PREDICTING AGRI-COMMODITY PRICES: AN ASSET PRICING APPROACH

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Abstract. Volatile and rising agricultural prices put significant strain on the global fight against poverty. An accurate reading of future food price movements can be an invaluable budgetary planning tool for various government agencies and food aid programs. Using the asset-pricing approach developed in Chen, Rogoff and Rossi (2010), we show that information from the currency and equity markets of several commodity-exporting economies can help forecast world agricultural prices. Our formulation builds upon the notion that because these countries' currency and equity valuations depend on the world price of their commodity exports, market participants would price expected future commodity price movements into the current values of these assets. Because the foreign exchange and equity markets are typically much more fluid than the agri-commodity markets (where prices tend to be more constrained by current supply and demand conditions), these asset prices can signal future agricultural price dynamics beyond information contained in the agri-commodity prices themselves. Our findings complement forecast methods based on structural factors such as supply, demand, and storage considerations.

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1. Introduction

The large commodity price surge and fluctuations since early 2000 have generated significant discussions on the causes and appropriate policy responses to them, at both the national and international levels.[1] Properly gauging agri-commodity price movements is crucial for inflation control and production planning. It is especially relevant to developing countries for the additional reason of poverty alleviation. Not only do many developing economies rely heavily on commodity productions for growth and export, governments often distribute foodgrains at subsidized prices to help combat poverty.[2] An accurate forecast of future food price movements is thus an invaluable budgetary planning tool for various government agencies and food aid programs. Using the asset-pricing approach put forth in Chen, Rogoff and Rossi (2010), this paper demonstrates that information in the currency and equity markets of a few key commodity exporters can help predict world agri-commodity price movements. The relationship holds well both in sample and out of sample, especially after controlling for structural breaks. Our findings suggest that financial market linkages offer additional sources of information that can complement forecasting models based on supply, demand, and other structural factors.

Our study uses quarterly data between 1980 and mid-2008 from three major commodity producers - Australia, Canada, and New Zealand - all with open and well-developed asset markets and a long history of flexible exchange rates. These countries produce and rely on a variety of commodity products, many of which are agricultural, as exports. Previous literature show that world commodity prices affect the terms of trade of these economies, and are a major determinant

[1] See, for example, Frankel and Rose (2009), Timmer and Dawe (2007), World Bank (2008), Sugden (2009) and references therein.

[2] India, for example, distributes through its Public Distribution System, thousands of tons of foodgrains each year at subsidized prices. See also Sugden (2009), and other papers in this volume.

for the value of their currencies.[3] We show that because their economies are so tightly dependent on commodity products, both their exchange rates and equity market indices can contain information on future movements in the global aggregate food and agricultural prices. They even have predictive power for rice and wheat prices in- and out-of-sample.

The mechanism for their predictive ability follows directly from the forward-looking present value formulation of asset prices discussed in Campbell and Shiller (1987), Engel and West (2005), and Chen, Rogoff, and Rossi (2010).[4] It is based on the notion that for these countries, global commodity price movements affect the valuation of a substantial share of their productions and exports, and thereby influence their currency and equity valuation. Knowing this connection, when market participants foresee a future commodity price shock, its anticipated impact on future asset values will be priced into the current asset prices, thus resulting in predictability. Due to the fluidity of these asset markets, exchange rates and equity market indices can capture and reflect such information about expectations more efficiently than simple time series models of the commodity prices themselves, which tend to be sensitive to contemporaneous global market supply and demand conditions. The derivative markets for commodities also tend to be far less developed and much more regulated than currency or stock markets. As each of these countries' currency and equity valuations embody information about the future price prospects of their relevant commodity exports, by combining them we can obtain forecasts for price movements in the *aggregate* agri-commodity market.

Our results show that for in-sample predictions, both the exchange rates and the equity indices contain useful information about agri-commodity price movements one quarter ahead. That

[3] See Amano and van Norden (1993) and Chen and Rogoff (2003), for example.

[4] Campbell and Shiller (1987) study present value formulation of equity prices while Engel and West (2005) and Chen et al (2010) analyze it in the context of the exchange rates.

is, these asset price changes Granger-cause commodity price movements. The Granger-causality finding is especially robust after controlling for structural breaks, using the approach developed in Rossi (2005). We detect strong evidence for structural breaks around late-2003-2004. In out-of-sample forecasting, there is overall strong support for the exchange rate-based forecast equations over the benchmark statistical models such as the random walk or a first-order autoregression. The model using equity market indices, on the other hand, show weaker evidence in out-performing the statistical models. Lastly, we look at how data from these three countries are useful for predicting rice and wheat prices as well as other individual commodity prices, and find favorable evidence, especially for wheat. Since these countries are relatively large exporters in the global wheat market, our results are consistent with the economic mechanism discussed above. Lastly, we see that even though these countries are not among the top producers in rice, their currency movements do offer some in-sample predictive ability, similar to the exchange rates of the top producers, such as Vietnam and Thailand. Our findings provide a simple and useful method for gauging aggregate agri-commodity price movements that can complement the structural approaches based on supply and demand assessment.

2. Background and Data Description

The term "commodity currencies" refers to the few floating currencies that co-move with the world prices of primary commodity products, due to these countries' heavy dependency on commodity production. While many countries in the world devote a large share of the productions in primary commodity products, our study focuses on three commodity-exporting economies (Australia, Canada, and New Zealand) with well developed asset markets and a sufficiently long history of market-based floating exchange rates.[5] These three economies have also been stable and devoid of major crises or hyper-inflationary episodes over the last couple of decades, unlike Brazil, Thailand, and many other major commodity exporters. The free and stable market characteristics are crucial for our analysis in evaluating whether their market-determined asset prices contain useful information about future movements in world agri-commodity prices.

As shown in Table 1, Australia, Canada, and New Zealand produce a variety of primary commodity products, many of them agricultural or food products. 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.[6] Substitution 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 exogenous terms-of-trade shock to these countries. These shocks in turn affect the currency and equity market values in these countries, due to their heavy production and export dependency. Previous literature, including Amano and van Norden (1993) and Chen and Rogoff (2003, 2006), show that world commodity prices are a robust and reliable fundamental in explaining the behavior of these countries' exchange rates, branding them "commodity currencies."

The theoretical underpinning of our analysis - why asset prices in major commodity producers

[5] We note that, in principle, the theoretical channels we discuss here may apply to countries that heavily import commodity products, not just countries that heavily export. Further investigation on the applicability of the "commodity currency" phenomenon to large importers is an interesting topic, but we leave it for future research.

[6] See Chen and Rogoff (2003), and Chen et al (2010) for further discussion on exogeneity.

should predict world commodity prices - is described in detail in Chen, Rogoff, and Rossi (2010). The basic intuition builds on the fact that for countries with a heavy dependency on commodity production, world commodity prices affect their production revenues and export earnings, and thus are a fundamental determinant for the value of their nominal exchange rates and equity valuations. Since exchange rates and stock prices are forward-looking, they incorporates expectations about the values of their future fundamentals such as commodity prices. The predictive relationship can be formalized through a present value framework, as demonstrated in Chen, Rogoff, and Rossi (2010). We refer interested readers to that paper. 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.

INSERT TABLE 1 HERE

2.1. Data Description and Empirical Strategy. We look at quarterly data from 1980Q1 to 2008Q2 of the four aggregate food and agricultural commodity price indices. All are obtained from the Global Financial Database, and contain different agricultural or food products as described below:

1. CRB Food index: Foodstuffs Sub-Index from the Commodity Research Bureau/BLS, which includes spot prices of hogs, steers, lard, butter, soybean oil, cocoa, corn, Kansas City wheat, Minneapolis wheat, and sugar.

2. Economist Food Commodity Dollar Index: this dollar index includes: Wheat 14.6%, coffee 12.8%, soyabeans 11.8%, maize 9.6%, soyameal 8.3%, rice 6.9%, sugar 6.6%, beef (American) 5.8%, beef (Australian) 5.8%, cocoa 5.3%, palm oil 4.1%, soyaoil 3.%, tea 2.9%, lamb 1.9% and coconut oil 0.5%. The weights are computed according to the value of world imports in 1999-2001 with the EU counting as a single market.

3. Economist Non-Food Agricultural Price Index: this dollar index includes Cotton 32.6%, Rubber 18.8%, timber 17.1%, Hides 11.2%, Australian Wool 6.8%, New Zealand Wool 6.8%, Palm Oil 3.8%, Coconut oil 2.2% and soyaoil 0.6%. Again, the weights are computed according to the value of world imports in 1999-2001 with the EU counting as a single market.

4. The S&P GSCI Agricultural Index: this Standard and Poor's sub-index includes: Wheat, Kansas Wheat, Corn, Soybeans, Cotton, Sugar, Coffee, and Cocoa (the principal physical commodities that are the subject of active, liquid futures markets.) The weight of each commodity in the index is determined by the average quantity of world production as per the last five years of available data.

   Figure I provides a visual presentation of (the log of) these indices, with 1980Q1 set to 100. We see that all four price indices are quite volatile, and experienced a surge in recent years. In addition to these aggregate agri-market indices, we also look at the prices of Rice: No. 2 (Medium): SW Louisiana (USD/CWT) and Wheat #2 Cash Price (US Dollars/Bushel).

In terms of predictors for the commodity prices, we use end-of-period exchange rates relative to the US dollar and stock market indices for the following countries: Australia, Canada, New Zealand, for our main analyses. We also use the total return indices from Global Financial Data, and they include Australia S&P/ASX 200 Accumulation Index, New Zealand NZSX 50 Benchmark Index, Canada S&P/TSX-300 Total Return Index, and S&P 500 Total Return Index (w/GFD extension) for the US. As discussed above, these three countries all have significant amount of agricultural production, but the choice is motivated by their open markets and free-floating currencies over the past decades. These economies are also well-developed and relatively stable, compared to other major agricultural exporters such as Argentina or Brazil, where crises, hyper-inflations, or currency management may obscure the relevant market information we aim to extract. As a robustness test, we also looked at the usefulness of these currencies and also the exchange rates of Vietnam and Thailand for predicting the price of rice, and the US nominal effective exchange rate for predicting the price of wheat. We also look at how the currencies individually predict a broad set of specific commodity good prices, which are taken from the IMF's International Financial Statistics.

