CAN EXCHANGE RATES FORECAST COMMODITY PRICES?*

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Abstract. We show that "commodity currency" exchange rates have remarkably robust power in predicting global commodity prices, both in-sample and out-of-sample, and against a variety of alternative benchmarks. This result is of particular interest to policymakers, given the lack of deep forward markets in many individual commodities, and broad aggregate commodity indices in particular. We also explore the reverse relationship (commodity prices forecasting exchange rates) but find it to be notably less robust. We offer a theoretical resolution, based on the fact that exchange rates are strongly forward looking, whereas commodity price fluctuations are typically more sensitive to short-term demand imbalances

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1. Introduction

This paper demonstrates that the exchange rates of a number of small commodity exporters have remarkably robust forecasting power over global commodity prices. The relationship holds both in-sample and out-of-sample. It holds when non-dollar major currency cross exchange rates are used, as well as when one controls for information in the forward or futures markets. We also find that commodity prices Granger-cause exchange rates in-sample, assuming one employs suitable methods to allow for structural breaks. However, this relationship is not robust out-of-sample.

The success of these exchange rates in forecasting global commodity prices is no deus ex machina. It follows from the fact that the exchange rate is forward looking and embodies information about future movements in the commodity markets that cannot easily be captured by simple time series models. For the commodity exporters we study, global commodity price fluctuations affect a substantial share of their exports, and represent major terms-of-trade shocks to the value of their currencies. When market participants foresee future commodity price shocks, this expectation will be priced into the current exchange rate through its anticipated impact on future export income and exchange rate values. In contrast, commodity prices tend to be quite sensitive to current global market conditions, as both demand and supply are typically quite inelastic.[1] Financial markets for commodities also tend to be far less developed and much more regulated than for the exchange rate. As a result, commodity prices tend to be a less accurate barometer of future conditions than are exchange rates, hence the asymmetry between forecast success in the forward and reverse

[1] Standard theories of the commodity markets focus on factors such as storage costs, inventory levels, and short-term supply and demand conditions (see Williams and Wright 1991, Deaton and Laroque 1992). The prices of agricultural products are well-known to have strong seasonality, and are commonly described by an adaptive "corn-hog cycle" model. Structural breaks in the supply and demand conditions (e.g. China's rapid growth, rising demand for biofuels) have also been put forth as one of the major contributors to the recent commodity price boom (e.g. World Bank 2009). It is intuitive that the prices of perishable commodities, or ones with large storage costs, cannot incorporate expected future prices far into the future; though the prices of certain storable commodities such as silver or gold may behave like forward-looking assets.

directions.[2]

Although properly gauging commodity price movements is crucial for inflation control and production planning alike, these prices are extremely volatile and have proven difficult to predict.[3] In a 2008 speech, Federal Reserve Chairman Ben Bernanke noted especially the inadequacy of price forecasts based on signals obtained from the commodity futures markets, and emphasized the importance of finding alternative approaches to forecast commodity price movements.[4] This paper offers such as an alternative. Our laboratory here is that of the "commodity currencies" which include the Australian, Canadian, and New Zealand dollars, as well the South African rand and the Chilean peso. As these floating exchange rates each embody market expectations regarding future price dynamics of the respective country's commodity exports, by combining them we are able to forecast price movements in the overall aggregate commodity market. Given the significant risk premia found in the commodity futures, our exchange rate-based forecasts may be an especially useful alternative.[5]

We are not the first to test the present value models of exchange rate determination by examining how it predicts fundamentals. For example, Engel and West (2005), following Campbell and Shiller (1987), show that because the nominal exchange rate reflects expectations of future changes in its

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

[3] Forecasting commodity prices is especially important for developing economies, not only for planning production and export activity, but also from the poverty alleviation standpoint. India, for example, distributes through its Public Distribution System, thousands of tons of foodgrains each year at subsidized prices. Accurate forecast of movements in foodgrains prices has significant budgetary benefit.

[4] See www.federalreserve.gov/newsevents/ speech/bernanke20080609a.htm

[5] See Gorton and Rouwenhorst (2006) and Gorton, Hayashi, and Rouwenhorst (2008) for a detailed description and empirical behavior of the commodity futures risk premia.

economic fundamentals, it should help predict them. However, previous tests employ standard macroeconomic fundamentals such as interest rates, output and money supplies which are plagued by issues of endogeneity, rendering causal interpretation impossible and undermining the whole approach.[6] This problem can be finessed for the commodity currencies, at least for one important exchange rate determinant: the world price for an index of their major commodity exports.

Even after so finessing the endogeneity problem, disentangling the dynamic causality between exchange rates and commodity prices is still complicated by the possibility of parameter instability, which confounds traditional Granger-causality regressions.[7] After controlling for instabilities using the approach of Rossi (2005b), however, we uncover robust in-sample evidence that exchange rates predict world commodity price movements. Individual commodity currencies Granger-cause their corresponding country-specific commodity price indices, and can also be combined to predict movements in the aggregate world market price index.

As one may be concerned that the strong ties global commodity markets have with the U.S. dollar may induce endogeneity in our data, we conduct robustness checks using nominal effective exchange rates as well as rates relative to the British pound.[8] Free from potential "dollar effect", the results confirm our predictability conclusions. We next consider longer-horizon predictability as an additional robustness check, and test whether exchange rates provide additional predictive

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

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

[8] For example, since commodities are mostly priced in dollars, one could argue that global commodity demands and thus their prices would go down when the dollar is strong. Another reason to consider non-dollar exchange rates is that the US accounts for roughly 25% of total global demand in some major commodity groupings, and therefore its size might be an issue.

power beyond information embodied in commodity forward prices and futures indices.[9]

In the final section, we summarize our main results and put them in the context of the earlier literature that focused on testing structural models of exchange rates.

2. Background and Data Description

Although the commodity currency phenomenon may extend to a broader set of countries, our study focuses on five small commodity-exporting economies with a sufficiently long history of market-based floating exchange rates, and explores the dynamic relationship between exchange rates and world commodity prices. We note that the majority of the commodity-exporting countries in the world either have managed exchange rates or haven't free-floated their currencies continuously. While their exchange rates may still respond to commodity prices, we exclude them in our analysis here as our interest is in how the market, rather than policy interventions, incorporates commodity price expectations in pricing currencies.

As shown in Appendix Table A.1, Australia, Canada, Chile, New Zealand, and South Africa produce a variety of primary commodity products, from agricultural and mineral to energy-related goods. Together, commodities represent between a quarter and well over a half of each of these countries' total export earnings. Even though for certain key products, these countries may have some degree of market power (e.g. New Zealand supplies close to half of the total world exports of lamb and mutton), on the whole, due to their relatively small sizes in the *overall* global commodity market, these countries are price takers for the vast majority of their commodity exports.[10] Substi-

[9] Forward markets in commodities are very limited – most commodities trade in futures markets for only a limited set of dates.

[10] In 1999, for example, Australia represents less than 5 percent of the total world commodity exports, Canada about 9 percent, and New Zealand 1 percent. One may be concerned that Chile and South Africa may have more market power in their respective exports, yet as shown and discussed further in Appendix C, we cannot empirically reject the exogeneity assumption.

tution across various commodities would also mitigate the market power these countries have, even within the specific market they appear to dominate. As such, global commodity price fluctuations serve as an easily-observable and essentially exogenous terms-of-trade shock to these countries' exchange rates.

From a theoretical standpoint, exchange rate responses to terms-of-trade shocks can operate through several well-studied channels, such as the income effect of Dornbusch (1980) and the Balassa-Samuelson effect commonly emphasized in the literature (Balassa 1964 and Samuelson 1964). In the next two subsections, we discuss possible structural mechanisms that explain the link between exchange rates and commodity prices as well as economic interpretations of our empirical results. We note that in the empirical exchange rate literature, sound theories rarely receive robust empirical support, not to mention that for most OECD countries, it is extremely difficult to actually identify an exogenous measure of terms-of-trade. The commodity currencies overcome these concerns. Not only are exogenous world commodity prices easy to observe from the few centralized global exchanges in real time, they are also a robust and reliable fundamental in explaining the behavior of these commodity currencies, as demonstrated in previous literature.[11]

Over the past few decades, all of these countries experienced major changes in policy regimes and market conditions. These include their adoption of inflation targeting in the 1990s, the establishment of Intercontinental Exchange and the passing of the Commodity Futures Modernization Act of 2000 in the United States, and the subsequent entrance of pension funds and other investors into commodity futures index trading. We therefore pay special attention to the possibility of structural breaks in our analyses.

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

2.1. Commodity Currencies. By commodity currencies we refer to the few floating currencies that co-move with the world prices of primary commodity products, due to these countries' heavy dependency on commodity exports. The theoretical underpinning of our analysis - why commodity currencies should predict commodity prices - can be conveniently explained in two stages. First, world commodity prices, being a proxy for the terms of trade for these countries, are a fundamental determinant for the value of their nominal exchange rates. Next, as we show in Section 2.2 below, because the nominal exchange rate can be viewed an asset price, it incorporates expectations about the values of its future fundamentals, such as commodity prices.

There are several channels that can explain why, for a major commodity producer, the real (and nominal) exchange rate should respond to changes in the expected future path of the price of its commodity exports. Perhaps the simplest mechanism follows the traded/nontraded goods model of Rogoff (1992), which builds upon the classical dependent-economy models of Salter (1959) and Swan (1960) and Dornbusch (1980). Rogoff's model assumes fixed factors of production, and a bonds-only market for intertemporal trade across countries (i.e., incomplete markets). The real exchange rate – the relative price of traded and nontraded goods – depends at any point in time on the ratio of traded goods consumption to nontraded goods consumption; see Rogoff (1992, eq.6). But traded goods consumption depends on present value of the country's expected future income (and on nontraded goods shocks except in the special case where utility is separable between traded and nontraded goods.) Thus the real exchange rate incorporates expectations of future commodity price earnings. If factors are completely mobile across sectors as in the classic Balassa and Samuelson (1964) framework employed by Chen and Rogoff (2003), the real exchange rate will only depend on the current price of commodities. But as long as there are costs of adjustment in moving factors (as in Obstfeld and Rogoff, 1996, Ch. 4), the real exchange rate will still contain a forward-looking component that incorporates future commodity prices. In general, therefore, the nominal exchange rate will also incorporate expectations of future commodity price increases.[12]

Introducing sticky prices is another way to motivate a forward-looking exchange rate relationship, either via the classic Dornbusch (1976) or Mussa (1976) mechanism or a more modern "New Open Economy Macroeconomics" model as in Obstfeld and Rogoff (1996).[13] In a Dornbusch framework, combining money market equilibrium, uncovered interest parity, and purchasing power parity condition leads to the familiar relationship:

$$s_t = \frac{1}{1+\alpha}[m_t - m_t^* - \gamma(y_t - y_t^*) + q_t] + \frac{\alpha}{1+\alpha} E_t s_{t+1}$$

where q_t is the real exchange rate, m_t and m_t^* are domestic and foreign money supplies, y_t and y_t^* are domestic and foreign output, and α is the interest elasticity of money demand.[14] When the model is solved out for the exchange rate in terms of current and expected future fundamentals, the result again is that nominal exchange rate depends on expected future commodity prices, here embodied in q_t.[15]

In addition to the channels discussed in the standard macro models above, the exchange rate-commodity price linkage can also operate through the asset markets and a portfolio channel. For example, higher commodity prices attract funds into commodity-producing companies or countries.

[12] We note that in principle, real exchange rate shocks need not translate to the nominal exchange rate, such as when the country is under a fixed exchange rate regime. If the monetary authorities stabilize the exchange rate, the real exchange rate response will pass through to domestic prices, inducing employment effects in the short run if prices are not fully flexible. This is why in our choice of commodity currencies, we only focus on countries with floating exchange rates.

[13] The exogenous commodity price shocks enter these models in a similar fashion as a productivity shock to the export sector, and the forward-looking element of nominal exchange rate is the result of intertemporal optimization. See, for example, Obstfeld and Rogoff (1996, Ch.10.2) and Garcia-Cebro and Varela-Santamaria (2007).

[14] See, for example, Engel and West (2005) equation 7 for a derivation of this standard result.

[15] We emphasize, however, that the net present value relation between nominal exchange rate and commodity prices do not need sticky prices, and the effect does not have to come from asset markets either, although it can.

This may imply additional empirical relationship between equity market behavior and world commodity prices. The objective of this paper is not to distinguish amongst these alternative models, but rather to explore and test the consequences of this fundamental linkage between nominal exchange rates and commodity prices. We will choose as our main starting point, therefore, a very general expression for the spot exchange rate:

$$s_t = \beta' f_t + E_t s_{t+1}$$

where the commodity price, cp_t is one of the fundamentals f_t. Again, this forward looking equation can be motivated from asset markets as in Engel and West (2005), but can also be motivated through goods markets assuming factor mobility is not instantaneous.

