Are the Commodity Currencies an Exception to the Rule?*

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Abstract. This paper first confirms and extends findings in the previous literature that for major commodity exporters with market-based exchange rates, the world price of their primary commodity exports is an important and robust determinant for their real exchange rate values. However, despite inducing strong contemporaneous currency responses, commodity prices tell us little about subsequent exchange rate movements a quarter ahead. To further investigate real exchange rate predictability, we use Bayesian model averaging and least angle regression as mechanisms to address model uncertainty and select predictors. We show that while various combinations of macroeconomic fundamentals – including commodity prices at times – can help predict quarterly exchange rate changes, no single specification emerges as the clear winner across both countries and time periods.

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1. Introduction

The empirical literature on the major currency cross exchange rates is notorious for its enduring puzzles, particularly the near impossibility of explaining exchange rate movements, even after the fact.[1] Recently, researchers have begun to note one possible exception to the rule, that of commodity currencies. For Australia, Canada, and a few other countries that depend heavily on primary commodity exports and operate under floating exchange rate regimes, the world price of commodity exports appears to have strong and systematic relation with their currency values.

The nascent correlation between exchange rateswas first noted by central bank researchers, including Amano and Norden (1993) and Gruen and Kortian (1996). Chen and Rogoff (2003), terming the Australian, Canadian, and New Zealand dollars "commodity currencies," discussed the theoretical channels and established that the world commodity price is indeed a strong and robust driver of these countries' real exchange rates. Follow-up work such as Cashin, Cesedpes, and Sahay (2004) look at a broad set of developing countries and find some limited correlation that is much less robust than for the three OECD countries. This finding should not be entirely surprising since virtually all of the potential developing country commodity currencies had gone through considerable turmoil in their inflation, exchange rate, and capital control regimes over most of the sample.[2] More recently, Chen, Rogoff, and Rossi (2010), Ito and Rose (2011), for example, explore the implications of the commodity price-exchange rate linkage and present new research directions. Chen and Tsay (2011), Ferraro, Rossi, and Rogoff (2012), among others, explore the linkage of prices in the FX, equity, and commodity markets using data of different frequencies.

This paper first extends the data set used in the original (Chen and Rogoff 2003) – both in terms of time and coverage – to re-examine the connection between real exchange rate behavior and (real) world commodity prices at the quarterly frequency. Besides the three countries mentioned above, we also include Chile and South Africa, both of which adopted flexible

[1] Meese and Rogoff (1983) were the first to show that it is virtually impossible to explain or predict nominal exchange rates using standard macroeconomic models at horizons up to 18 months, though they find some fit at longer horizons. See also Cheung, Chinn, and Pascual (2005) for example.

[2] The short sample is particularly problematic given the well known persistence in shocks to real exchange rates. Even Australia, Canada, and New Zealand have just settled into anything resembling a modern floating exchange rate regime only within the past few decades, severely limiting the sample available in the early work.

exchange rate and inflation targeting regimes within the last fifteen to twenty years. We also considerably refine the econometric technique used in our earlier studies to reflect the local-to-unit root behavior exhibited in these time series data. Given the significant instability found in the general empirical exchange rate literature, it would not be surprising if the addition of a few years of data would show that the commodity currency phenomenon has vanished as another victim, especially given the market volatility of the 2000's.[3] Remarkably, we find this is not the case; the correlation not only remains robust for our original set of commodity currencies, but it appears to extend to the newcomers as well.

In establishing this result, we employ local-to-unity asymptotics to test for real exchange rate response to commodity price shocks. Until now, the predominant approach in the literature has been to rely on unit root tests to justify cointegration analyses, even though on theoretical grounds, it is very difficult to justify a non-stationary real exchange rate. Empirically, unit root tests are well known to have very low power against the alternative of a highly persistent yet mean-reverting process. Inference based on local-to-unity asymptotics accounts for highly persistent regressors and remains robust to the autoregressive roots being near or exactly one (see Cavanagh, Elliott, and Stock 1995, Elliott 1998, among others). Adopting the Bonferroni method similar to the one proposed in Campbell and Yogo (2006), we find strong evidence that commodity prices – with AR roots either near one or exactly one – are an important driving force behind real exchange rate movements for this set of countries. We also note that the approximate magnitude of the effect, generally less than one-to-one, is consistent with a variety of theoretical models as the channel of transmission, encompassing the Balassa-Samuelson effect, sticky prices, income effect, fixed or flexible factor mobility, and alternative monetary policy such as inflation targeting.[4] However, our results raise a new puzzle. We find that by and large, commodity price shocks appear to have little lasting influence on exchange rate *dynamics* beyond the quarter, suggesting that the shocks to commodity prices (which themselves are highly persistent) tend to build immediately into real exchange rates. While this is theoretically plausible in certain special cases when commodity price shocks are perceived as permanent, one might expect that in general – that is, with limited and gradual factor mobility – there would be

[3] See Mark (1995) and subsequent work, e.g. Groen (1999), on the sensitivity of the result over sample period.
[4] See Chen and Rogoff (2003), Chen et al (2010) for further discussion on the relevant models.

some longer term persistence.[5] We do not resolve this question here, though it may have important ramifications for understanding flexible exchange rates more broadly, especially as the commodity currencies provide such an apparently unique exception to the rule that structural variables cannot systematically explain exchange rates.