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.[7] We examine the forecasting power of exchange rates and stock market indices for the food and agricultural commodity prices both in terms of Granger-causality and out-of-sample forecasting ability. 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, while the out-of-sample forecast procedure may prove more practical as it mimics the data constraint of real-time forecasting and is more sensitive to misspecification problems.

INSERT FIGURE I

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

3. Predicting Agri-Commodity indices

We first investigate the empirical evidence on Granger causality, using both the traditional testing procedure and one that is robust to parameter instability. We use both the exchange rates and the equity market indices as predictors. We demonstrate the prevalence of structural breaks and emphasize the importance of controlling for them. Under Rossi's (2005) procedure that is robust to a one-time structural break, we see that exchange rates and equity indices from these commodity-producing economies Granger-cause movements in the world aggregate commodity price indices. We then test whether this predictive content also translates into superior out-of-sample forecast performance, relative to both a random walk (RW) and an autoregressive (AR) benchmark.

3.1. In-Sample Granger-Causality (GC) Tests: Multivariate Predictions. Present value models of exchange rate determination imply that exchange rates must Granger-cause fundamentals. In other words, ignoring issues of parameter instabilities, we should reject the null hypothesis that $\beta_{1i} = 0, i = 1, 2, 3$ in the following multivariate regression:

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

where s represents either the exchange rate or the equity index. As is standard in Granger causality analyses, lags of the explanatory and dependent variables are also included in the regression. For notation simplicity, we omit them in the equations above (except for Δcp_t^W) and also in the subsequent equations. We include one lag each based on the BIC criterion, though our findings are robust to the inclusion of additional lags.[8] All variables in our analyses are first differenced, and the estimations are heteroskedasticity and serial correlation-consistent. Results are based on

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

the Newey and West (1987) procedure with bandwidth $T^{1/3}$ (where T is the sample size.)

We first look at in-sample predictive regressions for the two food indices, using the three exchange rates and then using the three stock market indices (Tables 2a and 2b). Panel A in Table 2a reports the results for the Commodity Research Bureau's Food commodity index, based on the above standard Granger-causality regression. Note that the tables report the p-values of the tests, so a number below 0.05 implies evidence in favor of Granger-causality at the 5% level. We see that while the traditional Granger-causality test shows that exchange rates Granger-cause food prices a quarter ahead, there is no evidence that the stock market indices do the same.

An important drawback in these Granger-causality regressions is that they do not take into account potential parameter instabilities. As discussed above, structural break is a serious concern due to changes in the policy and general market conditions in these countries. We thus check for parameter instability for the bivariate Granger-causality regressions and Panel B reports results based on Andrews (1993) test. We observe strong evidence of time-varying parameters in early 2000's. As such, we next consider the joint null hypothesis that $\beta_{1it} = \beta_{1i} = 0, i = 1, 2, 3$ by using Rossi's (2005) $Exp - W^*$ test, in the following regression setup:

$$E_t \Delta cp_{t+1}^{ag} = \beta_0 + \beta_{11t} \Delta s_t^{AUS} + \beta_{12t} \Delta s_t^{CAN} + \beta_{13t} \Delta s_t^{NZ} + \beta_2 \Delta cp_t^{ag} \tag{2}$$

Rossi (2005) develops several optimal tests for model selection between two nested models in the presence of underlying parameter instabilities in the data. We focus on the case in which β_t may shift from β to $\overline{\beta} \neq \beta$ at some unknown point in time, using the $Exp - W_T^*$ test statistics (we refer readers to the original paper or Appendix 2 of Chen et al (2010) for a full description of the test). We note that when this test rejects the null, it means that at least a some point over the sample period, if not over the whole sample, the Granger causality relation is present. It is especially useful if a structural break may lead to a canceling out of the pre- and post-break effect, producing an overall negligible and non-significant effect.

Panel C in Table 2a shows that the Rossi (2005) multivariate Granger-causality test indicates stronger evidence in favor of a time-varying relationship between stock market indices and the Food price index, with a p-value of 0.4. Table 2b performs the same predictive tests on the Economist Food Commodity Index. The table points to similar strong empirical evidence that exchange rates Granger cause food prices, and that the equity indices predictability result requires addressing parameter instability first.

INSERT TABLES 2a, 2b HERE

Tables 3a and 3b repeat the same exercise for the two agricultural commodity price indices: the Economist Non-Food Agricultural Price Index, and the S&P GSCI Agricultural Index. Panels A-C in these tables reveal the same message: there is strong empirical evidence that exchange rates and equity prices Granger cause world agri-commodity price movements. Information in these asset markets are useful for predicting global agricultural prices.

INSERT TABLES 3a and 3b HERE

3.2. Out-of-Sample Forecasts. This section **analyzes** whether exchange rates and equity indices can predict agri-commodity prices out of sample. We adopt a rolling forecast scheme based on eq.(1), and compare its forecast performance relative to three time-series benchmarks. First, we estimate eq.(1) and test for forecast encompassing relative to an autoregressive (AR) model of order one:

$$E_t \Delta cp_{t+1}^{ag} = \gamma_{0t} + \gamma_t \Delta cp_t^{ag} \tag{3}$$

where the order of the benchmark autoregressive model is selected by the Bayesian information criterion. We then compare our model with the random walk benchmark, both with and without drift. That is, we estimate eq.(1) without the lagged dependent variable Δcp_t^{ag}, and test for forecast encompassing relative to a random walk with drift ($\gamma_t = 0$ in the equation above). We then extend the comparison to a random walk without a drift ($\gamma_{0t} = \gamma_t = 0$ in the equation above). Below we use the random walk without drift benchmark as an example to explain the forecast evaluation procedure. To simplify notation, we use the generic variable name $x_{t-1} = [\Delta s_{t-1}^{AUS}, \Delta s_{t-1}^{CAN}, \Delta s_{t-1}^{NZ}, \Delta cp_{t-1}^{ag}]$ to represent the vector of regressors in eqs.(1) and (3).

To compare the out-of-sample forecasting ability of,

$$Model \ : \ y_t = x_{t-1}' \beta_t + \varepsilon_t \tag{4}$$

$$Random\ Walk \ : \ y_t = \varepsilon_t, \tag{5}$$

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 overall sample of size T into an in-sample window of size m and an out-of-sample window of size $n = T - m$. The in-sample window at time t contains observations indexed $t-m+1, \ldots, t$. Let $f_{t+1}(\widehat{\beta}_t) = x_t' \widehat{\beta}_t$ be the time-t forecast for y_{t+1} 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. Let f_{t+1}^{RW} denote the forecast of the random walk (that is, $f_{t+1}^{RW} = 0$).

To compare the out-of-sample predictive ability of (4) and (5), Diebold and Mariano (1995) and West (1996) suggest looking at the following:

$$d_t \equiv \left(y_t - f_t(\widehat{\beta}_t)\right)^2 - \left(y_t - f_t^{RW}\right)^2 \tag{6}$$

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 (5), 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 (6) that results in an approximately normally distributed test statistic.

Note that we choose a rolling out-of-sample forecast procedure (rather than a recursive one) because it is more 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 with the size m equal to seven years to estimate the model parameters and generate one-quarter ahead forecasts recursively (what we call "model-based forecasts"). We also do a test with a larger window size of twelve years and obtain qualitatively the same results.[9]

[9] To save space, we do not include results based on other window sizes in this paper.

The Panel D sections of Tables 2 and 3 report two sets of information on the forecast comparisons. The actual numbers reported are the difference between the mean square forecast errors (MSFE) of the model and the MSFE of the benchmark (AR(1), RW, or RW with drift). Both MSFEs are re-scaled by a measure of their variability, giving us a statistic similar to the standard Diebold and Mariano (1995) test statistic. A negative number here indicates that the model outperforms the benchmark in producing smaller MSFEs. However, to statistically evaluate the two models under proper inference, we rely on the Clark and McCracken's (2001) "ENCNEW" test of equal MSFEs presented above to compare these nested models. In this case, a rejection of the null hypothesis, which we indicate with asterisks, implies that the additional regressors (the exchange rates or the stock market indices) contain 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 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. 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, 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, and the bias correction is why it is possible for the model to outperform the benchmark even when the computed MSFE differences is positive.[10]

[10] In our example, if the random walk model is the true data generating process, both the random walk model and

As the Panel D sections of Tables 2a-b and 3a-b show that using either the three exchange rates or the stock indices together, we can forecast most of these aggregate agri-commodity price series significantly better than the benchmarks at the 5% level; exchange rates can often beat the benchmark at the 1% level. The Economist Non-Food Agricultural Index is the only series that our models do not predict well relative to the AR(1) or RW without drift benchmarks. We also note that most of the numbers are positive, indicating that in actual out-of-sample forecast, we do not obtain smaller RMSEs from the statistically preferred models due to having to estimate additional parameters, as explained above.

Figures IIa,b and IIIa,b plot the exchange rates-based forecasts along with the actual realized changes of the logged commodity price indices. The random walk forecast is simply the x-axis (forecasting no change). We note that overall, the commodity exchange rate-based forecasts can offer good forecasts over some sample periods.[11] While we do not compare our forecasts with ones obtained from other structural models of price movements, such as based on the supply of storage model, we consider these results as evidence that asset markets from these commodity economies contain useful information that can complement forecast models based on real factors. In addition, because exchange rates and stock indices 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. The asset pricing approach we present here can also be extended to look at higher frequencies than typically possible under the standard supply and demand-based agri-commodity price analyses.

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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.