Finally, we note that, in principle, the theoretical channels we discuss above may as well apply to countries that heavily import commodity products, not just countries that heavily export. That is, commodity price fluctuations may induce exchange rates movements (in the opposite direction) for large commodity importers. However, we suspect that empirically, this relationship may be muddled by the use of these imported raw materials as intermediate inputs for products that are subsequently exported. To preserve a clean testing procedure, we do not include large importers in our analyses.[16]

2.2. The Present Value Approach. In this section, we discuss the asset-pricing approach which encompasses a variety of structural models, as discussed above, that relate the nominal exchange rate s_t to its fundamentals f_t and its expected future value $E_t s_{t+1}$. This approach gives

[16] We believe further investigation on the applicability of the "commodity currency" phenomenon to large importers is an interesting topic, but we leave it for future research.

rise to a present value relation between the nominal exchange rate and the discounted sum of its expected future fundamentals:

$$s_t = \gamma \sum_{j=0}^{\infty} \psi^j E_t(f_{t+j}|I_t) \tag{1}$$

where ψ and γ are parameters dictated by the specific structural model, and E_t is the expectation operator given information I_t. It is this present value equation that shows that exchange rate s should Granger-cause its fundamentals f. (Note that using the model of Rogoff (1992), or Obstfeld and Rogoff (1996, Ch. 4), one can motivate a similar relationship with the real exchange rate q on the left hand side of eq.(1) We prefer here to focus on the nominal exchange rate, as it is, in principle, measured more accurately and at very high frequency, as are commodity prices. But one could in principle extend the exercise here to the real exchange rate.).

While the present value representation is well accepted from a theoretical standpoint, there is so far little convincing empirical support for it in the exchange rate literature.[17] The difficulty lies in the actual testing, as the standard exchange rate fundamentals considered in the literature - cross country differences in money supply, interest rates, output, or inflation rates - are essentially all endogenous and jointly determined with exchange rates in equilibrium. They may also directly react to exchange rate movements through policy responses. Under such conditions, a positive finding that exchange rate s Granger-causes fundamental f could simply be the result of endogenous response or reverse causality, and is thus observationally equivalent to a present value model. For instance, a positive finding that exchange rates Granger-cause money supply or interest rate changes may be the direct result of monetary policy responses to exchange rate fluctuations, as would be the

[17] The present value approach to modeling nominal exchange rate is discussed in standard textbooks such as Mark (2001) and Obstfeld and Rogoff (1996), as well as emphasized in recent paper such as Engel and West (2005). It follows the same logic as the dividend yields or the consumption-wealth ratio embodying information about future dividend growths or stock returns (see Campbell and Shiller 1988, Campbell and Mankiw 1989, and the large body of follow-up literature.)

case with a Taylor interest rate rule that targets Consumer Price Index (CPI) inflation. Exchange rate changes may also precede inflation movements if prices are sticky and pass-through is gradual. As such, positive Granger-causality results for these standard fundamentals are difficult to interpret and cannot be taken as evidence for the present value framework, *unless* the fundamental under consideration is exogenous to exchange rate movements. Commodity prices are a unique exchange rate fundamental for these countries because the causality is clear, and a test of the present value theoretical approach is thus meaningful. (Note that the present value approach is widely used in pricing assets, and one would expect that, beside the exchange rates, other asset prices, such as certain stock prices or equity market indices, may also predict the global commodity price index.[18])

The present value model in eq.(1) shows why exchange rates can predict exogenous world commodity prices even if commodity prices do not predict future exchange rates. The intuitive explanation is that exchange rates directly embody information about future commodity prices, but for commodity prices to be able to forecast future exchange rates, they must first have the ability to forecast their own future values (a future exchange rate fundamental). The linkage is therefore less direct. We will illustrate this with an example. Suppose that commodity price changes are driven by a variable X_t that is perfectly forecastable and known to all market participants but not to econometricians: $\Delta cp_t = X_t$. The example may be extreme, but there are plausible cases where it may not be a bad approximation to reality. For instance, commodity prices may depend in part on fairly predictable factors, such as world population growth, as well as cobweb ("corn-hog") cycles that are predictable by market participants' expertise but are not easily described by

[18] We are grateful to Helene Rey for sharing suggestive unpublished results which show that the Australian, Canadian, and Chilean stock price indices have joint predictive ability for the global commodity price index, similar to that of the exchange rates. We leave further exploration of the linkage between equity, commodity, and the exchange rate markets for future research.

simple time series models (see, for example, Williams and Wright 1991). Such factors are totally extraneous to exchange rate dynamics. Thus, there may be patterns in commodity pricing that could be exploited by knowledgeable market participants, but not by the econometrician. Note that econometricians omitting such variables may likely find parameter instabilities, such as those that we detect in our regressions.

To make the example really stark, let's assume that the sequence $\{X_\tau\}_{\tau=t,t+1,\ldots}$, known to market participants, is generated by a random number generator and therefore unpredictable by anyone who does not know the sequence. Since commodity prices are perfectly forecastable by the markets, eq.(1) and $f_t = cp_t$ imply:

$$\Delta s_{t+1} = \gamma \sum_{j=1}^{\infty} \psi^j \Delta cp_{t+j} + z_{t+1}. \tag{2}$$

where z are other exchange rate determinants that are independent of commodity prices.

Note that Δcp_t will be of no use for the econometrician in forecasting Δs_{t+1}, as it will be of no use for forecasting Δcp_{t+1}. But Δs_t will be useful in forecasting Δcp_{t+1}, because it embodies information about X_{t+1}. This asymmetry is indeed starkly observed in our empirical findings on out-of-sample forecasts, as shown in Section 3 below. We find exchange rates to forecast commodity prices well, but not vice versa.[19] Our results follow directly from the fact that exchange rates are strongly forward looking and do not directly depend on the variables explaining commodity prices. The dependency comes only through the net present value relationship. In particular, as in Campbell and Shiller (1987, p. 1067), when a variable s_t is the present value of a variable cp_t, then

[19] The point of having X_t generated by a random number generator is to produce the simplest case where using past exchange rates and commodity prices is not going to help forecast X. Of course, if there is some serial correlation in the commodity prices, there may be some exchange rate predictability through this autoregressive linkage, as we indeed observe.

either s_t Granger-causes cp_t relative to the bivariate information set consisting of lags of s_t and cp_t, or s_t is an exact distributed lag of current and past values of x_t. This justifies our empirical analysis focused on eq. (3), which we explain later in the paper.[20]

2.3. Data Description and Empirical Strategy. We use quarterly data over the following time-periods: Australia (from 1984:1 to 2008:1), Canada (from 1973:1 to 2008:1), Chile (from 1989:3 to 2008:1), New Zealand (from 1987:1 to 2008:1), and South Africa (from 1994:1 to 2008:1).[21] The main results are presented using samples that end before the financial crisis, and in Appendix C, we investigate the robustness of our main findings by extending the data to 2009:3. For each commodity economy, we aggregate the relevant dollar spot prices in the world commodity markets to construct country-specific, export-earnings-weighted commodity price indices (labeled "*cp*"). Individual commodity price data are collected from the International Monetary Fund (IMF), Global Financial Database, the Bank of Canada, and the Reserve Bank of New Zealand. Appendix Table A.1 provides the country-specific weights used to aggregate individual world commodity prices into country-specific indices. For nominal exchange rates ("*s*"), we use the end-of-period U.S. dollar rates from the Global Financial Data for the majority of our analyses. We also present results based on nominal effective exchange rates (from the International Finance Statistics, IFS) and cross rates relative to the British pound as robustness checks. To capture price movements in the overall aggregate world commodity markets, we use the aggregate commodity price index ("cp^W") from

[20] In general, eq. (2) implies that exchange rate Granger-cause an infinite series of future commodity prices, and the exact expression in eq. (3) follows under special assumptions. For example, from eq. (2), assuming $E_t z_t = 0$ and that commodity prices are unforecastable by market participants beyond period $t+2$ ($E_t \Delta cp_{t+2} = E_t \Delta cp_{t+3} = ... = 0$), gives eq. (3), where $\beta_1 = \frac{1}{\gamma\psi}$ and $\beta_2 = -\frac{1}{\gamma\psi}\gamma$.

[21] Canada began floating its currency in 1970, and Australia and New Zealand abandoned their exchange rate pegs in 1983 and 1985 respectively. For Chile and South Africa, our sample periods are chosen a bit more arbitrarily: Chile operated under a crawling peg for most of the 1990s, and the starting point for South Africa roughly corresponds to the end of apartheid. We note that we also conducted all the analyses presented in this paper using monthly data up to 2008. The results are qualitatively similar and are available upon request.

the IMF, which is a world export-earnings-weighted price index for over forty products traded on various exchanges.[22] (We choose the IMF index because it is one of the most comprehensive, but note that our results are robust to using other aggregate commodity indices, such as the Goldman Sachs index, the Commodity Research Bureau Index, among others.[23]) Finally, we use the Dow Jones-AIG Futures and Spot indices, as well as forward price data from Bloomberg for a selected set of metal products - gold, silver, platinum, and copper - to compare with our exchange rate-based forecasts.[24]

As standard unit root tests cannot reject that these series contain unit roots, we proceed to analyze the data in first-differences, which we denote with a preceding Δ.[25] In Section 4 and Appendix C, we present an alternative predictive regression specification that is robust to the possibility that the autoregressive roots in these data may not be exactly one, although very close to it (i.e. they are "local-to-unity"). We see that our findings are robust to these different assumptions. In addition, we note that even in the individual data series, we observe strong evidence of structural breaks, found mostly in early 2000. This finding foreshadows one of our major conclusions that controlling for parameter instabilities is crucial in analyzing the exchange rate-fundamental connection.

[22] The IMF publishes two aggregate indices: one includes fuel prices and starts in 1992, and one without fuel prices that starts in 1980. In the analyses below, we report results based on the longer series without oil.

[23] These indices in general contain between ten and twenty commodities, including energy products. Some are "three-dimension" index that pull information across futures contracts of different maturities, and they employ a variety of weighting schemes.

[24] Specifically, we use the 3-month "DJ-AIGCI Forward Index" which is composed of longer-dated commodity futures contracts, and the Dow Jones-AIG Commodity Spot Index, which is based on spot prices and does not account for the effects of rolling futures contracts or the costs associated with actually holding physical commodities.

[25] A detailed analysis of the times series properties of individual series, including structural break test results, are available upon request. Note also that we do not consider cointegration but use first differences since we are not testing any specific models and are interested in short-term behavior. Chen and Rogoff (2003) showed that, in analyzing real exchange rates, Dynamic OLS estimates of cointegrated models and estimates of models in differences produce very similar results. (From a practical point of view, real exchange rates and nominal ones behave very similarly.) Chen (2005) examines commodity-priced augmented monetary models in the cointegration framework.

We examine the dynamic relationship between exchange rates and commodity prices both in terms of Granger-causality and out-of-sample forecasting ability.[26] We regard these two tests as important alternative approaches to evaluating the predictive content of a variable. The in-sample tests take advantage of the full sample size and thus are likely to have higher power in the presence of constant parameters. They are however more prone to overfitting, and as such, are more likely to detect predictability that often fails to translate to out-of-sample success. The out-of-sample forecast procedure, on the other hand, is a tougher and more realistic test, as it mimics the data constraint of real-time forecasting and is more robust to time-variation and misspecification problems.[27]

In the in-sample analyses below, we adopt the procedure developed in Rossi (2005b), which is test a for Granger causality that is robust to potential structural breaks. It simultaneously tests for the null hypothesis of no time variation and no Granger causality. When the null is rejected, it indicates that there is evidence for Granger causality in at least part of the sample. This is because the rejection has to reflect either: (i) the parameters are constant but different from zero, i.e. there is Granger causality by definition; or (ii) the parameters are time varying; in which case they cannot be equal to zero over the whole sample, again providing evidence for Granger causality somewhere in the sample. Traditional Granger causality test only captures (i) above, but with the Rossi (2005b) test, we can capture structural breaks that may be caused by the policy and market

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

[27] Note that all data are available in real-time and are never revised. As is well-known in the literature, in-sample predictive tests and out-of-sample forecasting tests can and often provide different conclusions, which could result from their differences in the treatment of time-varying parameters, the possibility of over-fitting, sample sizes, and other biases...etc. See Inoue and Kilian (2004). We do not promote one over the other here, but recognize the trade-offs.

changes discussed above.[28]

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

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

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

Concerning the reverse exercise of forecasting exchange rates, addressing parameter instability again plays a crucial role in uncovering evidence for in-sample exchange rate predictability from commodity prices. The out-of-sample analyses, however, show little evidence of exchange rate

[28] In the presence of multiple changes in the coefficients, the Rossi (2005b) procedure identifies the largest change in the coefficients instead of all the breaks. Because our goal is to find empirical evidence against no Granger causality, identifying the biggest break is sufficient. We note that it is not possible, by construction, that the changes offset each other in a way to mislead the test results. See Appendix B for further details.

forecastability beyond a random walk, suggesting the reverse regression to be more fragile.

All the analyses in this section are based on U.S. dollar exchange rates. In Section 4, we demonstrate the robustness of our results by looking at different numeraire currencies, and longer-horizon predictive regressions robust to "local-to-unity" regressors. Appendix B provides an overview of the time series methods that we use.

3.1. Can Exchange Rates Predict Commodity Prices?. We first investigate the empirical evidence on Granger causality, using both the traditional testing procedure and one that is robust to parameter instability. We demonstrate the prevalence of structural breaks and emphasize the importance of controlling for them. Our benchmark Granger-causality analyses below include one lag each of the explanatory and dependent variables, though our findings are robust to the inclusion of additional lags.[29] For ease of presentation, we focus our main discussion below using a driftless random walk as the main benchmark, since it is the most relevant for exchange rate forecasting. Our results are robust to using alternative benchmarks such as a random walk with drift and an autoregressive specification, as demonstrated in the tables.

