a RSFE smaller than 1). The column p-DM reports the p-values of the Diebold and Mariano (1995) test, while the column p-CW reports the p-values1 of the Clark and West (2007) test. The columns p-CMCk CRR and p-CMCk Corrected report the p-values of the Clark and McCracken (2001) test as computed by CRR, including taking squares twice where once is the correct way, and the corrected version of it. When computing the p-values we have followed the same procedure as CRR. That is, a p-value of 0.1 indicates the the p-values actually is smaller than 0.1 but larger than 0.05

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