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

INSERT FIGURE IIa, IIb, IIIa, IIIb HERE

4. Predicting the Prices of Wheat, Rice, and Other Products

In this section we look how well the asset pricing approach performs for predicting the price of specific agricultural products such as wheat and rice, as well as other individual commodity prices. For the aggregate commodity indices we have been looking at, using the asset prices from markets that collectively produce a broad set of agri-commodity products make the most sense. For a specific product, on the other hand, the asset pricing channel discussed in Sect 2 above suggests that one should look at information from specific countries that have a large share of production and export in this product. The trade-off, however, is as we discussed earlier, that many commodity-exporting countries do not have well-developed asset markets nor a stable economy, and their exchange rates are often subject to heavy management, preventing an efficient aggregation of market information.

We first look at the wheat market. Table 4 shows the world's top wheat exporters in 2009. We note that two out of the three countries we have been looking at are major wheat producers as well. We first look at how well using the same predictors as in the above sections works for predicting the cash price of wheat #2. Table 5a shows that they work quite well! In-sample Granger-causality results are strong for both the exchange rates and the equity indices. We again find evidence of structural break around the year 2004, and controlling for it strengthens the in-sample predictability. Panel D again selects the asset price models over the time-series benchmarks in most cases, and shows that the exchange rate-based forecasts result in smaller MSFEs than the random walk benchmarks. In Table 5a, we replace predictors from New Zealand with the US nominal exchange rate (NEER) and the S&P 500 total return index. This forecast model uses asset market information from the world's major wheat exporters only. Table 5b shows that both the in-sample and out-of-sample results support the exchange rate-based models strongly (1% significance), though the equity market index-based model does not perform well in out-of-sample forecast. This result is certainly not surprising, as one would not expect the movements of S&P 500 to incorporate much information from the global wheat market.

INSERT TABLES 4, 5a and 5b HERE

We next look at the rice market. Table 6 shows the world's major rice exporters and their respective market shares in 2009. Here we see a very different set of players, including Thailand and Vietnam. Again, we first test how well asset prices in Australia, Canada, and New Zealand perform in predicting the price of rice (#2 medium; SW Louisiana). Table 7a shows that even though their exchange rates offer useful information both in-sample and out-of-sample, their equity markets contain no significant information about future rice price movements. Compared to the results for wheat above, the evidence of predictability using these three countries is certainly weaker. We next take a look at whether the Thailand baht, Vietnam dong, and the US NEER together contain useful information to help forecast the price of rice, as these countries are key world exporters of rice. Table 7b shows that there is evidence for in-sample Granger causality over some sub-sample period, but these exchange rates perform poorly in out-of-sample forecasts, and do not outperform any of the statistical benchmarks. Given that these economies (except for the U.S.) do not have well-developed equity markets, we do not look at forecasts using their stock market indices. These results suggest that overall, the currency values of Australia, Canada, and New Zealand are quite useful for predicting commodity price movements, even for products that they do not necessarily have large world market shares. This may be due to the fact that these exchange rates are well-known to be "commodity currencies" by market participants, so they tend to be efficient at incorporating market expectations in the commodity markets.

INSERT TABLES 6, 7a and 7b HERE

We finally consider whether it is possible to predict individual commodity prices by using individual countries' exchange rates versus the U.S. Dollar. We consider the following main model for predicting individual commodity prices:

$$E_t \Delta cp_{t+1}^{ag} = \beta_{0t} + \beta_{11t} \Delta s_t^j + \beta_{2t} \Delta cp_t^{ag} \tag{7}$$

for countries $j =$ Australia (AU), Canada (CA), and New Zealand (NZ); cp^{ag} are individual commodity prices for a variety of products for which the country is a significant producer/exporter on the world market. We compare the forecasting ability of this model with that of an autoregressive model of order one, for which $E_t \Delta cp_{t+1}^{ag} = \beta_{0t} + \beta_{2t} \Delta cp_t^{ag}$. In the analyses here, we use commodity prices and exchange rate data from the IFS as before, but extend the quarterly data to 19980Q1 to 2009Q4.

The horizontal axis in Figures IV(a-c) report p-values of Clark and West's (2006) test for equal predictive ability of model (7) and the AR model for commodity prices, against the alternative that model (7) is a better predictor out-of-sample. Commodities for which the p-value is less than 0.1 are predictable by using exchange rates. The figure considers commodities for which each country is a significant producer/exporter; large characters denote commodities for which the country is especially a large producer/exporter.

Figure IV(a) reports results for Australia. It shows that the Australian exchange rate has a significant out-of-sample predictive content for several commodities. In particular, aluminium and coal (Australia) are all significant at 0.10 critical value, as well as cotton, wool, copper, sugar, fine and coarse wool, wheat (Argentinian), and nickel. In the case of Canada, depicted in Figure IV(b), the Canadian dollar is a predictor for some natural gas prices (Russian and Indonesian, but not US), and pulp, as well as wheat, zinc, gold, coal, nickel, aluminium and potash. However, it does not appear useful to predict some measures of newsprint nor beef. Figure IV(c) shows positive results for New Zealand, whose exchange rate has a significant out-of-sample predictive content for several commodities for which New Zealand is an especially large producer (lamb, aluminium, wool, both coarse and fine), in addition to pulp. Overall, these figures show that the exchange rates do have some predictive ability for the individual commodities of which these countries produce and export a significant share.

In parallel to the analysis in Chen, Rogoff and Rossi (2010), we also consider traditional currency predictive regressions in the spirit of Meese and Rogoff (1983), where commodity prices are used to predict exchange rates. That is, we look at the following model:

$$E_t \Delta s_{t+1}^j = \beta_{0t} + \beta_{11t} \Delta cp_t^{ag} + \beta_{2t} \Delta s_t^j \tag{8}$$

and its forecasting ability is compared to that of an AR model of order one for exchange rates: $E_t \Delta s_{t+1}^j = \beta_{0t} + \beta_{2t} \Delta s_t^j$.[12] The vertical axis in Figures IV(a-c) report p-values of Clark and West's (2006) test for equal predictive ability of model (**??**) and the AR model for commodity prices, against the alternative that model (**??**) is a better predictor out-of-sample. Only very few of these commodity prices are useful predictors for the exchange rate (only coal, for the Australian exchange rate).

[12] For brevity, we report results for the AR benchmark only, although results are similar when considering the RW benchmark.

INSERT FIGURES IVa, IVb, IVc HERE

We also consider regressions involving the stock market indices, where Δm_t^j and Δm_{t+1}^j are used in place of Δs_t^j and Δs_{t+1}^j in equation (7), with Δm_t^j denote the first difference of country $j's$ equity index (in logs). The empirical results are reported in Figures V(a-c), where on the x-axis we report the p-values for testing whether the model forecasts (7) are significantly better than the autoregressive forecasts. Again, the results reveal a very interesting pattern: the Australian stock market index appears to be a good predictor of wool, aluminium and coal, as well as nickel, copper, cotton; the Canadian stock market index helps forecasting natural gas, petroleum, and pulp, as well as copper, nickel, zinc, aluminium, coal, zinc and potash prices. Finally, the New Zealand stock market index helps forecasting wool, aluminium and lamb, as well as pulp prices[13]

Overall, we conclude that there is quite widespread empirical evidence in favor of the hypothesis that both exchange rates and stock market indices of individual countries have predictive ability for the price of their major products, while there is scant evidence that commodity prices have predictive content for exchange rates or stock indices for those countries.

INSERT FIGURES Va, Vb, Vc HERE

5. Conclusion

This paper investigates whether information in the asset markets of major commodity producers can help forecast future agri-commodity price movements. After controlling for time-varying parameters, we find that the exchange rates and the equity market indices of Australia, Canada,

[13] There are instances in which some commodity prices may help forecasting individual country's stock market indices (in the figures, the model with commodity prices is significant for commodities whose y-axis is below 0.10). This happens only for the Australian stock market, and involves only very few commodities, such as coal, sugar, and beef.

and New Zealand offer robust and useful information for forecasting future movements of major world food and agricultural commodity price indices. The predictability results show up both in in-sample Granger causality regressions as well as in out-of-sample forecast comparisons with time-series benchmarks. While we do not directly compare our asset prices-based forecasts with traditional models using supply, demand, and storage considerations, we believe results found in this paper are complementarity to these other methods, which we leave for future research. In addition, the asset-pricing approach proposed in this paper offers additional advantages. The asset prices are easy to observe at high frequencies and are not subject to revisions. Combining market information from several markets, one can readily obtain a forecast for the aggregate world agri-commodity market.

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7. Tables

Table 1. Commodity Export Compositions

Australia		Canada		New Zealand	
Product	Wt.	Product	Wt.	Product	Wt.
Wheat	8.3	Aluminum	5	Aluminum	8.3
Beef	7.9	Beef	7.8	Apples	3.1
Wool	4.1	Canola	1.2	Beef	9.4
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
Copper	2.8	Hogs	1.8	Logs	3.5
Nickel	2.6	Lumber	13.6	Pulp	3.1
Zinc	1.5	Nat. Gas	10.7	Sawn Timber	4.6
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		

Source: Reserve Bank of Australia, Statistics Canada, and Reserve Bank of New Zealand.

Table 2a. Predicting the CRB Food Commodity Dollar Index

In-Sample Granger Causality and Out-of-Sample Forecasts

$$E_t \Delta cp^{Food}_{t+1} = \beta_0 + \sum_j \beta_{1j} \Delta x^j_t \text{ where j = AUS, CAN, and NZ}$$

	x_t = **Exchange Rates**	x_t = **Stock Indices**
Panel A. Multivariate Granger-Causality Tests		
	.00***	.28
Panel B. Andrews' (1993) QLR Test for Instabilities		
	.00*** (2003:4)	.00*** (2004:4)
Panel C. Rossi's (2005) Multivariate Granger-Causality Tests		
	.00***	.00***
Panel D. Out-of-Sample Forecasting Ability		
AR(1) benchmark:	1.35***	0.74**
RW benchmark:	1.12***	0.35***
RW with drift:	1.13***	0.48**

Notes: The table reports results from various tests using the AUS, NZ and CAN exchange rates and stock indices to jointly predict aggregate world food commodity prices (cp^{Food}) a quarter ahead. Panels A-C report the p-values; Panel D reports the MSFE differences between the model-based forecasts and the RW and AR benchmark forecasts.