In-Sample Granger-Causality (GC) Tests. Present value models of exchange rate determination imply that exchange rates must Granger-cause fundamentals. We can use this implication as a weak test of the present value model. In other words, ignoring issues of parameter instabilities, we should reject the null hypothesis that $\beta_0 = \beta_1 = 0$ in the regression:

$$E_t \Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t \tag{3}$$

As shown in the next section and in Table VI(b), the qualitative results remain if we test for the

[29] Additional lags are mostly found to be insignificant based on the Bayesian Information Criterion (BIC).

null hypothesis of only $\beta_1 = 0$. In addition, we note that our empirical findings are robust to the inclusion of additional lags of Δcp_t, even though specifications with multiple lags do not directly follow from eq. (2).[30]

Panel A in Table I reports the results based on the above standard Granger-causality regression for the five exchange rates and their corresponding commodity price indices. All variables are first differenced, and the estimations are heteroskedasticity and serial correlation-consistent. Results are based on the Newey and West (1987) procedure with bandwidth $T^{1/3}$ (where T is the sample size.) The table reports the p-values for the tests, so a number below 0.05 implies evidence in favor of Granger-causality (at the 5% level). We note that overall, traditional Granger-causality tests find little evidence of exchange rates Granger-causing commodity prices (only South Africa is significant at 5%).[31]

An important drawback in these Granger-causality regressions is that they do not take into account potential parameter instabilities. We find that structural breaks are a serious concern not only theoretically as discussed above, but also empirically as observed in the individual time series data under consideration. Table II reports results from the parameter instability test, based on Andrews (1993), for the bivariate Granger-causality regressions. We observe strong evidence of time-varying parameters in several of these relationships in early 2000, likely reflecting the policy changes discussed earlier. As such, we next consider the joint null hypothesis that $\beta_{0t} = \beta_0 = 0$ and $\beta_{1t} = \beta_1 = 0$ by using Rossi's (2005b) $Exp - W^*$ test, in the following regression setup:

$$E_t \Delta cp_{t+1} = \beta_{0t} + \beta_{1t} \Delta s_t + \beta_2 \Delta cp_t \tag{4}$$

[30] The results are available upon request.

[31] We also estimated R^2 of the in-sample regressions. The values are 3% for Australia, 5% for New Zealand, 1% for Canada, 7% for Chile and 3% for South Africa.

See Appendix B for a detailed description of Rossi's (2005b) test. Table III, Panel A shows that this test of Granger-causality, which is robust to time-varying parameters, indicates much stronger evidence in favor of a time-varying relationship between exchange rates and commodity prices. As shown later in the analyses using nominal effective exchange rates and rates against the British pound, addressing parameter instability is again crucial in uncovering these Granger-causality relationships.

INSERT TABLES I, II AND III HERE

Out-of-Sample Forecasts. We now ask whether in-sample Granger-causality translates into out-of-sample forecasting ability. We adopt a rolling forecast scheme based on eq.(3). We choose the rolling forecast procedure because it is relatively robust to the presence of time-varying parameters, and requires no explicit assumption as to the nature of the time variation in the data. We use a rolling window, rather than a recursive one, as it adapts more quickly to possible structural changes. We report two sets of result. First, we estimate eq.(3) and test for forecast encompassing relative to an autoregressive (AR) model of order one ($E_t \Delta cp_{t+1} = \gamma_{0t} + \gamma_t \Delta cp_t$; the order of the benchmark autoregressive model is selected by the Bayesian information criterion). Second, we present results based on a random walk benchmark due to its significance in the exchange rate literature. Here, we consider both a random walk and a random walk with drift. For the random walk (RW) benchmark, we estimate eq.(3) without the lagged dependent variable Δcp_t, and test for forecast encompassing relative to $E_t \Delta cp_{t+1} = 0$. For the random walk with drift (RWWD) comparison, we estimate eq.(3), again without the lagged dependent variable Δcp_t, and test for forecast encompassing relative to $E_t \Delta cp_{t+1} = \gamma_{0t}$. Specifically, we use a rolling window with size equal to half of the total sample size to estimate the model parameters and generate one-quarter ahead forecasts recursively (what we call "model-based forecasts"). Table IV reports three sets of information on the forecast comparisons. First, the numbers reported are the difference between the mean square forecast errors (MSFE) of the model and the MSFE of the benchmark (RW, RWWD or AR(1)), both re-scaled by a measure of their variability.[32] A negative number indicates that the model outperforms the benchmark. In addition, for proper inference, we use Clark and McCracken's (2001) "ENCNEW" test of equal MSFEs to compare these nested models. A rejection of the null hypothesis, which we indicate with asterisks, implies that the additional regressor contains out-of-sample forecasting power for the dependent variable. We emphasize that the ENCNEW test is the more formal statistical test of whether our model outperforms the benchmark, as it corrects for finite sample bias in MSFE comparison between nested models. The bias correction is why it is possible for the model to outperform the benchmark even when the computed MSFE differences is positive. This fact might be surprising and deserves some intuition. Clark-McCracken's correction accounts for the fact that when considering two nested models, the smaller model has an unfair advantage relative to the larger one because it imposes, rather than estimates, some parameters.[33] In other words, under the null hypothesis that the smaller model is the true specification, both models should have the same mean square forecast error *in population.* However, despite this equality, the larger model's *sample* mean square error is expected to be greater. Without correcting the test statistic, the researcher may therefore erroneously conclude that the smaller model is better, resulting in size distortions where the larger model is rejected too often. The Clark and McCracken (2001) test makes a correction that addresses this finite sample bias.

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

[33] In our example, if the random walk model is the true data generating process, both the random walk model and the model that uses the exchange rates are correct, as the latter will simply set the coefficient on the lagged exchange rate to be zero. However, when estimating the models in finite samples, the exchange rate model will have a higher mean squared error due to the fact that it has to estimate the parameter. See Clark and West (2006) for a more detailed explanation.

Panel A in Table IV shows that exchange rates help forecast commodity prices, even out-of-sample.[34] The exchange rate-based models outperform both an AR(1) and the random walks, with and without drift, in forecasting changes in world commodity prices, and this result is quite robust across the five countries. The strong evidence of commodity price predictability in both in-sample and out-of-sample tests is quite remarkable, given the widely documented pattern in various forecasting literature that in-sample predictive ability often fails to translate to out-of-sample success. In addition, because exchange rates are available at extremely high frequencies, and because they are not subject to revisions, our analysis is immune to the common critique that we are not looking at real time data forecasts, and can be extended to look at higher frequencies than typically possible under the standard macro fundamental-based exchange rate analyses.

INSERT TABLE IV HERE

3.2. Can Exchange Rates Predict Aggregate World Commodity Price Movements? Multivariate Predictions and Forecast Combinations. Having found that individual exchange rates can forecast the price movements of its associated country's commodity export basket, we next consider whether combining the information from all of our commodity currencies can help predict price fluctuations in the aggregate world commodity market. For the world market index, we use the aggregate commodity price index from the IMF (cp^W) described earlier.[35] We show that forecasts of commodity prices improve by combining multiple commodity currencies. Intuitively, a priori, one would expect that global commodity prices depend mainly on global shocks, whereas commodity currency exchange rates depend on country-specific shocks, in addition to global shocks

[34] We also estimated R^2 of the out-of-sample regressions. The values are 3% for Australia, 8% for New Zealand, 2% for Canada, 8% for Chile and 9% for South Africa.

[35] As discussed in Section 2, we report here results based on the non-fuel commodity index from the IMF, as it covers a broad set of products and goes back to 1980. Additional results based on alternative aggregate indices, including the IMF index with energy products, are available upon request.

(mainly through commodity prices.) Thus, a weighted average of commodity currencies should, in principle, average out some of the country specific shocks and produce a better forecast of aggregate global commodity price.

We first look at the in-sample predictability of the world price index and consider multivariate Granger-causality regressions using the three longest exchange rate series (South Africa and Chile are excluded to preserve a larger sample size):[36]

$$E_t \Delta cp_{t+1}^W = \beta_0 + \beta_{11} \Delta s_t^{AUS} + \beta_{12} \Delta s_t^{CAN} + \beta_{13} \Delta s_t^{NZ} + \beta_2 \Delta cp_t^W \tag{5}$$

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

We next extend the analysis to look at out-of-sample forecasts. We consider two approaches: multivariate forecast and combination of univariate forecasts. The multivariate forecast uses the same three exchange rates as in equation (5) above to implement the rolling regression forecast procedure described in the previous section. We again use Clark and McCracken's (2001) "ENC-NEW" test to evaluate the model's forecast performance relative to the three benchmark forecasts. Table V Panel D shows that using the three commodity currencies together, we can forecast the world commodity price index significantly better than both a random walk and an autoregressive model at the 5% level. The model's forecasts also beat those of a random walk with drift, although not significantly. This forecast power is also quite apparent when we plot the exchange rates-based

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

forecasts along with the actual realized changes of the (log) global commodity price index in Figure I. The random walk forecast is simply the x-axis (forecasting no change). We see that overall, the commodity currency-based forecasts track the actual world price series quite well, and fit strikingly better than a random walk.[37]

INSERT TABLE V AND FIGURE I HERE

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

$$E_t \Delta cp_{t+1}^{W,i} = \beta_{0,i} + \beta_{1,i} \Delta s_t^i \quad \text{where } i = AUS, CAN, NZ \tag{6}$$

While there are different methods to weigh the individual forecasts, it is well known that simple combination schemes tend to work best (Stock and Watson 2003 and Timmermann 2006.) We consider equal weighting here, and compare our out-of-sample forecast of future global commodity prices, $\left(\Delta \widehat{cp}_{t+1}^{W,AUS} + \Delta \widehat{cp}_{t+1}^{W,CAN} + \Delta \widehat{cp}_{t+1}^{W,NZ}\right)/3$, with the benchmark forecasts (Table V Panel E.) Again, we observe that the MSFE differences are all negative, indicating the better performance of the exchange rate based approach.[38] This finding is illustrated graphically in Figure II, which plots the forecasted global commodity price obtained via forecast combination, along with the actual data (both in log differences). The random walk forecast, of no change, is the x-axis. The

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

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

figure shows that the combined forecast tracks the actual world price series much better than the random walk.

INSERT FIGURE II HERE

As a robustness check, we also examine whether each individual exchange rate series by itself can predict the global market price index.[39] We note that this exercise is perhaps more a test to see whether there is strong co-movement amongst individual commodity price series, rather than based on any structural model. The first lines (labeled "s_t GC cp_{t+1}") in Table VI(a) report results for the predictive performance of each country-specific exchange rates. Remarkably, the finding that exchange rates predict world commodity prices appears extremely robust: individual commodity currencies have strong predictive power for price changes in the aggregate global commodity market. As an example, Figure III shows how well the Chilean exchange rate alone can forecast changes in the aggregate commodity market index since 1999.

INSERT TABLE VI(a) AND FIGURE III HERE

While we report in-sample test results against a driftless random walk benchmark in our earlier tables, the same qualitative conclusion prevails when we exclude the intercept term and consider only the coefficient on the explanatory variable in our tests. Table VI(b) shows the main results for predicting the aggregate global commodity price index with exchange rates and vice versa. Panels A-C report the p-values for testing the null hypothesis that $\beta_1 = 0$ in the following regressions:

[39] The sample sizes now differ for each country, and for Chile and South Africa, we have less than 10 years of our-of-sample forecasts as they have a shorter history of floating exchange rate.

$$E_t \Delta cp^W_{t+1} = \beta_0 + \beta_1 \Delta s^j_t, \quad (7)$$

$$E_t \Delta s^j_{t+1} = \beta_0 + \beta_1 \Delta cp^W_t, \quad (8)$$

where j=AUS, NZ, CAN, CHI, SA. Panel D shows the results for testing the null hypothesis that $\beta_{11} = \beta_{12} = \beta_{13} = 0$ in the multivariate Granger-causality regression below:

$$E_t \Delta cp^W_{t+1} = \beta_0 + \beta_{11} \Delta s^{AUS}_t + \beta_{12} \Delta s^{CAN}_t + \beta_{13} \Delta s^{NZ}_t + \beta_2 \Delta cp^W_t \quad (9)$$

We see that our conclusions are indeed robust to this alternative test.

INSERT TABLE VI(b) HERE

3.3. Can Commodity Prices Predict Exchange Rates?. Having found strong and robust evidence that exchange rates can Granger-cause and forecast out-of-sample future commodity prices, we now consider the reverse exercise of forecasting these exchange rates. First, we show positive in-sample results by allowing for structural breaks. In terms of out-of-sample forecasting ability, however, commodity currencies exhibit the same Meese-Rogoff puzzle as other major currencies studied in the literature; none of the fundamentals, including commodity prices, consistently forecasts exchange rate movements better than a random walk.[40]

The lower panels (Panel B) in Tables I-IV, and Tables VI(a) and (b) present results on exchange rate predictability by commodity prices. We first consider whether commodity prices Granger-

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

cause nominal exchange rate changes, using standard tests that ignore the possibility of parameter instability. We look for rejection of the null hypothesis that the $\beta_0 = \beta_1 = 0$ in the following regression:

$$E_t \Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta s_t \tag{10}$$

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

$$E_t \Delta s_{t+1} = \beta_{0t} + \beta_{1t} \Delta cp_t + \beta_2 \Delta s_t \tag{11}$$

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

The major difference between the two directions comes from comparing out-of-sample forecasting ability. Comparing results in part B to part A within each panel in Table IV, we see that there are no negative numbers in part B and overall little evidence of exchange rate predictability, giving us exactly the Meese-Rogoff stylized fact. We note the same pattern in Table VI(a) Panel D, where individual exchange rates forecast aggregate world commodity price index better than a random walk, but world commodity price index in general does not help forecast exchange rates. (Allowing for a possible drift term in the random walk, Table VI(b) Panel C shows the same conclusion.)