***/**/* indicates significance at the 1/5/10% level.

Table 2b. Predicting the Economist Food Commodity Dollar Index

In-Sample Granger Causality and Out-of-Sample Forecasts

$$E_t \Delta cp_{t+1}^{Food} = \beta_0 + \sum_j \beta_{1j} \Delta x_t^j \text{ where j = AUS, CAN, and NZ}$$

	x_t **= Exchange Rates**	x_t **= Stock indices**
Panel A. Multivariate Granger-Causality Tests		
	.00***	.60
Panel B. Andrews' (1993) QLR Test for Instabilities		
	.03** (2003:4)	.00*** (2004:4)
Panel C. Rossi's (2005) Multivariate Granger-Causality Tests		
	.00***	.04**
Panel D. Out-of-Sample Forecasting Ability		
AR(1) benchmark:	0.05**	0.84
RW benchmark:	-0.16***	0.16***
RW with drift:	-0.24***	0.42***

Notes: The table reports results from various tests using the AUS, NZ and CAN exchange rates and stock market indices to jointly predict aggregate commodity prices (cp^{Food}) a quarter ahead. Panels A-C report the p-values; Panel D reports the MSFE differences between the model-based forecasts and the RW and AR benchmark forecasts.

***/**/* indicates significance at the 1/5/10% level.

Table 3a. Predicting the Economist Non-Food Agricultural Price Index

In-Sample Granger Causality and Out-of-Sample Forecasts

$$E_t \Delta cp^{Ag}_{t+1} = \beta_0 + \sum_j \beta_{1j} \Delta x^j_t \text{ where j = AUS, CAN, and NZ}$$

	x_t = **Exchange Rates**	x_t = **Stock Indices**
Panel A. Multivariate Granger-Causality Tests		
	.61	.38
Panel B. Andrews' (1993) QLR Test for Instabilities		
	.00*** (2003:4)	.04** (2004:4)
Panel C. Rossi's (2005) Multivariate Granger-Causality Tests		
	.00***	.00***
Panel D. Out-of-Sample Forecasting Ability		
AR(1) benchmark:	1.01	1.59
RW benchmark:	1.14	1.39
RW with drift:	0.95**	1.35*

Notes: The table reports results from various tests using the AUS, NZ and CAN exchange rates and stock indices to jointly predict aggregate world food commodity prices (cp^{Ag}) a quarter ahead. Panels A-C report the p-values; Panel D reports the MSFE differences between the model-based forecasts and the RW and AR benchmark forecasts.

***/**/* indicates significance at the 1/5/10% level.

Table 3b. Predicting the S&P GSCI Agricultural Index

In-Sample Granger Causality and Out-of-Sample Forecasts

$$E_t \Delta cp_{t+1}^{Ag} = \beta_0 + \sum_j \beta_{1j} \Delta x_t^j \text{ where j = AUS, CAN, and NZ}$$

	x_t = **Exchange Rates**	x_t = **Stock indices**
Panel A. Multivariate Granger-Causality Tests		
	.00***	.07*
Panel B. Andrews' (1993) QLR Test for Instabilities		
	.00*** (2003:4)	.00*** (2004:4)
Panel C. Rossi's (2005) Multivariate Granger-Causality Tests		
	.00***	.00***
Panel D. Out-of-Sample Forecasting Ability		
AR(1) benchmark:	0.82***	1.03**
RW benchmark:	0.69***	0.88***
RW with drift:	0.50***	1.15***

Notes: The table reports results from various tests using the AUS, NZ and CAN exchange rates and stock indices to jointly predict aggregate world food commodity prices (cp^{Ag}) a quarter ahead. Panels A-C report the p-values; Panel D reports the MSFE differences between the model-based forecasts and the RW and AR benchmark forecasts.

***/**/* indicates significance at the 1/5/10% level.

Table 4. Key Wheat Exporters, 2009

Exporters	in 1,000 metric tons	% of World Total
U.S.	25,000	20.27
Canada	18,500	15.00
Russia	16,500	13.38
Australia	14,500	11.76
Ukraine	8,500	6.89

Source: adopted from USDA(2009) Table 2: Global Wheat Exporters in October 2009

Table 5a. Predicting Wheat #2 Cash Price (US Dollars/Bushel)

In-Sample Granger Causality and Out-of-Sample Forecasts

$E_t \Delta cp_{t+1}^{Wheat} = \beta_0 + \sum_j \beta_{1j} \Delta x_t^j$ where j = AUS, NZ, and CAN

	x_t = **Exchange Rates**	x_t = **Stock Indices**
Panel A. Multivariate Granger-Causality Tests		
	.05**	.01***
Panel B. Andrews' (1993) QLR Test for Instabilities		
	.00*** (2003:4)	.00*** (2004:4)
Panel C. Rossi's (2005) Multivariate Granger-Causality Tests		
	.00***	.00***
Panel D. Out-of-Sample Forecasting Ability		
AR(1) benchmark:	0.24***	0.86
RW benchmark:	-0.03***	1.09***
RW with drift:	-0.20***	1.08**

Notes: The table reports results from various tests using the AUS, NZ, and CAN exchange rates and stock market indices to jointly predict wheat prices (cp^{Wheat}) a quarter ahead. Panels A-C report the p-values; Panel D reports the MSFE differences between the model-based forecasts and the RW and AR benchmark forecasts.

***/**/* indicates significance at the 1/5/10% level.

Table 5b. Predicting Wheat #2 Cash Price (US Dollars/Bushel)

In-Sample Granger Causality and Out-of-Sample Forecasts

$$E_t \Delta cp_{t+1}^{Wheat} = \beta_0 + \sum_j \beta_{1j} \Delta x_t^j \text{ where j = AUS, CAN, and US}$$

	x_t = **Exchange Rates**	x_t = **Stock indices**
Panel A. Multivariate Granger-Causality Tests		
	.03**	.11
Panel B. Andrews' (1993) QLR Test for Instabilities		
	.02** (2003:4)	.00** (2003:4)
Panel C. Rossi's (2005) Multivariate Granger-Causality Tests		
	.00***	.00***
Panel D. Out-of-Sample Forecasting Ability		
AR(1) benchmark:	0.08***	2.52
RW benchmark:	-0.23***	2.50
RW with drift:	-0.44***	2.41

Notes: The table reports results from various tests using the AUS, CAN, and US (NEER) exchange rates and stock market indices to jointly predict wheat prices (cp^{Wheat}) a quarter ahead. Panels A-C report the p-values; Panel D reports the MSFE differences between the model-based forecasts and the RW and AR benchmark forecasts. ***/**/* indicates significance at the 1/5/10% level.

Table 6: Key Rice Exporters, 2009

Exporters	in 1,000 metric tons	% of World Total
Thailand	10,000	33.73
Vietnam	5,500	18.55
Pakistan	3.300	11.13
U.S.	3,050	10.29
India	1,500	5.06

Source: Childs and Baldwin (2009) Table 1- Global Rice Exporters in October 2009

Table 7a. Predicting Price of Rice: No. 2 (Medium) SW Louisiana (USD/CWT)

In-Sample Granger Causality and Out-of-Sample Forecasts

$E_t \Delta cp^{Rice}_{t+1} = \beta_0 + \sum_j \beta_{1j} \Delta x^j_t$ where j = AUS, NZ, and CAN

	x_t = **Exchange Rates**	x_t = **Stock Indices**
Panel A. Multivariate Granger-Causality Tests		
	.42	.57
Panel B. Andrews' (1993) QLR Test for Instabilities		
	.12	.22
Panel C. Rossi's (2005) Multivariate Granger-Causality Tests		
	.00***	.41
Panel D. Out-of-Sample Forecasting Ability		
AR(1) benchmark:	0.65***	2.72
RW benchmark:	0.90***	2.11
RW with drift:	0.65***	1.77

Notes: The table reports results from various tests using the AUS, NZ, and CAN exchange rates and stock market indices to jointly predict wheat prices (cp^{Rice}) a quarter ahead. Panels A-C report the p-values; Panel D reports the MSFE differences between the model-based forecasts and the RW and AR benchmark forecasts.

***/**/* indicates significance at the 1/5/10% level.

Table 7b: Predicting Price of Rice: No. 2 (Medium) SW Louisiana (USD/CWT)

In-Sample Granger Causality and Out-of-Sample Forecasts

$$E_t \Delta cp_{t+1}^{Rice} = \beta_0 + \sum_j \beta_{1j} \Delta x_t^j \text{ where j = THAI, VIET, and US}$$

	x_t = **Exchange Rates**
Panel A. Multivariate Granger-Causality Tests	
	.26
Panel B. Andrews' (1993) QLR Test for Instabilities	
	.00*** (2003:4)
Panel C. Rossi's (2005) Multivariate Granger-Causality Tests	
	.00***
Panel D. Out-of-Sample Forecasting Ability	
AR(1) benchmark:	1.67
RW benchmark:	1.20
RW with drift:	1.10

Notes: The table reports results from various tests using the THAI, VIET, and US (NEER) exchange rates to jointly predict the price of rice (cp^{Rice}) a quarter ahead. Panels A-C report the p-values, and Panel D reports the MSFE differences between the model-based forecasts and the RW and AR forecasts. ***/**/* indicates significance at the 1/5/10% level.

Figure 1. Agricultural and Food Commodity Price Indices

(in natural log; 1980Q1 = 100)

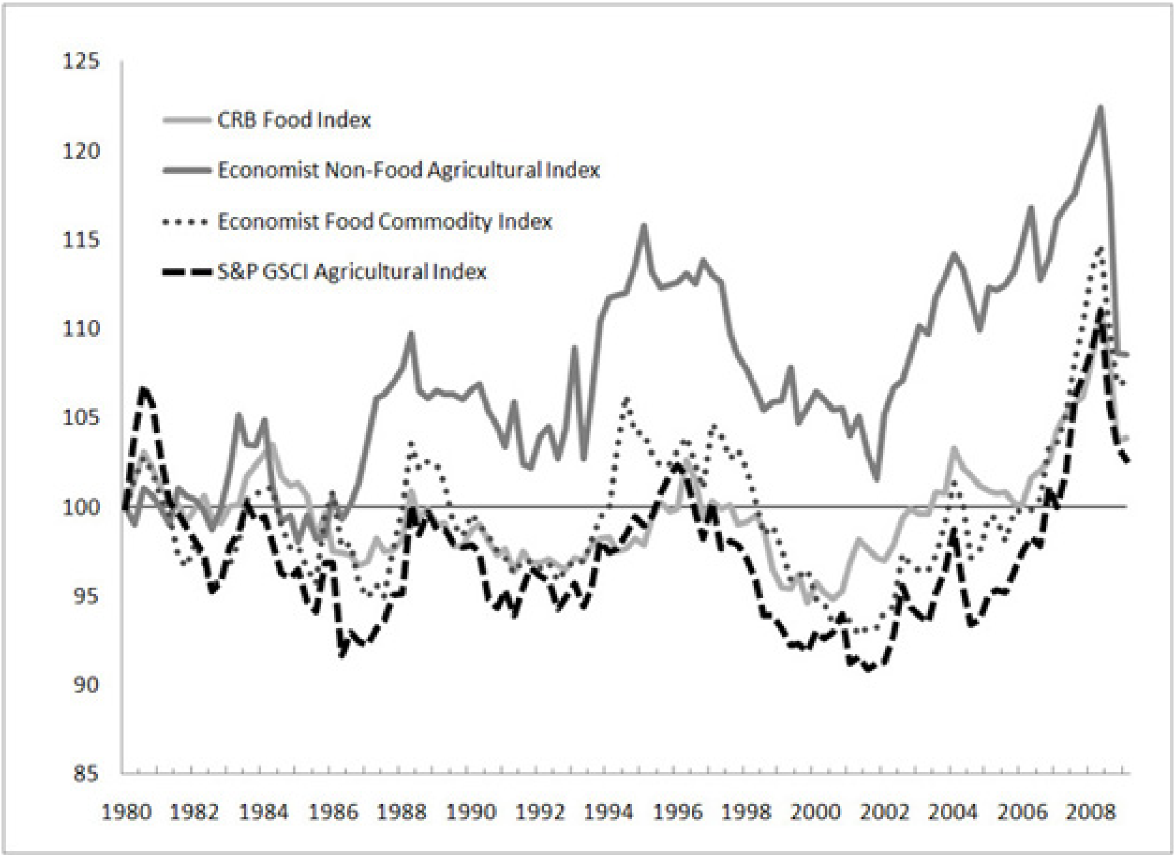
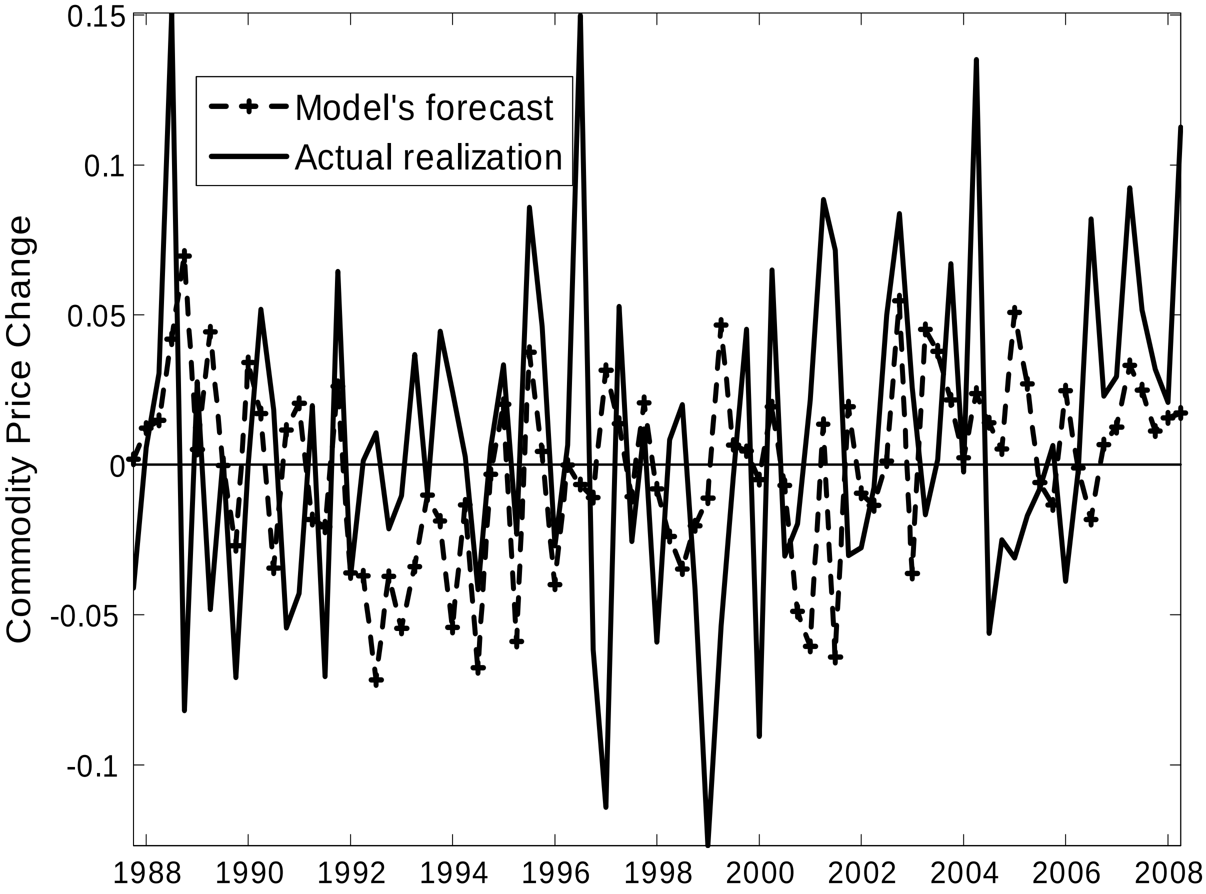


Figure IIa. Forecasting the CRB Food Commodity Price Index

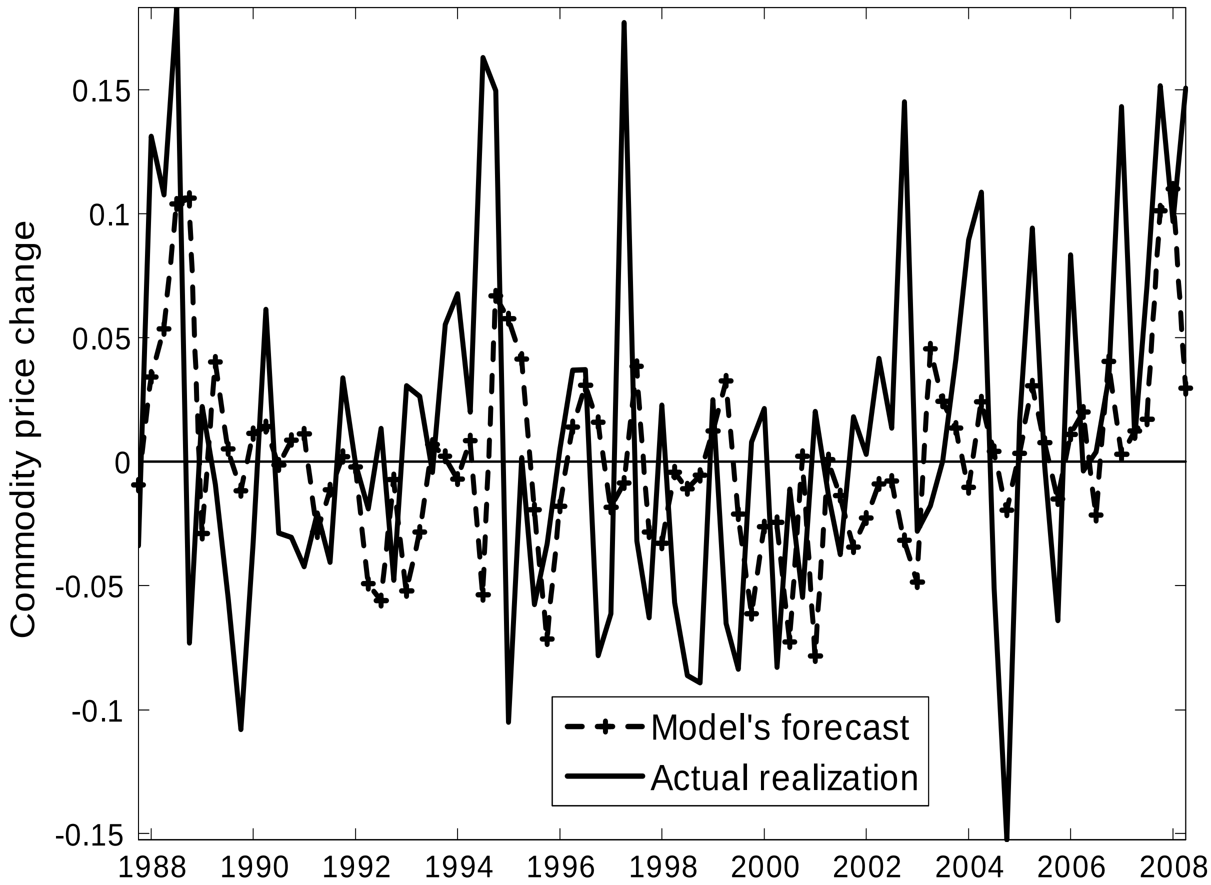
$$\text{Exchange Rate Model}: E_t\Delta cp_{t+1}^{Food} = \beta_0 + \beta_{11}\Delta s_t^{AUS} + \beta_{12}\Delta s_t^{CAN} + \beta_{13}\Delta s_t^{NZ}$$