As discussed extensively in Section 2, this asymmetry in forecastability should not be surprising, given that commodity prices are a fundamental determinant to these commodity currencies and the net present value relationship.

4. Robustness Analyses

The previous section shows strong evidence that the U.S. dollar-based exchange rates of the five commodity-exporters can forecast price movements in global commodity markets. This finding raises some questions as well as potentially interesting implications, which we explore in this section. First, we consider whether this dynamic connection between movements in the currencies and in the commodity prices may result from a "dollar effect", as both are priced in U.S. dollars. Second, we explore longer-horizon predictions, up to two years ahead, using an alternative predictive regression specification that is robust to highly persistent regressors. To assess the practical relevance of our findings, we next compare exchange rate-based commodity price forecasts with those based on commodity derivative prices, using information from several metal forward markets and the Dow Jones-AIG commodity futures indices as examples. To conserve space, we present in the main text below only a brief discussion and the results for each issue. More details are provided in Appendix C, where we also look more carefully at the exogeneity assumption of commodity prices for Chile and South Africa, how our results fare under the global financial crisis that broke out in mid-2008, and the usefulness of these exchange rates for forecasting the standard macro exchange rate fundamentals.[41]

[41] Including other explanatory variables using other methodologies might also be interesting to explore. Groen and Pesenti (2009) consider factor-augmented models that include exchange rates and find that, of all the approaches, the

4.1. Alternative Benchmark Currencies. Since commodity products are priced in dollars, there may be some endogeneity induced by our use of dollar cross rates in the analyses above. For instance, one could imagine that when the dollar is strong, global demand for dollar-priced commodities would decline, inducing a drop in the associated commodity prices. Any aggregate uncertainty about the U.S. dollar may also simultaneously affect commodity prices and the value of the dollar (relative to the commodity currencies.) To remove this potential reverse causality or endogeneity, we report in Tables VII(a) and VII(b) the same analyses from Section 3 above, using the nominal effective exchange rates of these countries as well as their bilateral rates relative to the British pound We see that for both the in-sample predictive Granger-causality regressions and out-of-sample forecast comparisons, our previous conclusions hold up strongly (and at times even more pronounced.)

INSERT TABLE VII(a) and VII(b) HERE

4.2. Long-Horizon Predictability. We have analyzed the dynamic connections between nominal exchange rates and fundamentals using data in first-differences thus far. This approach is appropriate for short-horizon analyses, and is consistent with the view that the data contain unit roots, which both has overwhelming empirical support and is theoretically sensible.[42] Here we consider an alternative specification and inference procedure that is robust to the possibility that the largest autoregressive (AR) roots in these series may not be exactly one, despite being very close to one. We look at longer-horizon predictive regressions by modeling the regressors as highly persistent, and use tests statistics based on local-to-unity asymptotics (see Appendix C for details).

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exchange-rate-based model (3) and the predictive least squares factor augmented model are more likely to outperform the naive statistical benchmarks.

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

The confidence intervals in Table VIII show that our earlier results are very robust: the in-sample predictive regressions work well in both directions for horizons up to two years.

INSERT TABLE VIII HERE

4.3. Commodity Derivatives. Our results provide strong and robust evidence that commodity currency exchange rates can forecast future spot commodity prices. An obvious question then is how their predictive power compares to information in the derivatives markets. Do exchange rates contain additional information beyond what's in the forward or futures prices? We begin by looking first at the copper forward market, and then an aggregate forward price index of three metal products, as well as the Dow Jones-AIG commodity futures index. (We note that for the type of fixed-horizon forecasts conducted in this paper, futures prices and price indices are not the ideal comparison. This is because standardized futures contracts have only a few fixed delivery dates per year, and the indices contain price information averaged over contracts of different maturity dates. Forward prices, on the other hand, provide an easy comparison with our forecasts. However, forward trading in commodities is thin, and data availability appears limited to a few metal products only.)

Given the data limitations, we first explore whether individual exchange rates have any predictive power for future copper spot price above and beyond the copper market forward premium. Let f^{cu}_{t+1} denote the one-quarter ahead forward price of copper at time t, cp^{cu}_t the spot price of copper, and s_t the bilateral exchange rate of each country relative to the U.S. dollar. We consider the following two regression specifications:

$$E_t \Delta cp^{cu}_{t+1} = \beta_0 + \beta_1 \left(f^{cu}_{t+1} - cp^{cu}_t \right) + \beta_2 \Delta cp^{cu}_t + \beta_3 \Delta s_t \tag{12}$$

$$E_t \Delta cp_{t+1}^{cu} = \beta_0 + \left(f_{t+1}^{cu} - cp_t^{cu}\right) + \beta_2 \Delta cp_t^{cu} + \beta_3 \Delta s_t \tag{13}$$

The first regression is a forward premium regression of market efficiency, augmented to include the lagged exchange rate changes. The second regression further imposes the forward premium coefficient to be unity.[43] We test whether $\beta_3 = 0$. Table IX shows that both in sample and out of sample, the Chilean exchange rate has strong predictive power for future copper prices. This confirms our economic intuition behind the exchange rate-commodity price linkage discussed in Section 2. Amongst our five countries, copper constitutes a significant share of the overall commodity exports only for Chile. As such, world copper price is an especially important fundamental for the Chilean exchange rate. It is therefore not surprising that market expectations for future copper prices is only priced into the Chilean currency.

Next, since our model suggests that commodity currencies in general should contain information about aggregate commodity indices rather than about specific individual products, we construct an equal-weighted index of gold, silver, and platinum prices to see if our exchange rates can forecast this index better than the corresponding forward rate index.[44] Specifically, we construct a spot metal price index and a forward rate index as below:

$$\Delta cp_{t+1}^{M} = \frac{1}{3}(\Delta cp_{t+1}^{\text{Gold}} + \Delta cp_{t+1}^{\text{Silver}} + \Delta cp_{t+1}^{\text{Platinum}}) \tag{14}$$

$$f_{t+1}^{M} - cp_{t+1}^{M} = \frac{1}{3}\sum_i (f_{t+1}^{i} - cp_{t+1}^{i}) \text{ where i = Gold, Silver, and Platinum} \tag{15}$$

We use all five of our exchange rates to forecast changes in the spot index Δcp_{t+1}^{M} out of sample,

[43] We test both of these equations with and without including the lagged commodity price term ($\beta_2 \Delta cp_t$), and find qualitatively similar results.

[44] With the availability of more forward price data, we can extend our analysis to look a more comprehensive aggregate index.

using to the following specification:

$$E_t \Delta cp^M_{t+1} = \beta_0 + \sum_j \beta_{1j} \Delta s^j_t \text{ where j = AUS, CAN, CHI, NZ, and SA} \tag{16}$$

Figure IV shows the comparison of the actual spot price movements, exchange rate-based forecasts, and the averaged forward rates.[45] We note that the forward rate index severely under-predict actual spot price movements. More importantly, despite the fact that we are only looking at a limited set of products, we see that the exchange rates together provide a much better prediction of the actual spot price movements.

INSERT TABLE IX AND FIGURE IV HERE

Finally, we look at the aggregate commodity markets and compare our exchange rate model against the 3-month DJ-AIGCI forward index (of futures contracts) in predicting the corresponding DJ-AIG spot commodity price index.[46] Figure V shows what the prediction based on futures prices is way off, compared to the exchange rate-based predictions. In fact, the MSFE for the exchange rate-based model is 0.005, significantly better than the 0.08 based on the forward index.[47]

INSERT FIGURE V HERE

These results suggest that the information embodies in the exchange rates is not only different from what's in the commodity derivatives, it is also more useful as an indicator for actual spot

[45] The time frame for comparison is limited by data availability. With only five years of forward price data, we are unable to conduct the same marginal predictability analyses as above.

[46] The AIG indexes are available starting in 1999. See http://www.djindexes.com/ for a detailed descriptions of these indexes.

[47] In addition, we also conducted the same comparison for sub-indexes, such as industrial metal index and the precious metal index. For prediction the industrial metal spot index, the MSFE of the exchange rate model is 0.012, and is significantly better than the one based on the industrial metal forward index, which has a MSFE of 0.0304. When forecasting the precious metal spot price index, forecasts based on our model and on the forward sub-index are not significantly different.

commodity price movements in the future. This finding has obvious significance for policy, and we believe warrant further investigation which we leave for future research.[48]

5. Conclusion

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

Our results appear robust to multivariate regressions, choice of the numeraire currency, forecast combinations, highly persistent (local-to-unit root) regressors, and longer-horizon predictions. Of course, further robustness tests and testing of alternative specifications will be informative. One might eventually extend the approach to look at countries that have few or no commodities, such

[48] Indeed, Federal Reserve Chairman Bernanke mentioned in his June 9th, 2008 speech that the markets for longer-dated futures contracts are often quite illiquid, suggesting that the associated futures prices may not effectively aggregate all available information. He then raised the question of whether it is possible to improve our forecasts of commodity prices, using information from futures markets but possibly other information as well. Our results offer a viable answer.

as most of Asia, to see if commodity prices affect the value of their currencies, and if their currency fluctuations may offer predictive power for, say, oil prices. In addition, this paper focuses on establishing a structural link between exchange rates and future commodity prices through the terms of trade and income channel; alternatively, one might conjecture a financial linkage across asset markets, where equity or bond markets in these countries also offer useful information for commodity market behavior. Alternative forecast methods that efficiently incorporate information in various financial and macroeconomic indicators, possibly in a non-linear fashion, may also provide forecast improvements. We leave these potentially interesting issues for future research.

6. Appendix A. Composition of the Commodity Price Indices

INSERT TABLE A.1 HERE

7. Appendix B: Time Series Methods

This section provides a description of the test statistics used in this paper. Let the model be: $y_t = x'_{t-1}\beta_t + \varepsilon_t$, $t = 1, ..T$, where x_{t-1} is a $p \times 1$ vector of explanatory variables.[49]

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

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

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

$$\widehat{S} = \left(\frac{1}{T}\sum_{t=2}^{T} x_{t-1}\widehat{\varepsilon}_t\widehat{\varepsilon}_t x'_{t-1}\right) + \sum_{j=2}^{T-1}\left(1 - |\frac{j}{T^{1/3}}|\right)\left(\frac{1}{T}\sum_{t=j+1}^{T} x_{t-1}\widehat{\varepsilon}_t\widehat{\varepsilon}_{t-j}x'_{t-1-j}\right), \tag{17}$$

$\widehat{\varepsilon}_t \equiv y_t - x'_{t-1}\widehat{\beta}$, and $\widehat{\beta}$ is the full-sample OLS estimator:

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

Under the null hypothesis of no Granger-causality ($\beta = 0$), W_T is a chi-square distribution with p degrees of freedom. If there is no serial correlation in the data, only the first component in (17) is

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

relevant.

7.2. Rossi (2005b). Rossi (2005b) shows that traditional Granger-causality tests above may fail in the presence of parameter instabilities. She therefore develops optimal tests for model selection between two nested models in the presence of underlying parameter instabilities in the data. The procedures are based on testing jointly the significance of additional variables that are present only under the largest model and their stability over time.[50] She is interested in testing whether the variable x_t has no predictive content for y_t in the situation where the parameter β_t might be time-varying. Among the various forms of instabilities that she considers, we focus on the case in which β_t may shift from β to $\overline{\beta} \neq \beta$ at some unknown point in time.