Note. The figure plots the realized changes in the logged CRB Food Commodity Price Index (labeled "Actual realization") and their exchange rate-based forecasts (labeled "Model's forecast")

Figure IIb. Forecasting the Economist Food Commodity Price Index

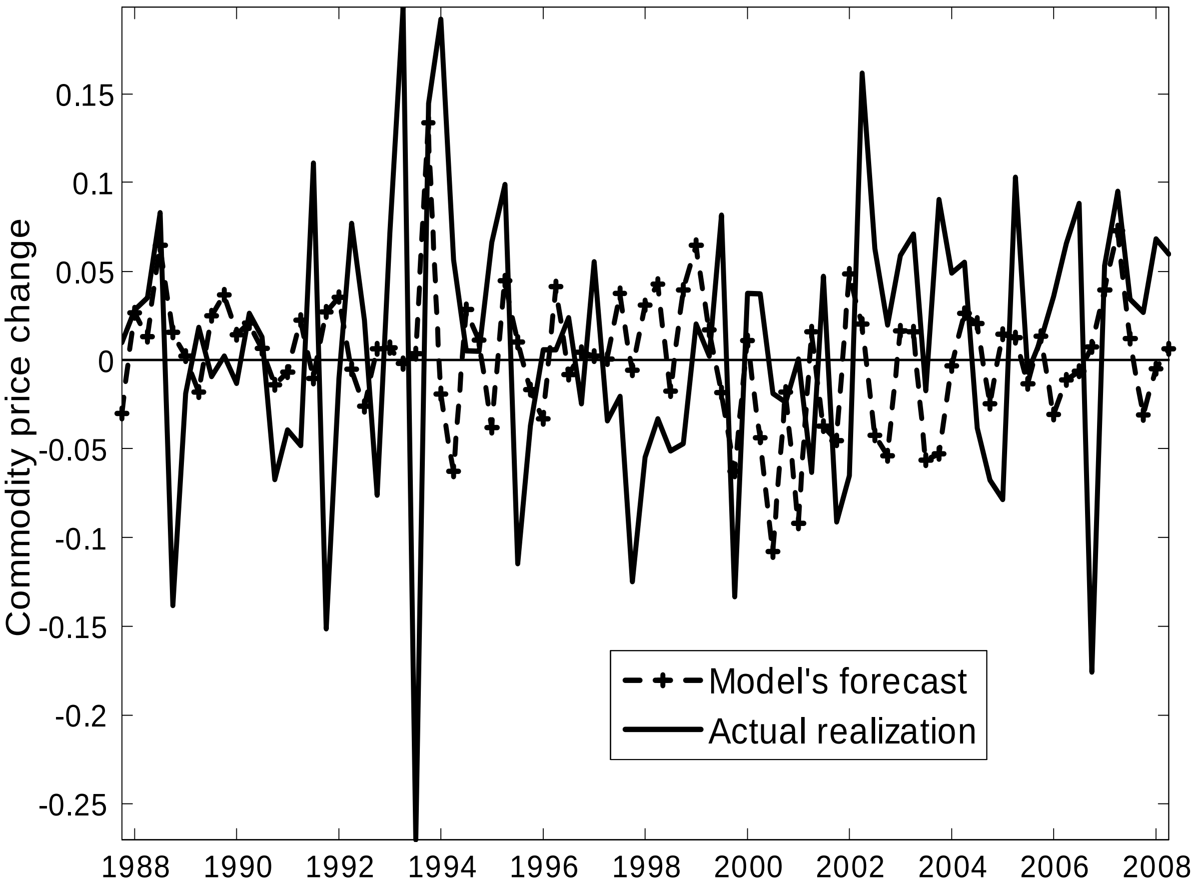
Exchange Rate Model : $E_t \Delta cp_{t+1}^{Food} = \beta_0 + \beta_{11} \Delta s_t^{AUS} + \beta_{12} \Delta s_t^{CAN} + \beta_{13} \Delta s_t^{NZ}$



Note. The figure plots the realized changes in the logged Economist Food Commodity Price Index (labeled "Actual realization") and their exchange rate-based forecasts (labeled "Model's forecast")

Figure IIIa. Forecasting Economist Non-Food Agricultural Index

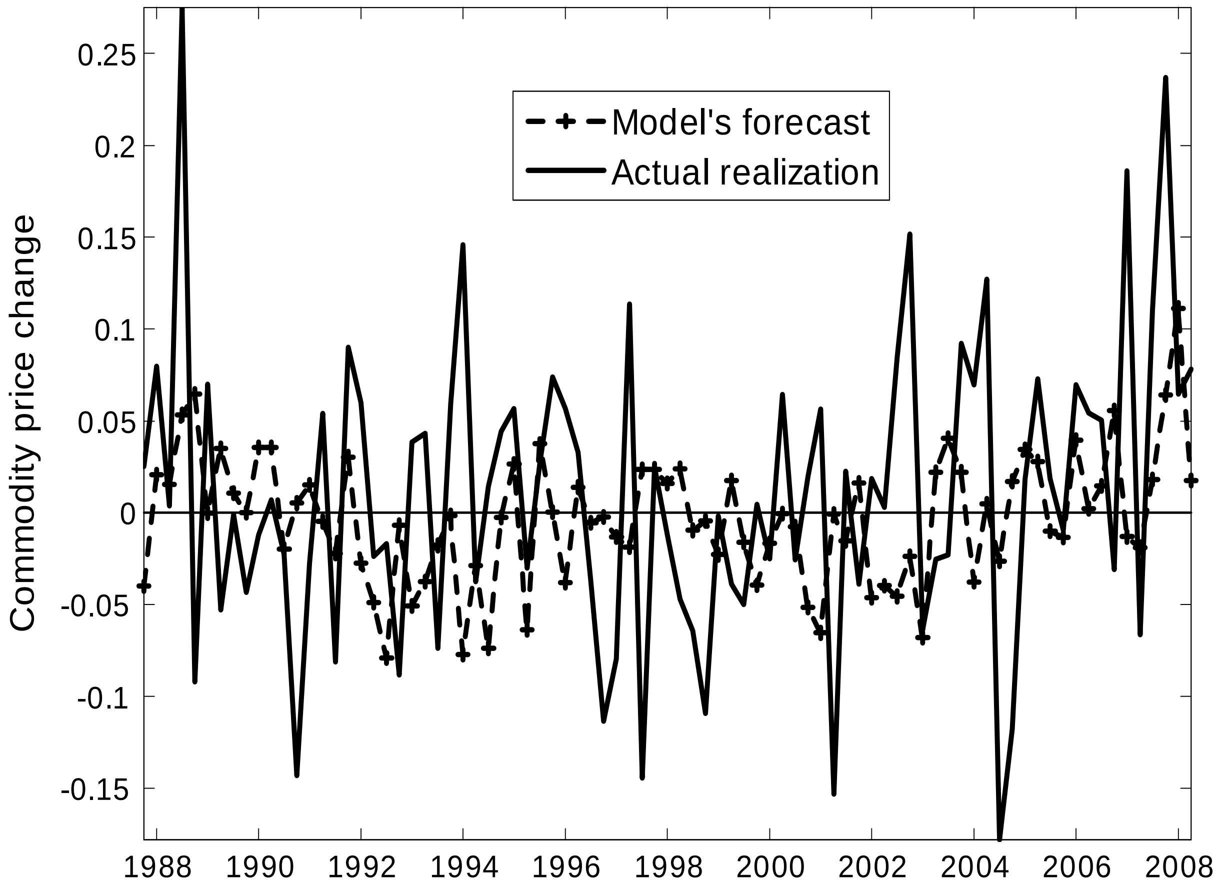
$$\text{Exchange Rate Model}: E_t \Delta cp_{t+1}^{Ag} = \beta_0 + \beta_{11} \Delta s_t^{AUS} + \beta_{12} \Delta s_t^{CAN} + \beta_{13} \Delta s_t^{NZ}$$



Note. The figure plots the realized changes in the logged Economist Non-Food Agricultural Price Index (labeled"Actual realization") and their exchange rate-based forecasts (labeled "Model's forecast")

Figure IIIb. Forecasting the S&P GSCI Agricultural Index

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

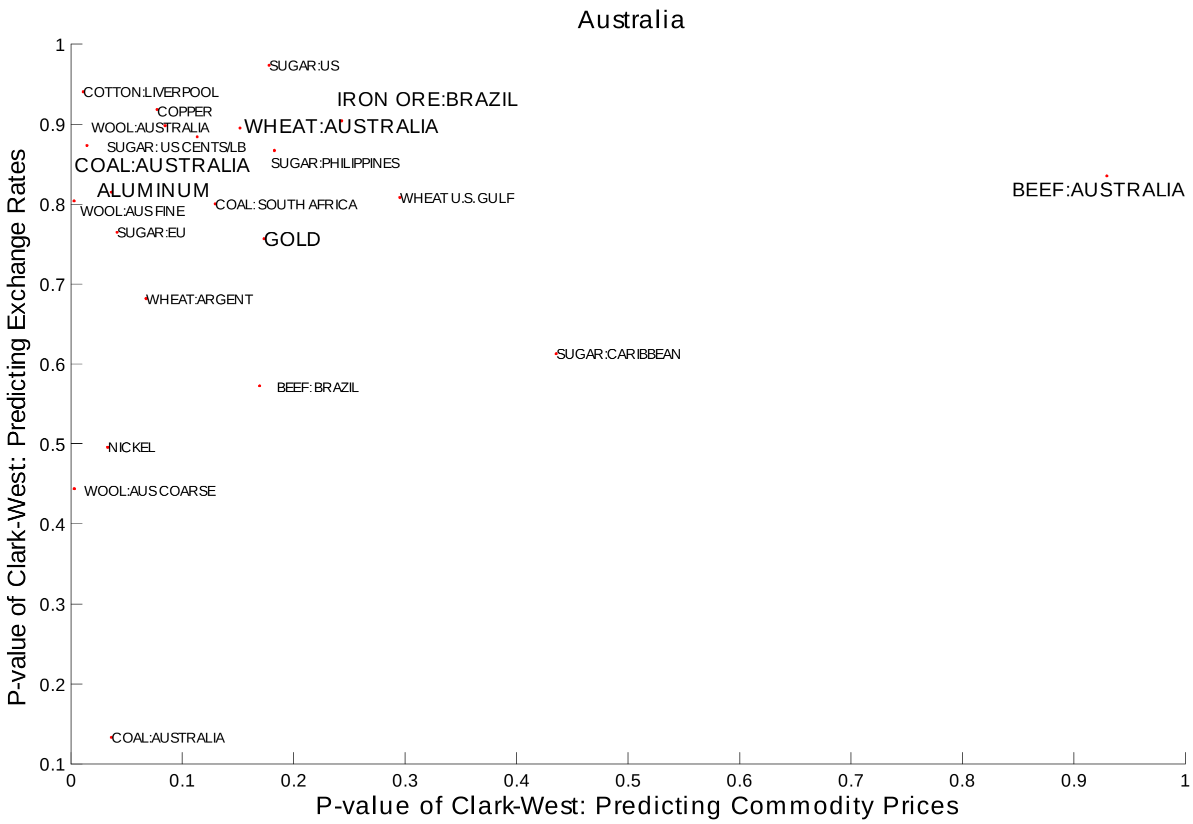


Note. The figure plots the realized changes in the logged S&P GSCI Agricultural Commodity Price Index (labeled"Actual realization") and their exchange rate-based forecasts (labeled "Model's forecast")

Figure IVa. Individual Commodity Prices and Australian Exchange Rate

X-axis: Model is $E_t \Delta cp^{ag}_{t+1} = \beta_{0t} + \beta_{11t} \Delta s^{AU}_t + \beta_{2t} \Delta cp^{ag}_t$ vs. $E_t \Delta cp^{ag}_{t+1} = \beta_{0t} + \beta_{2t} \Delta cp^{ag}_t$.

Y-axis: Model is $E_t \Delta s^{AU}_{t+1} = \beta_{0t} + \beta_{11t} \Delta cp^{ag}_t + \beta_{2t} \Delta s^{AU}_t$ vs. $E_t \Delta s^{AU}_{t+1} = \beta_{0t} + \beta_{2t} \Delta s^{AU}_t$.

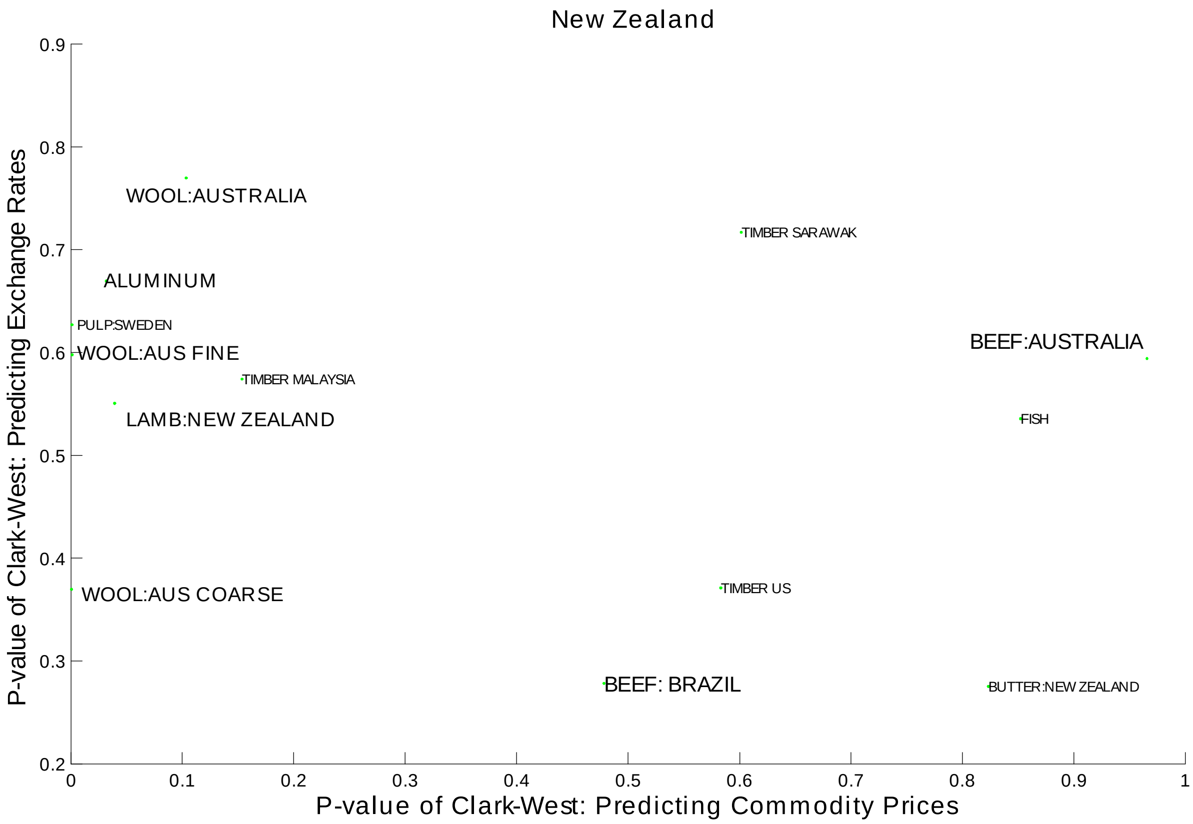


Note. Scatterplot points refer to commodity "ag" (labeled in each point), and the figure reports p-values of tests for equal out-of-sample predictive ability between the regression model (7) and the AR model (x-axis) and the regression model (8) and the random walk (y-axis). P-values are based on the Clark and West (2007) test for equal out-of-sample predictive ability.

Figure IVc. Individual Commodity Prices and New Zealand Exchange Rate

X-axis: Model is $E_t \Delta cp^{ag}_{t+1} = \beta_{0t} + \beta_{11t} \Delta s^{NZ}_t + \beta_{2t} \Delta cp^{ag}_t$ vs. $E_t \Delta cp^{ag}_{t+1} = \beta_{0t} + \beta_{2t} \Delta cp^{ag}_t$.

Y-axis: Model is $E_t \Delta s^{NZ}_{t+1} = \beta_{0t} + \beta_{11t} \Delta cp^{ag}_t + \beta_{2t} \Delta s^{NZ}_t$ vs. $E_t \Delta s^{NZ}_{t+1} = \beta_{0t} + \beta_{2t} \Delta s^{NZ}_t$.

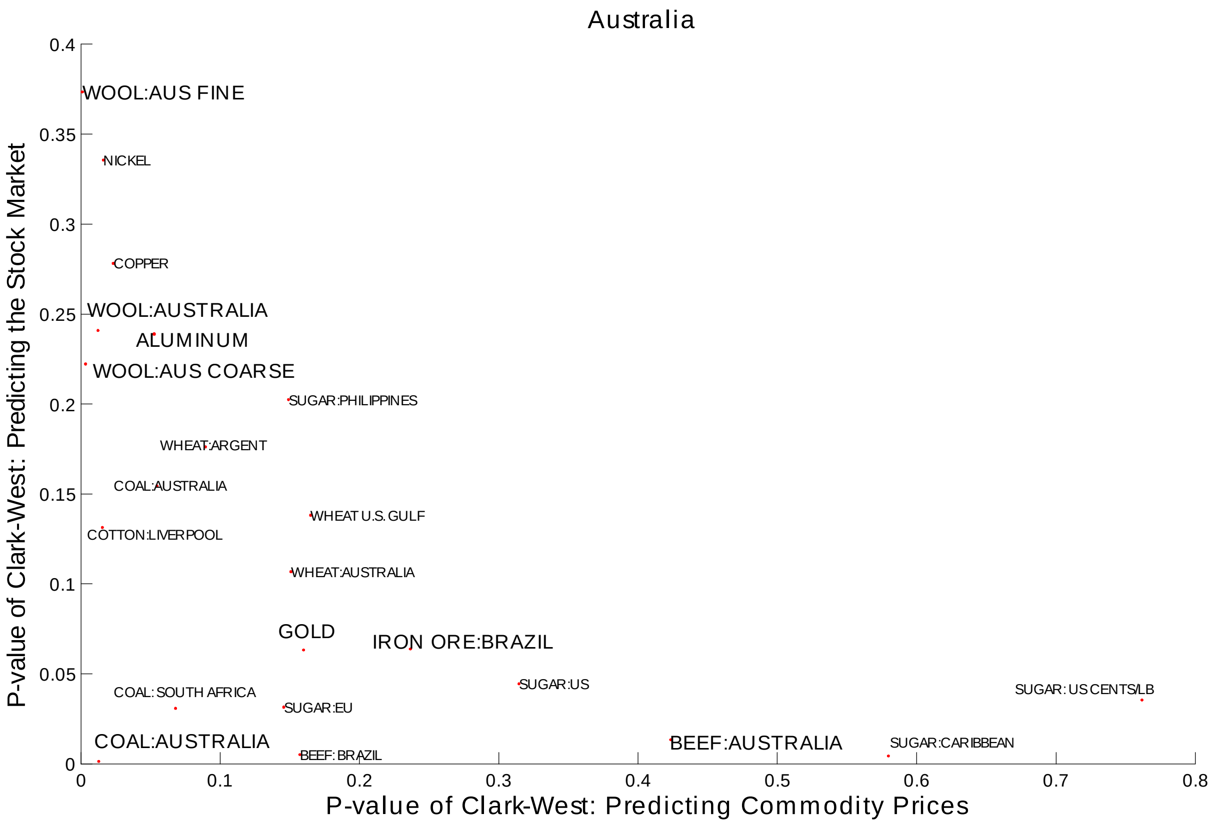


Note. Scatterplot points refer to commodity "ag" (labeled in each point), and the figure reports p-values of tests for equal out-of-sample predictive ability between the regression model (7) and the AR model (x-axis) and the regression model (8) and the AR model (y-axis). P-values are based on the Clark and West (2007) test for equal out-of-sample predictive ability.