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

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

The test builds on two components: $\frac{\tau}{T}\widehat{\beta}_{1\tau} + \left(1-\frac{\tau}{T}\right)\widehat{\beta}_{2\tau}$ and $\widehat{\beta}_{1\tau} - \widehat{\beta}_{2\tau}$. The first is simply the full-sample estimate of the parameter, $\frac{\tau}{T}\widehat{\beta}_{1\tau} + \left(1-\frac{\tau}{T}\right)\widehat{\beta}_{2\tau} = \widehat{\beta}$; a test on whether this component is zero is able to detect situations in which the parameter is constant but different from zero. However, if the regressor Granger-causes the dependent variable in such a way that the parameter changes

[50] Rossi (2005b) considered the general case of testing possibly nonlinear restrictions in models estimated with Generalized Method of Moments (GMM). Here, we provide a short description in the simple case of no Granger-causality restrictions in models whose parameters are consistently estimated with Ordinary Least Squares (OLS), like the Granger-causality regressions implemented in this paper. She also considers the case of tests on subsets of parameters, that is the case where $y_t = x'_{t-1}\beta_t + z'_{t-1}\delta + \varepsilon_t$ and the researcher is interested in testing only whether x_t Granger-causes y_t.

but the average of the estimates equals zero, then the first component would not be able to detect such situations. The second component is introduced to perform that task. It is the difference of the parameters estimated in the two sub-samples; a test on whether this component is zero is able to detect situations in which the parameter changes at time τ. The test statistic is the following:

$$Exp - W_T^* =$$

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

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

$$\widehat{S}_1 = \left(\frac{1}{\tau}\sum_{t=2}^{\tau} x_{t-1}\widehat{\varepsilon}_t\widehat{\varepsilon}_t x_{t-1}'\right) + \sum_{j=2}^{\tau-1}\left(1 - \left|\frac{j}{\tau^{1/3}}\right|\right)\left(\frac{1}{\tau}\sum_{t=j+1}^{\tau} x_{t-1}\widehat{\varepsilon}_t\widehat{\varepsilon}_{t-j} x_{t-1-j}'\right), \tag{18}$$

$$\begin{aligned} \widehat{S}_1 = {} & \left(\frac{1}{T-\tau}\sum_{t=\tau+1}^{T-\tau} x_{t-1}\widehat{\varepsilon}_t\widehat{\varepsilon}_t x_{t-1}'\right) \\ & + \sum_{j=\tau+1}^{T-\tau}\left(1 - \left|\frac{j}{(T-\tau)^{1/3}}\right|\right)\left(\frac{1}{T-\tau}\sum_{t=j+1}^{T-\tau} x_{t-1}\widehat{\varepsilon}_t\widehat{\varepsilon}_{t-j} x_{t-1-j}'\right). \end{aligned} \tag{19}$$

Under the joint null hypothesis of no Granger-causality and no time-variation in the parameters ($\beta_t = \beta = 0$), $Exp - W_T^*$ has a distribution whose critical values are tabulated in Rossi's (2005b) Table B1. If there is no serial correlation in the data, only the first component in (18) and (19) is relevant.

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

$$Model \quad : \quad y_t = x'_{t-1}\beta_t + \varepsilon_t \tag{20}$$

$$Random\ Walk \quad : \quad y_t = \varepsilon_t, \tag{21}$$

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

To compare the out-of-sample predictive ability of (20) and (21), Diebold and Mariano (1995), West (1996) suggest focusing on:

$$d_t \equiv \left(y_t - f_t(\widehat{\beta}_t)\right)^2 - \left(y_t - f_t^{RW}\right)^2 \tag{22}$$

They show that the sample average of d_t, appropriately re-scaled, has an asymptotic standard Normal distribution. However, this is not the case when the models are nested, as in our case. Clark and McCracken's (2001) show that, under the null hypothesis that the model is (21), the tests of Diebold and Mariano (1995) and West (1996) do not have a Normal distribution. They propose a new statistic, ENCNEW, which is the following:

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

Its limiting distribution is non-standard, and critical values are provided in Clark and McCracken (2001). Clark and West (2006) propose a correction to (22) that results in an approximately normally distributed test statistic.

8. Appendix C. Additional Robustness Analyses

This Appendix discusses in details the results reported in the robustness analyses from Section 4 as well as the following issues mentioned in the main text: 1) the validity of the exogeneity assumption of commodity prices for Chile and South Africa; 2) how our model behaves under the financial crisis that broke out in mid-2008, and 3) whether the exchange rate predicts commodity prices better than predicting the standard macro fundamentals in out-of-sample forecasts.

8.1. Alternative Benchmark Currencies. We re-examine the predictive Granger-causality regressions and out-of-sample forecast exercises using nominal effective exchange rates and bilateral exchange rates relative to the British pound. Table VII(a) and VII(b) report results parallel to those in Tables I-IV. Panels A and B report the p-values for the Granger-causality and Andrews' (1993) QLR tests for the predictive regressions. Panel C shows predictability results robust to parameter instabilities, using Rossi's (2005b) $Exp-W^*$ test. Lastly, Panel D reports the relative MSFEs from comparing exchange rate-based models to the AR(1) benchmark and the random walk in out-of-sample forecasts.

Overall, we see that our earlier conclusions are extremely robust, and the importance of addressing parameter instability is even more pronounced here. Ignoring structural breaks, hardly any of the traditional Granger-causality tests in Panel A reject the null hypothesis of no relationship between exchange rates and commodity prices. However, as before, we uncover substantial instabilities in such regressions (Panel B), found mostly around 2002-2005. When such instability is taken into account, we see strong indication in favor of Granger-causality. In particular, we see the evidence is stronger when we use exchange rates to predict the commodity price indices than the other way around. Panel D shows that the predictive power of exchange rates for future commodity prices carries over to out-of-sample forecasts as well.[51]

8.2. Highly Persistent Regressors and Long-Horizon Predictability. This section considers an alternative specification and inference procedure that is robust to the possibility that the largest autoregressive (AR) roots in these series may not be exactly one, despite being very close to one. This is achieved by modeling the regressors in the predictive regressions as highly persistent and use tests statistics based on local-to-unity asymptotics. We focus on three countries only: Australia, Canada, and New Zealand, as they have longer sample periods which are necessary for more meaningful testing of long-horizon predictability. Letting s_t and cp_t denote the levels of nominal exchange rate and fundamental (commodity prices) at time t, the short horizon exchange rate predictive regression can be expressed as follows:

$$\Delta s_{t+1} = \mu_1 + \beta \ cp_t + \gamma \ \Delta s_t + \epsilon_{1,t+1} \tag{23}$$

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

[51] Using monthly data, we also observe strong predictability of commodity prices, both in- and out-of-sample, using nominal effective exchange rates. This is another indication that "the dollar effect" is not dominating our findings.

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

Assuming the same stochastic process for cp_t above, the corresponding long-horizon regression can be expressed as:[52]

$$\Sigma_{j=1}^{h}\Delta s_{t+j} = \beta_h \; cp_t + \lambda \Delta s_t + \xi_{t,h} \tag{24}$$

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

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

$$\Sigma_{j=1}^{h}\Delta cp_{t+j} = \beta_h s_t + \lambda \Delta cp_t + \xi_{t,h} \tag{25}$$

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

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

Table VIII reports the 95% confidence intervals for β estimated from (23) in the rows with "$h = 1$"(one quarter-ahead forecast), and confidence intervals for β_h estimated from (24) and (25)

[52] Regression (23) includes the lagged endogenous variable, where we assume $|\gamma| < 1$. The formula in Rossi (2007a) has to be modified to take this into account. Her expression (4.14) becomes: $\beta_h = \beta \sum_{j=1}^{h} \rho^{j-1} (1-\gamma)^{-1}$, and the confidence interval follows straightforwardly from this. Direct calculations show that $\lambda \equiv h\Sigma_{j=1}^{h}\gamma^j$.

in the rows under "$h = 4$" and "$h = 8$", for one- and two-year-ahead forecasts, respectively.[53] When the confidence intervals do not contain zero, we consider them as evidence in favor of predictive ability. The table shows that the predictability at long horizons is quite strong, both from exchange rates to commodity prices and vice-versa (with the exception of predicting the Canadian commodity price index). This supports our earlier findings, based on first-differenced specifications, that the in-sample dynamic connection between commodity prices and exchange rates is very strong and robust.[54]

8.3. Exogeneity. As discussed in Section 2, the exogeneity of world commodity prices to the small open economies we consider is important interpret the Granger-causality results as favorable evidence for the net present value model of exchange rate determination (although it is important to note that this assumption is not necessary for interpreting the out-of-sample forecasting results).

One might be worried that commodity prices may possibly instead be endogenous due to the market power that these countries hold in specific commodity product markets. For some countries such as Australia, Canada and New Zealand, this is not a concern as their commodity exports are over a fairly diffused set of products, and as demonstrated in Chen and Rogoff (2003), world commodity prices are exogeneity to these small economies. However, Chile is one of the most important producers of copper, and therefore its market power might invalidate the exogeneity assumption. Similar concerns arise regarding South Africa, a big exporter of a few precious metals.

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

[54] We also conducted additional analyses using standard fundamentals, although these are highly endogenous, as we have noted. In the interest of space, we do not report the full table here. Overall, we find that for most countries and most fundamentals, we are able to reject the null hypothesis of no predictability (i.e. most confidence intervals exclude zero). In this paper, we do not consider out-of-sample forecasts at long horizons for two reasons: first, the main puzzle in the literature is the lack of short horizon forecastability of exchange rates and commodity prices, as the literature, in some instances, did find empirical evidence in favor of long-horizon predictability (cfr. Mark 2001). Second, the evidence in favor of long horizon predictability is nevertheless plagued by spurious regressions problems as well as difficulties in assessing significance (cfr. Rossi 2005a).

To address these potential concerns, we use the aggregate world commodity price index as an instrument, and verify that the exogeneity assumption holds using the Hausman (1978) test for endogeneity.

The Hausman test compares the OLS estimator with an Instrumental Variables (IV)-GMM estimator; under the null hypothesis of exogeneity, the two estimators should not be statistically different.[55] Table C.1 reports the results for the full sample test. It is clear that the exogeneity of the country-specific commodity price indices is not rejected for both Chile and South Africa.

INSERT TABLE C.1

8.4. Including the Latest Financial Crises Data. To evaluate the consequences of considering different sample periods, we recursively compare the models' forecasting performance against an AR(1) benchmark over a range of dates, using the window sizes discussed in Section 3. This exercise mimics how a forecaster would have evaluated the models' forecasting performance in real time. We consider only Australia, Canada, and New Zealand here, due to the small sample sizes available for Chile and South Africa. We look at how individual exchange rate forecasts the corresponding commodity price index for the country. Figure C.1 plots the Clark and West (2006) statistics calculated at different points in time, specified on the x-axis. For example, the results in Section 3 correspond to the values shown in the figure for 2008Q1. The evidence is favorable to the exchange rate model when the line is above the 10% critical value line. Figure C.1 shows that

[55] We exploit the fact that when these small countries' exchange rate changes (e.g. due to changes in their domestic economic conditions), it will have no effect on the aggregate world commodity prices (product substitutions and the small size of these economies limit their market power in the global market; see Chen and Rogoff 2003). For example, since Chile is a major copper producer, one may expect that when the Chile's economy is bad, both its exchange rate and world copper prices would be affected, leading to endogeneity in our analysis. But we should not expect the aggregate commodity market prices, covering forty some products, to be driven by Chilean-specific events. Therefore, we can instrument Chile's country specific commodity price with the world commodity price index as a test of exogeneity. When the OLS and the GMM-IV estimates are not significantly different, this suggests that our country-specific results are not likely to be driven by endogeneity.

the predictability is very robust until the onset of the financial crisis.

INSERT FIGURE C.1 HERE

8.5. Standard Macro Fundamentals. In addition to commodity prices, here we also consider additional fundamentals in the spirit of more traditional models of exchange rate determination. The additional fundamentals that we consider are short and long term interest rate differentials, output differentials and inflation differentials. Table C.2 shows that exchange rates have consistently significant out of sample predictive ability mainly for commodity prices, and that the results for the other fundamentals are much more mixed and sporadic. We note that exchange rates do improve forecasts of output differentials for some countries, which would be consistent with the income effect of commodity price shocks we discuss in Section 2. However, the endogeneity of problem complicates interpretation.[56]

INSERT TABLE C.2 HERE

[56] Unreported results show that Granger causality cannot be rejected for most of these other fundamentals, in line with the results in Engel and West (2005) and Rossi (2007b). However, our results show that in-sample Granger causality does not imply out-of-sample forecasting ability, which is a much more stringent test.

9. References

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10. Tables

Table I. Bivariate Granger-Causality Tests

	AUS	NZ	CAN	CHI	SA
A. P-values of $H_0 : \beta_0 = \beta_1 = 0$ in $\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$					
	.17	.11	.06*	.10*	.01***
B. P-values of $H_0 : \beta_0 = \beta_1 = 0$ in $\Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta s_t$					
	.41	.45	.92	.70	.40

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

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

	AUS	NZ	CAN	CHI	SA
A. P-values for stability of (β_{0t}, β_{1t}) in: $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t} \Delta s_t + \beta_2 \Delta cp_t$					
	.00***	.13	.13	.56	.00***
	(2004:2)				(2005:4)
B. P-values for stability of (β_{0t}, β_{1t}) in: $\Delta s_{t+1} = \beta_{0t} + \beta_{1t} \Delta cp_t + \beta_2 \Delta s_t$					
	.00***	.00***	.05**	.00***	.00***
	(2004:2)	(2004:3)	(2002:3)	(2005:1)	(2005:4)

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

Table III. Granger-Causality Tests Robust to Instabilities,

Rossi (2005b)

	AUS	NZ	CAN	CHI	SA
A. P-values for $H_0 : \beta_t = \beta = 0$ in $\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \beta_2 \Delta cp_t$					
	.02**	.07*	.05**	.22	.00***
B. P-values for $H_0 : \beta_t = \beta = 0$ in $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t + \beta_2 \Delta s_t$					
	.00***	.09*	.36	.00***	.00***

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

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

	AUS	NZ	CAN	CHI	SA
Panel (a): Autoregressive benchmark					
A. MSFE differences: Model: $E_t\Delta cp_{t+1}= \beta_{0t}+\beta_{1t}\Delta cp_t+\beta_{2t}\Delta s_t$ vs.AR(1): $E_t\Delta cp_{t+1}= \gamma_{0t}+\gamma_{1t}\Delta cp_t$					
	1.81***	0.32***	1.05**	-0.16**	1.34***
B. MSFE differences: Model: $E_t\Delta s_{t+1}= \beta_{0t}+\beta_{1t}\Delta s_t+\beta_{2t}\Delta cp_t$ vs.AR(1): $E_t\Delta s_{t+1}= \gamma_{0t}+\gamma_{1t}\Delta s_t$					
	0.24	0.23	1.63	1.81**	1.57
Panel (b): Random walk benchmark					
A. MSFE differences: Model: $E_t\Delta cp_{t+1}= \beta_{0t}+\beta_{1t}\Delta s_t$ vs. Random walk: $E_t\Delta cp_{t+1}= 0$					
	-2.11***	-1.61***	-0.01	-0.44***	-1.39***
B. MSFE differences: Model: $E_t\Delta s_{t+1}= \beta_{0t}+\beta_{1t}\Delta cp_t$ vs. Random walk: $E_t\Delta s_{t+1}= 0$					
	0.53*	0.23**	0.59	0.99	2.09
Panel (c): Random walk with drift benchmark					
A. MSFE differences: Model: $E_t\Delta cp_{t+1}= \beta_{0t}+\beta_{1t}\Delta s_t$ vs. Random walk with drift: $E_t\Delta cp_{t+1}= \gamma_{0t}$					
	-0.14*	-0.75***	1.04	-0.43**	1.68***
B. MSFE differences: Model: $E_t\Delta s_{t+1}= \beta_{0t}+\beta_{1t}\Delta cp_t$ vs. Random walk with drift: $E_t\Delta s_{t+1}= \gamma_{0t}$					
	0.06	0.15**	1.79**	0.90	1.37

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

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

Panel A. Multivariate Granger-Causality Tests
.00***
Panel B. Andrews' (1993) QLR Test for Instabilities
.03** (2003:4)
Panel C. Multivariate Granger-Causality Tests Robust to Instabilities, Rossi (2005b)
.00***
Panel D. Out-of-Sample Forecasting Ability
AR(1) benchmark: 0.00**
Random walk benchmark: -0.64**
Random walk with drift benchmark: -0.26
Panel E. Forecast Combination
AR(1) benchmark: -1.03
Random walk benchmark: -1.69*
Random walk with drift benchmark: -1.42

Notes: The table reports results from various tests using the AUS, NZ and CAN exchange rates to jointly predict aggregate global future commodity prices (cp^W). Panels A-C report the p-values, and Panels D and E report the MSFE differences between the model-based forecasts and the RW and AR forecasts. *** indicates significance at the 1% level, and ** significance at 5%.

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

Driftless Random Walk Benchmark and Out-of-Sample Forecasts

		AUS	NZ	CAN	CHI	SA
	Panel A. Granger-Causality Tests					
s_t GC cp^W_{t+1}		.00***	.00***	.01***	.11	.17
cp^W_t GC s_{t+1}		.85	.42	.82	.01***	.02**
	Panel B. Andrews' (1993) QLR Test for Instabilities					
s_t GC cp^W_{t+1}		.08*	.22	.39	.00***	.08*
		(2003:4)			(2003:3)	(2003:3)
cp^W_t GC s_{t+1}		.01***	.00***	.15	.00***	.02**
		(2003:4)	(2003:4)		(2003:4)	(2003:4)
	Panel C. Granger-Causality Tests Robust to Instabilities, Rossi (2005b)					
s_t GC cp^W_{t+1}		.00***	.00***	.04**	.00***	.21
cp^W_t GC s_{t+1}		.17	.04**	.36	.00***	.00***
	Panel D. Out-of-Sample Forecasting Ability					
AR(1) benchmark:	$s_t \Rightarrow cp^W_{t+1}$	-1.26***	-0.43***	-0.12***	-2.18***	0.01***
	$cp^W_t \Rightarrow s_{t+1}$	2.12	1.98	1.44	1.07***	0.52
Random walk benchmark:	$s_t \Rightarrow cp^W_{t+1}$	-1.90***	-0.89***	-0.71***	-2.23***	0.47***
	$cp^W_t \Rightarrow s_{t+1}$	1.69	0.87	1.45	1.65	078**
Random walk with drift	$s_t \Rightarrow cp^W_{t+1}$	-1.25***	-0.50**	-0.09***	-2.17***	-0.06***
benchmark:	$cp^W_t \Rightarrow s_{t+1}$	1.27	0.25	1.01	0.53**	1.53

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

Table VI(b). Aggregate Global Commodity Price Index and Exchange Rates vs. Random Walk with Drift Benchmark

	AUS	NZ	CAN	CHI	SA
	Panel A. Granger-Causality Tests				
s_t GC cp^W_{t+1}	.00***	.00***	.02**	.06*	.15
cp^W_t GC s_{t+1}	.59	.22	.64	.44	.71
	Panel B. Andrews' (1993) QLR Test for Instabilities				
s_t GC cp^W_{t+1}	1.00	.15	.37	.00***	.15
				(2003:3)	
cp^W_t GC s_{t+1}	.26	.11	.86	1.00	.53
	Panel C. Granger-Causality Tests Robust to Instabilities, Rossi (2005b)				
s_t GC cp^W_{t+1}	.00***	.00***	.04**	.00***	.12
cp^W_t GC s_{t+1}	.66	.26	1.00	1.00	1.00
	Panel D. Joint tests				
Granger-causality Test			.00***		
Andrews' (1993) QLR Test for Instabilities			.40		
Granger-causality Test Robust to Instabilities, Rossi (2005b)			.00***		

Note. Panels A-C report p-values for tests for $\beta_1 = 0$ based on two regressions:

(i) $\Delta cp^W_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp^W_t$ (labeled s_t GC cp^W_{t+1}) and (ii) $\Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp^W_t + \beta_2 \Delta s_t$ (labeled cp^W_t GC s_{t+1}). Estimated break-dates are reported in parentheses. Panel D reports results for testing $\beta_{11} = \beta_{12} = \beta_{13} = 0$ in the multivariate regression below:

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

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

Table VII(a). Nominal Effective Exchange Rate

		AUS	NZ	CAN	CHI	SA
	Panel A. Multivariate Granger-Causality Tests					
s_t GC cp_{t+1}		.18	.22	.11	.22	.00***
cp_t GC s_{t+1}		.06*	.07*	.62	.32	.38
	Panel B. Andrews' (1993) QLR Test for Instabilities					
s_t GC cp_{t+1}		.00***	.02**	.02**	.03**	.00***
		(2004:2)	(2004:4)	(2002:4)	(2005:1)	(2005:4)
cp_t GC s_{t+1}		.01***	1.00	.16	.00***	.17
		(2004:2)	- -	- -	(2005:1)	
	Panel C. Granger-Causality Tests Robust to Instabilities, Rossi (2005b)					
s_t GC cp_{t+1}		.01***	.26	.03**	.00***	.00***
cp_t GC s_{t+1}		.01**	.00***	.79	.00***	.22
	Panel D. Out-of-Sample Forecasting Ability					
AR(1) benchmark:	$s_t \Rightarrow cp_{t+1}$	-0.65***	1.19***	0.92*	0.44***	-0.01***
	$cp_t \Rightarrow s_{t+1}$	0.45	0.36**	0.37***	0.51	0.94
RW benchmark:	$s_t \Rightarrow cp_{t+1}$	-2.10***	-1.46***	-0.98	0.05**	-1.89***
	$cp_t \Rightarrow s_{t+1}$	0.61	-0.07***	-1.45***	2.20	1.17
RW with drift	$s_t \Rightarrow cp_{t+1}$	-1.32***	-0.01**	0.89	0.49*	-0.38***
benchmark:	$cp_t \Rightarrow s_{t+1}$	0.40	-0.06***	-0.16***	0.39	0.61

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

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

		AUS	NZ	CAN	CHI	SA
	Panel A. Multivariate Granger-Causality Tests					
s_t GC cp_{t+1}		.16	.41	0.06*	.15	.01***
cp_t GC s_{t+1}		.78	.06*	.50	.21	.15
	Panel B. Andrews' (1993) QLR Test for Instabilities					
s_t GC cp_{t+1}		.00***	.01***	.03**	.01***	.00***
		(2004:2)	(2004:4)	(2002:3)	(2005:1)	(2005:4)
cp_t GC s_{t+1}		.07***	1.00	1.00	.05**	.00***
		(2004:2)			(2004:4)	(2005:4)
	Panel C. Granger-Causality Tests Robust to Instabilities, Rossi (2005b)					
s_t GC cp_{t+1}		.00***	.01***	.00***	.02**	.00***
cp_t GC s_{t+1}		.09*	.08*	1.00	.05**	.00***
	Panel D. Out-of-Sample Forecasting Ability					
AR(1) benchmark:	$s_t \Rightarrow cp_{t+1}$	1.00***	1.80***	0.87***	-0.64***	1.05***
	$cp_t \Rightarrow s_{t+1}$	0.48	0.36	0.86	0.54***	0.95
RW benchmark:	$s_t \Rightarrow cp_{t+1}$	-1.61***	-0.66***	-0.36**	-0.52**	-1.67***
	$cp_t \Rightarrow s_{t+1}$	0.47	0.63	1.24	0.88*	1.27
RW with drift	$s_t \Rightarrow cp_{t+1}$	1.15**	1.13*	0.87*	-0.61	1.00***
benchmark:	$cp_t \Rightarrow s_{t+1}$	0.46	0.45	0.93	0.72	0.99

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

Table VIII. Short- and Long-Horizon Predictive Regressions

(Robust to Highly Persistent Regressors)

A. Confidence Interval for β_h in: $E_t \Sigma_{j=1}^{h} \Delta cp_{t+j} = \beta_h s_t + \gamma \Delta cp_t$

h:	1	4	8
AUS	(0.00;0.02)	(0.00;0.03)	(0.00;0.03)
NZ	(-0.03;-0.02)	(-0.06;-0.07)	(-0.06;-0.08)
CAN	(-0.04;0.001)	(-0.05;0.002)	(-0.05;0.002)
CHI	(0.17;0.22)	(0.20;0.36)	(0.20;0.37)
SA	(0.02;0.03)	(0.02;0.05)	(0.02;0.05)

B. Confidence Interval for β_h in: $E_t \Sigma_{j=1}^{h} \Delta s_{t+j} = \beta_h cp_t + \gamma \Delta s_t$

h:	1	4	8
AUS	(0.22;0.25)	(0.61;0.98)	(0.80;1.81)
NZ	(0.16;0.18)	(0.24;0.38)	(0.24;0.42)
CAN	(-0.01;-0.002)	(-0.01;-0.004)	(-0.02;-0.005)
CHI	(-0.03;-0.01)	(-0.04;-0.02)	(-0.04;-0.03)
SA	(0.03;0.09)	(0.04;0.14)	(0.04;0.14)

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

Table IX. Forward Rate Regressions for Copper

	AUS	NZ	CAN	CHI
	Panel A. Granger-Causality Tests			
"forward premium 1"	.85	.09	.75	.03**
"forward premium 2"	.21	.44	.72	.01***
	Panel B. Andrews' (1993) QLR Test for Instabilities			
"forward premium 1"	1.00	.80	.84	.71
"forward premium 2"	.56	.58	.23	.00***
				(2005:1)
	Panel C. Granger-Causality Tests Robust to Instabilities, Rossi (2005b)			
"forward premium 1"	.87	.12	1.00	.24
"forward premium 2"	.29	.61	.44	.00***
	Panel D. Out-of-Sample Forecasting Ability			
"forward premium 1"	1.92***	-0.01***	1.12**	-0.18***
"forward premium 2"	0.02	0.66	1.16	-1.54***

Note. Panels A-C report p-values for tests for $\beta_3 = 0$ based on two regressions: (i) $E_t \Delta cp^{cu}_{t+1} = \beta_0 + \beta_1 (f^{cu}_{t+1} - cp^{cu}_t) + \beta_2 \Delta cp^{cu}_t + \beta_3 \Delta s_t$ (labeled "forward premium 1") and (ii) $E_t \Delta cp^{cu}_{t+1} = \beta_0 + (f^{cu}_{t+1} - cp^{cu}_t) + \beta_2 \Delta cp^{cu}_t + \beta_3 \Delta s_t$ (labeled "forward premium 2"). Estimated break-dates are reported in parentheses. Panel D reports the differences between model-based out-of-sample forecasts and the forecasts of the model that does not include the lagged exchange rate. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively.