Figure Va. Individual Commodity Prices and Australian Stock Market

X-axis: Model is $E_t \Delta cp^{ag}_{t+1} = \beta_{0t} + \beta_{11t} \Delta s^{AU}_t + \beta_{2t} \Delta cp^{ag}_t$ vs. $E_t \Delta cp^{ag}_{t+1} = \beta_{0t} + \beta_{2t} \Delta cp^{ag}_t$.

Y-axis: Model is $E_t \Delta m^{AU}_{t+1} = \beta_{0t} + \beta_{11t} \Delta cp^{ag}_t + \beta_{2t} \Delta m^{AU}_t$ vs. $E_t \Delta m^{AU}_{t+1} = \beta_{0t} + \beta_{2t} \Delta m^{AU}_t$.

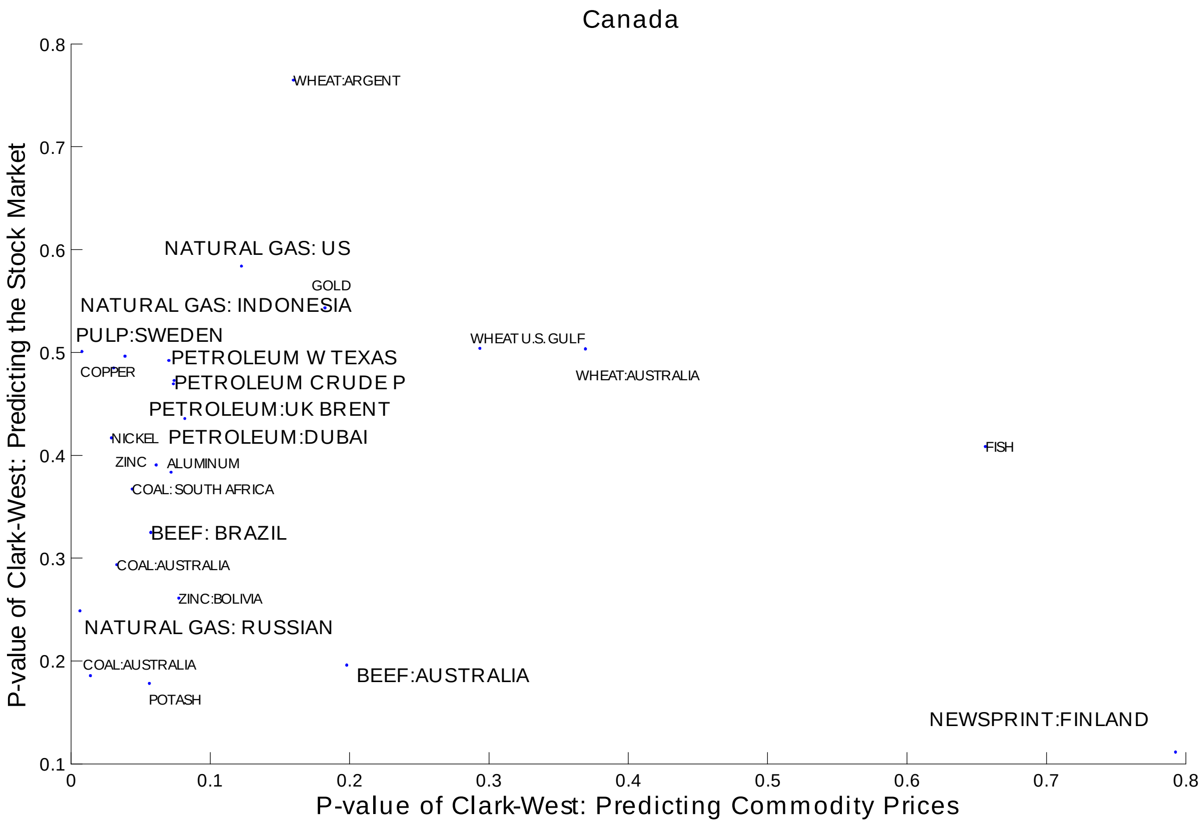


Note. Scatterplot points refer to commodity "ag" (labeled in each point), and the figure reports p-values of tests for equal out-of-sample predictive ability between the regression model (7) and the AR model (x-axis) and the regression model (8) and the AR model (y-axis). P-values are based on the Clark and West (2007) test for equal out-of-sample predictive ability.

Figure Vb. Individual Commodity Prices and Canadian Stock Market

X-axis: Model is $E_t \Delta cp_{t+1}^{ag} = \beta_{0t} + \beta_{11t} \Delta m_t^{CA} + \beta_{2t} \Delta cp_t^{ag}$ vs. $E_t \Delta cp_{t+1}^{ag} = \beta_{0t} + \beta_{2t} \Delta cp_t^{ag}$.

Y-axis: Model is $E_t \Delta m_{t+1}^{CA} = \beta_{0t} + \beta_{11t} \Delta cp_t^{ag} + \beta_{2t} \Delta s_t^{CA}$ vs. $E_t \Delta m_{t+1}^{CA} = \beta_{0t} + \beta_{2t} \Delta m_t^{CA}$.

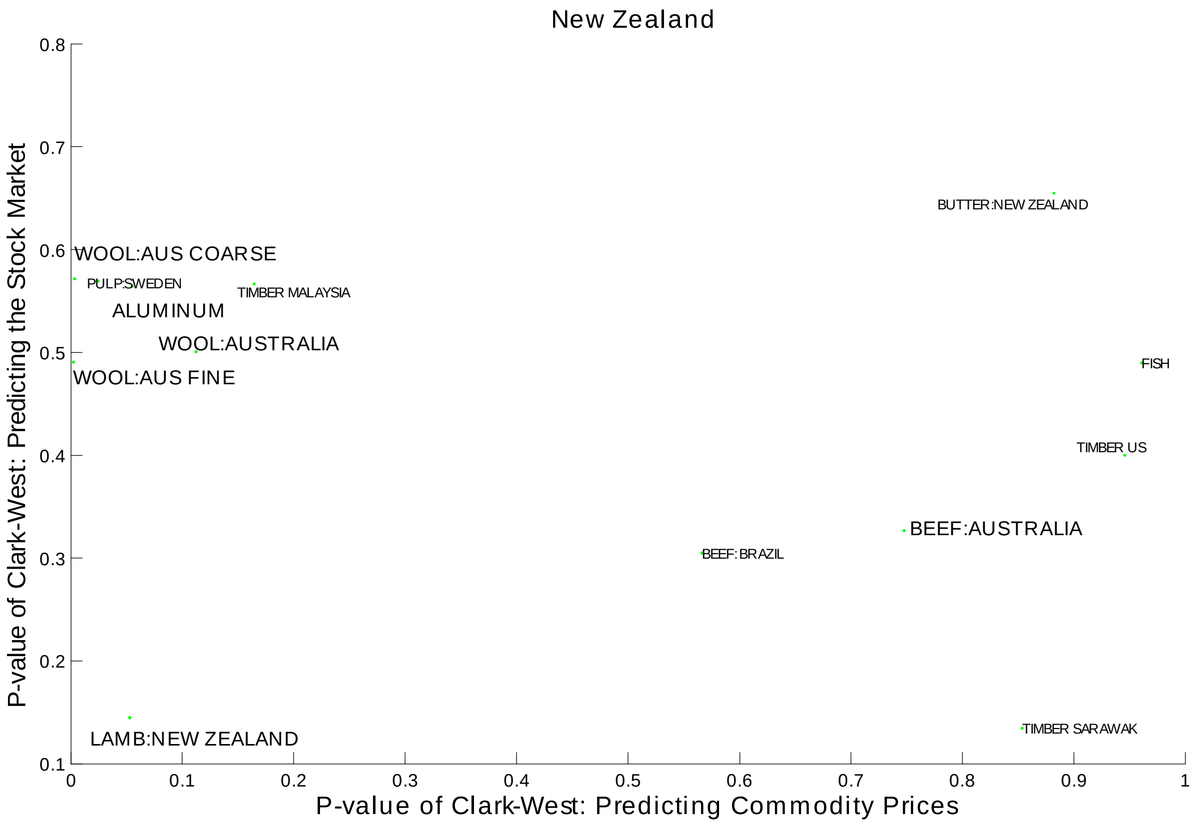


Note. Scatterplot points refer to commodity "ag" (labeled in each point), and the figure reports p-values of tests for equal out-of-sample predictive ability between the regression model (7) and the AR model (x-axis), and the regression model (8) and the AR model (y-axis). P-values are based on the Clark and West (2007) test for equal out-of-sample predictive ability.

Figure Vc. Individual Commodity Prices and New Zealand Stock Market

X-axis: Model is $E_t\Delta cp^{ag}_{t+1} = \beta_{0t} + \beta_{11t}\Delta m^{NZ}_t + \beta_{2t}\Delta cp^{ag}_t$ vs. $E_t\Delta cp^{ag}_{t+1} = \beta_{0t} + \beta_{2t}\Delta cp^{ag}_t$.

Y-axis: Model is $E_t\Delta m^{NZ}_{t+1} = \beta_{0t} + \beta_{11t}\Delta cp^{ag}_t + \beta_{2t}\Delta m^{NZ}_t$ vs. $E_t\Delta m^{NZ}_{t+1} = \beta_{0t} + \beta_{2t}\Delta m^{NZ}_t$.



Note. Scatterplot points refer to commodity "ag" (labeled in each point), and the figure reports p-values of tests for equal out-of-sample predictive ability between the regression model (7) and the AR model (x-axis) and the regression model (8) and the AR model (y-axis). P-values are based on the Clark and West (2007) test for equal out-of-sample predictive ability.