Table A.1. Commodity Export Compositions

Australia		Canada		New Zealand		South Africa	
1983Q1-2008Q1		1972Q1-2008Q1		1986Q1-2008Q1		1994Q1-2008Q1	
Product	Wt.	Product	Wt.	Product	Wt.	Product	Wt.
Wheat	8.3	Aluminum	5	Aluminum	8.3	Coal	22
Beef	7.9	Beef	7.8	Apples	3.1	Gold	48
Wool	4.1	Canola	1.2	Beef	9.4	Platinum	30
Cotton	2.8	Coal	1.8	Butter	6.5		
Sugar	2.5	Copper	2	Casein	6.7		
Barley	1.9	Corn	0.5	Cheese	8.3		
Canola	1	Crude Oil	21.4	Fish	6.7		
Rice	0.5	Fish	1.3	Kiwi	3.7		
Aluminum	8.1	Gold	2.3	Lamb	12.5	Chile	
Copper	2.8	Hogs	1.8	Logs	3.5	1989Q1-2008Q1	
Nickel	2.6	Lumber	13.6	Pulp	3.1	Product	Wt.
Zinc	1.5	Nat. Gas	10.7	Sawn Timber	4.6	Copper	100
Lead	0.7	Newsprint	7.7	Skim MP	3.7		
Coking coal	14.7	Nickel	2.4	Skins	1.6		
Steaming coal	9.7	Potash	1.6	Wholemeal MP	10.6		
Gold	9.4	Pulp	12.8	Wool	7.7		
Iron ore	9.3	Silver	0.3				
Alumina	7.4	Wheat	3.4				
LNG	4.8	Zinc	2.3				

Table C.1. Hausman Test for Exogeneity

	CHI	SA
	Panel A. Endogeneity test on the coefficient on commodity prices (β_1)	
Hausman Test Statistic	0.16	0.34
p-value	.91	.83
	Panel B. Endogeneity joint test on both coefficients (β_1 and β_0)	
Hausman Test Statistic	0.24	0.05
p-value	.61	.80

Note. Panels A-B report the Hausman endogeneity test and its p-values based on the regression $E_t \Delta s_t = \beta_0 + \beta_1 \Delta cp_t$ using the global commodity price index, Δcp_t^W, and a constant as instruments. Results are robust to the inclusion of a time trend. The test statistics are obtained with a Newey-West HAC covariance matrix estimator with a bandwidth equal to $T^{1/3}$ (for Australia, the bandwidth was set equal to 2 to ensure a positive variance). Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively.

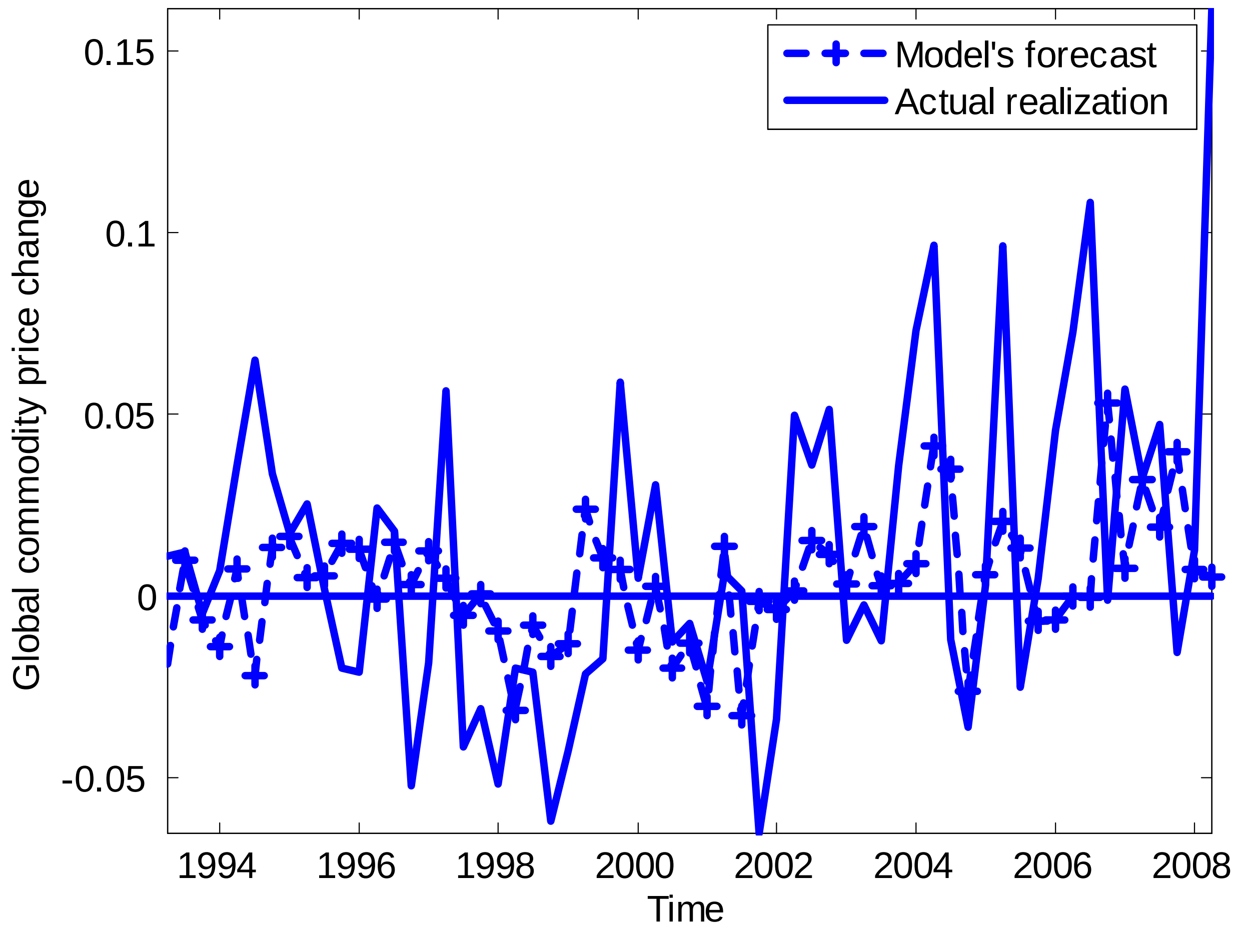
Table C.2. Out-of-Sample Forecasting Ability Tests with Alternative Fundamentals

	AUS	NZ	CAN	CHI	SA
Panel (a): Autoregressive benchmark					
MSFE difference between the model: $E_t \Delta f_{t+1} = \beta_{0t} + \beta_{1t}\Delta f_t + \beta_{2t}\Delta s_t$					
and the AR(1): $E_t \Delta f_{t+1} = \gamma_{0t} + \gamma_{1t}\Delta f_t$					
Interest Diff. (s.r.)	0.52***	0.74	-0.34***	- -	1.46
Interest Diff. (l.r.)	0.02	0.34***	0.51	- -	1.53
Inflation Diff.	0.82	0.08**	1.45	0.27	-0.97***
Output Diff.	1.09	0.56***	0.70***	1.15***	1.15
Comm. Prices	1.81***	0.38***	1.05**	-0.16**	1.34***
Panel (b): Random walk benchmark					
MSFE difference between the model: $E_t \Delta f_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t$					
and the random walk: $E_t \Delta f_{t+1} = 0$					
Interest Diff. (s.r.)	1.80	0.28**	-0.17***	- -	1.52
Interest Diff. (l.r.)	2.16	1.36	0.56	- -	1.57
Inflation Diff.	2.24	0.80	1.59	0.29	-0.75***
Output Diff.	0.53	0.58**	0.87	1.08	-1.05***
Comm. Prices	-2.11***	-1.43***	-0.01	-0.44***	-1.39***

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

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

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

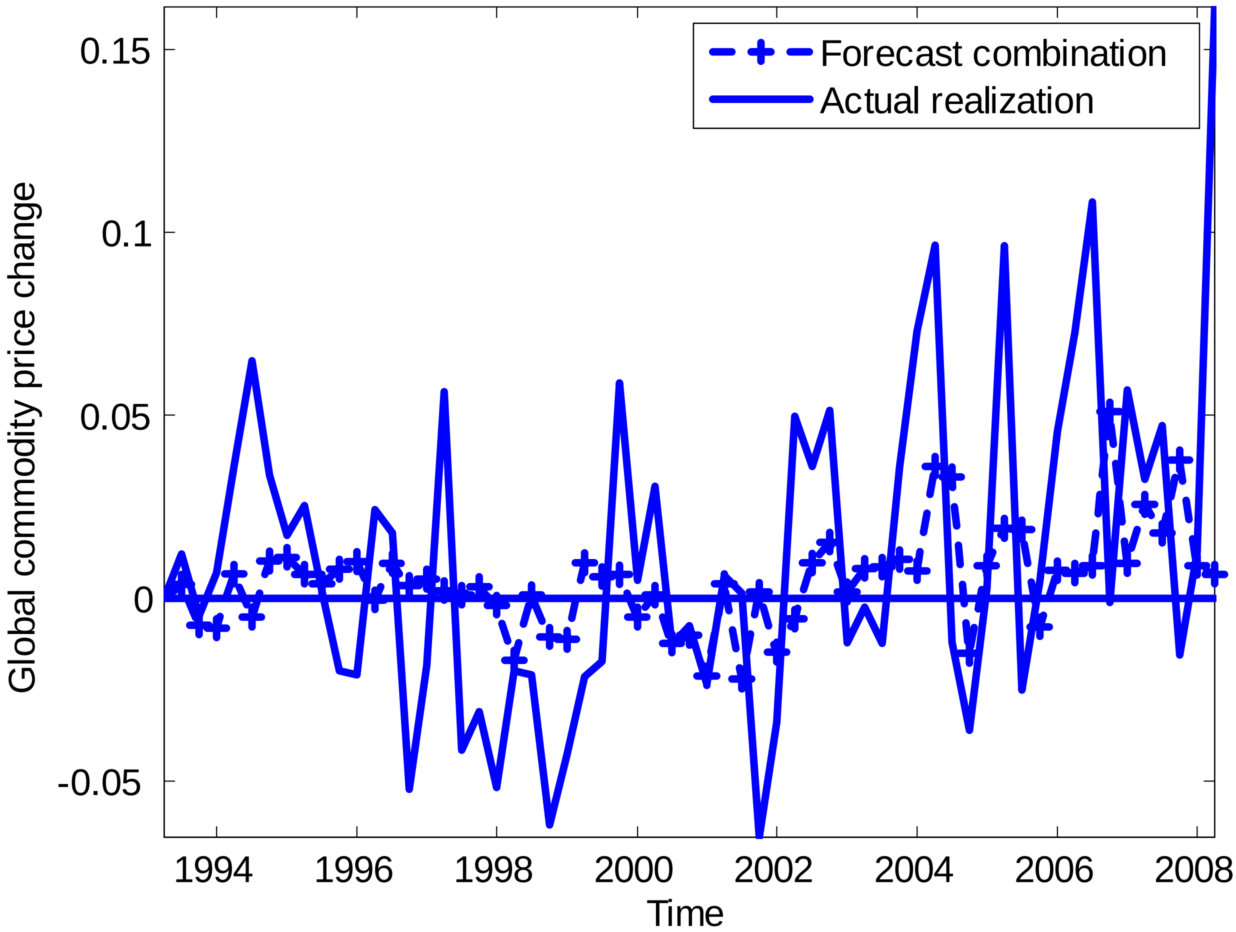


Note. The figure plots the realized change in the global commodity price level (labeled "Actual realization") and their exchange rate-based forecasts (labeled "Model's forecast")

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

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

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

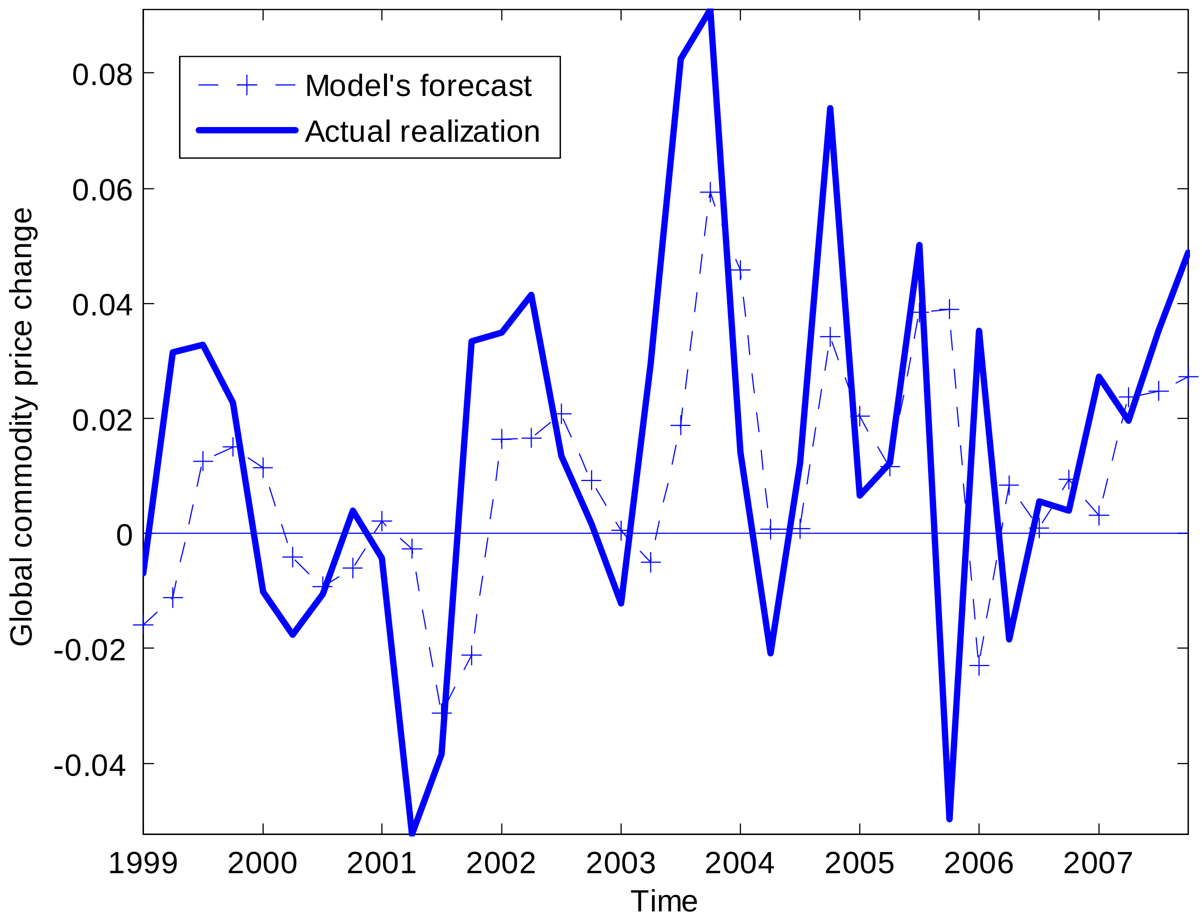


Note. The figure plots the realized change in the global commodity price level (labeled "Actual realization") and their forecasts based on the three exchange rates (labeled "Forecast combination")

Figure III. Forecasting Aggregate Global Commodity Price with Chilean Exchange Rates

$Sample : 1999Q1 - 2007Q4$

Model : $E_t \Delta cp^W_{t+1} = \beta_0 + \beta_1 \Delta s^{CHI}_t$



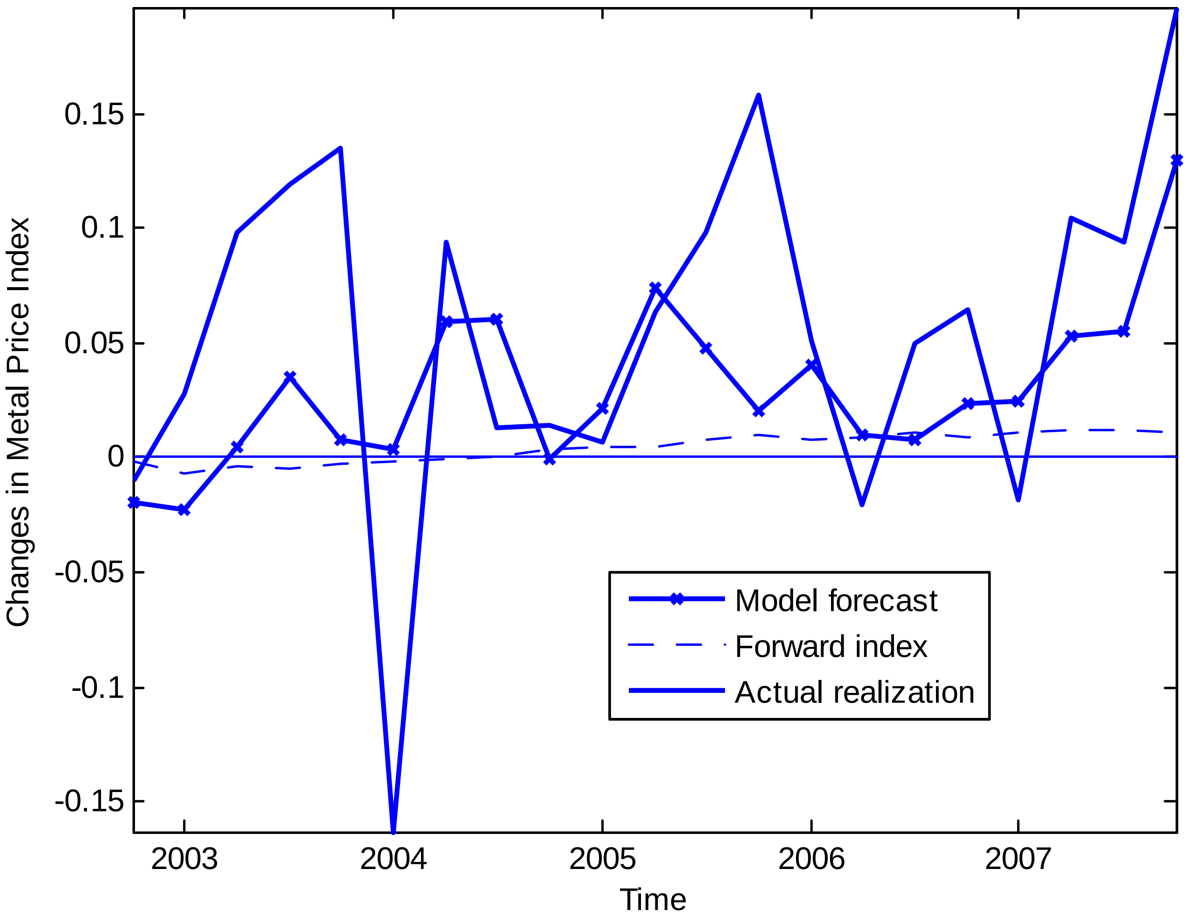
Note. The figure plots the realized change in the global commodity price level (labeled "Actual realization") and their exchange rate-based forecasts (labeled "Model's forecast")

Figure IV. Forecasting Metal Price Index with Exchange Rates vs. with Forward Rates

$$Sample : 2002Q4 - 2007Q4$$

$$\text{Model} : E_t \Delta cp_{t+1}^{M} = \beta_0 + \beta_{11}\Delta s_t^{AUS} + \beta_{12}\Delta s_t^{CAN} + \beta_{13}\Delta s_t^{NZ} + \beta_{14}\Delta s_t^{CHI} + \beta_{15}\Delta s_t^{SA}$$

$$\text{Forward index: } f_{t+1,t}^{M} - cp_t^{M}$$



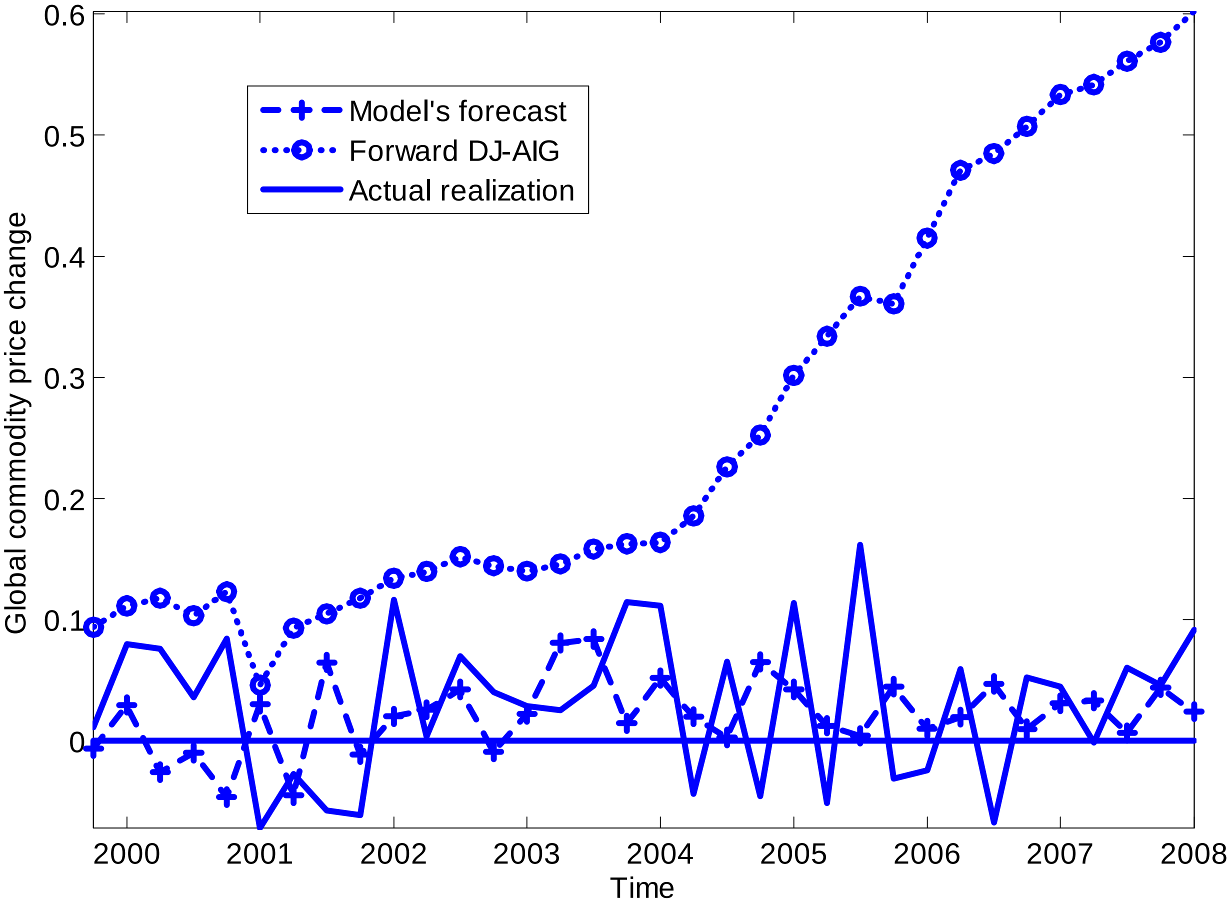
Note. The figure plots the realized change in the spot metal price index (labeled "Actual realization"), the corresponding forward rate, and the exchange rate-based forecast (labeled "Model forecast")

Figure V. Forecasting the DJ-AIG Spot Commodity Price Index:

Forward Index vs. Exchange Rates

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

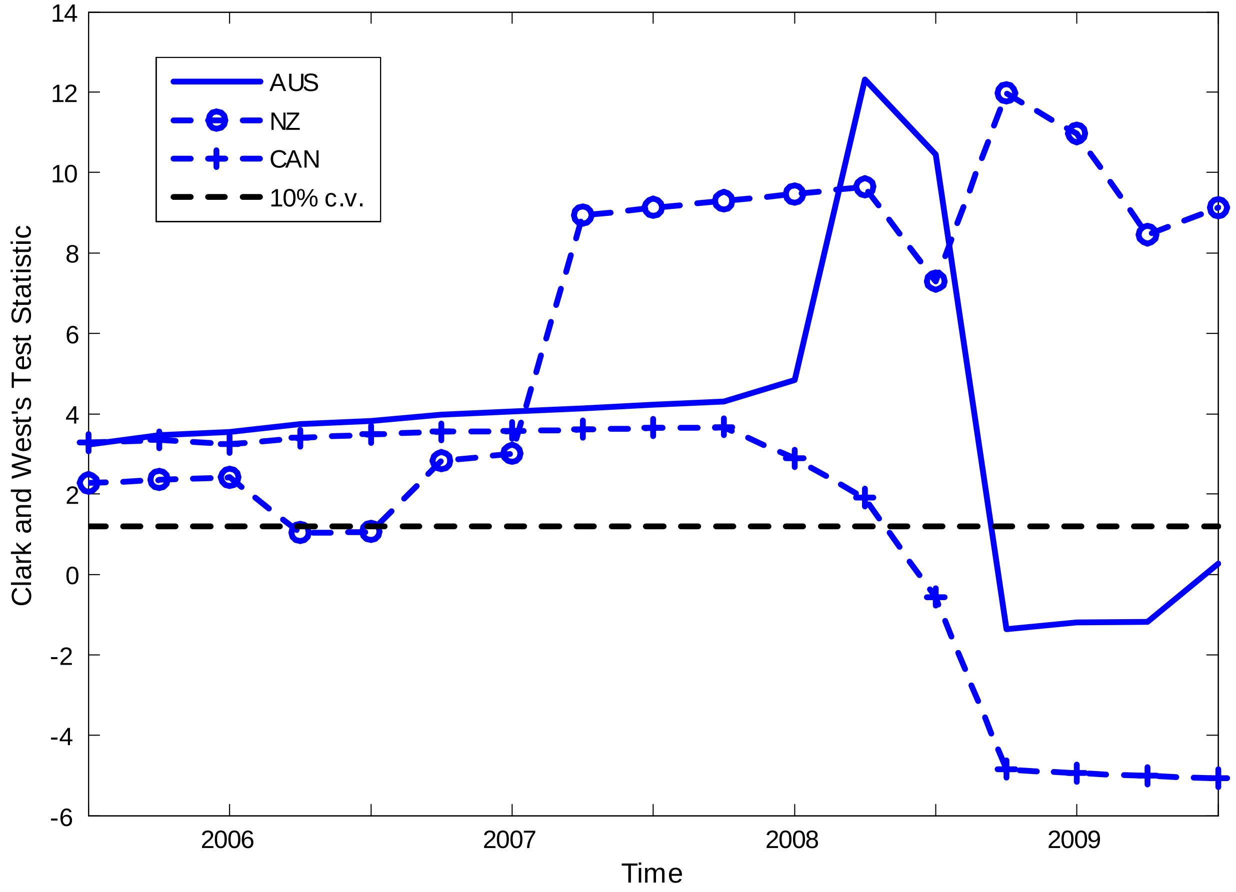
$$\text{Forward}: E_t \Delta cp_{t+1}^{DJ-AIG} = f_{t+1}^{DJ-AIG} - cp_t^{DJ-AIG}$$



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

Figure C.1. Out-of Sample Forecast Performance using Different Samples

Model : $E_t \Delta cp^i_{t+1} = \beta_{0t} + \beta_{1t} \Delta cp^i_t + \beta_{2t} \Delta s^i_t$; AR(1) Benchmark : $E_t \Delta cp^i_{t+1} = \gamma_{0t} + \gamma_{1t} \Delta cp^i_t$



Note. The figure plots the realized relative MSFE of the Model vs. the AR(1) benchmark calculated at different points in time (labeled on the x-axis) using the rolling windows discussed in the main paper. The data include the most recent sample up to the financial crisis.