In the second part of the paper, we examine the predictability of commodity currencies using a selected set of standard macroeconomic variables. In doing so, we remain agnostic about the exact model specification and avoid pre-selecting a particular model. Our rationale is that since exogenous commodity price shocks may be absorbed by other endogenous macro variables before feeding into the real exchange rate dynamically, our set of potential candidate predictors may help us identify the relevant structural mechanism that can explain exchange rate dynamics.[6] Put it more precisely, our predictive analysis incorporates the uncertainty in the model selection process.[7] Several alternative methods have been developed to address model uncertainty, and here we follow the Bayesian Model Averaging (BMA) framework of Raftery, Madigan, and Hoeting (1997).[8] BMA involves combining outcomes from alternative models using weights based on relative model likelihood derived from the Bayesian posterior odds. Aside from the conceptual justification of accounting for model uncertainty, BMA is also empirically appealing as a mechanism to produce out-of-sample forecasts. The forecast literature on inflation and GDP forecasts have found that judiciously combining multiple forecast outcomes tends to produce superior results than relying on a single model (see, for example, Stock and Watson 1999, Wright 2008, and references there within). The argument here is that averaging serves as a shrinkage mechanism to combine useful information from different sources while avoiding the need to estimate many free parameters.

Using BMA, our analysis on in-sample predictive equations reveals several noteworthy patterns. The first is that simple random walk model of real exchange rate is by and large

[5] Shocks that are perceived as permanent would create immediate effects in, for example, the Balassa-Samuelson case with perfect factor mobility, or the case analyzed by Rogoff (1992) where factors are sector specific but utility is separable in traded and non-traded goods consumption.
[6] While this will not necessarily resolve our theoretical conundrums, it can perhaps shed some light on the underlying transmission mechanism.
[7] As statistical inferences are sensitive to our model choice, making forecast conditional on a single selected model would thus underestimate forecast uncertainty. In the exchange rate literature, model uncertainty is a particularly serious problem (essentially none of the theoretical models has shown much promise), so model uncertainty should not be ignored.
[8] One could alternatively implement a frequentists' bootstrap technique based on information criterion (Buckland, Bunham, Augustin 1997) to address model uncertainty.

dominated by models containing other macroeconomic variables, such as real GDP differentials or interest differentials. This suggests that information about the current level of economy on average is useful for explaining future exchange rate movements, or at least can do it better than a pure autoregressive process. We also note that despite being the most robust *contemporaneous* determinant, the commodity price term is often *not* selected by BMA in the dynamics analyses. While its impact of commodity price shocks could be absorbed by other macroeconomic variables that are shown to be useful predictors, there does not appear to be a clear pattern of *which* indicator shows up *when*. That is, there may not be one clear-cut, stable structural transmission mechanism of terms-of-trade shocks to the exchange rates. It also points to the advantage of incorporating model uncertainty in conducting forecast exercises. We confirm these observations using least angle regressions (LARS) of Efron et al. (2004), another well-known variable selection methodology.

Finally, we use recursive regressions and the posterior weights obtained from BMA to produce pseudo out-of-sample forecasts. We find that for Australia, forecast combination based on BMA produces surprisingly good forecasts, beating the random walk forecasts by a substantial amount. However, somewhat disappointingly, it did not appear to carry over to the other two major commodity currencies: Canada and New Zealand. We do not offer an explanation for the differences across the countries at this point. The fact that Australia proves to be such an "exception to the rule" is good news; the reason behind its success is clearly something that deserves further exploration.

2. Do Commodity Price Shocks Drive Real Exchange Rates?

This section focuses on the bilateral relation between real exchange rates and their corresponding real commodity export price index for Australia, Canada, Chile, New Zealand, and South Africa.[9] Their overall correlations can be observed in Figures 1 through 6. Table 1 shows the overall data-coverage as well as the general dates around when each of these countries adopted an inflation targeting policy. For a more detailed description about these commodity currency economies, their export patterns and history, we refer readers to our earlier work, Chen and Rogoff (2003) and Chen et al. (2010).

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[9] Data used in this paper are collected from the International Financial Statistics of the IMF, country central banks, and Global Financial Data.

2.1. Levels Relation using Local-to-Unity Asymptotics

To test whether the real exchange rates in these economies respond to fluctuations in the world prices of their commodity exports, we consider the following regression specification:

$$\begin{aligned} \ln(RER_t) &= \alpha + \beta \ln(CP_t) + \mu_t \\ \ln(CP_t) &= \gamma + \rho \ln(CP_{t-1}) + \nu_t \\ b(L)\nu_t &= \varepsilon_t \end{aligned} \tag{1}$$

where *ln(RER)* is the log of the CPI-real exchange rate, and ln(CP) the export-share weighted real price index of country's major commodity exports, in logs (see Appendix Table 1 for the country-specific list of products). In this specification, we assume commodity prices follow an exogenous AR(p) process, and that all the roots of the lag polynomial b(L) are fixed and within the unit circle. We also assume that innovations, μ_t and ε_t, are i.i.d. normal with a known covariance matrix. The parameter of interest is β, the elasticity of real exchange rate response to commodity price movements.

Previous approaches to finding the determinants of real exchange rates mostly rely either on first-order asymptotics, where the largest autoregressive root of the regressor is modeled as fixed and within the unit circle ($|\rho|<1$), or on a cointegration framework, where the regressor is assumed to have a unit root ($\rho=1$). On theoretical grounds, it is very difficult to justify non-stationary real exchange rates, especially for major OECD currency pairs. However, despite the theoretical appeal, estimations based on first-order asymptotic distribution theory can produce severe size distortions in finite samples when the regressor is highly persistent.[10] The alternative approach in the literature is to use unit root test results to justify cointegration analyses, such as the error-correction framework or dynamic OLS.[11] This practice seems to flourish despite the well-known fact that unit root tests, especially in the relevant sample size range, have very low power against the alternative of a highly persistent yet mean-reverting process. This poses a serious inference problem because, as discussed in Elliott (1998), Jansson and Moreira (2006) among others, if the regressors have roots that are not exactly one, the cointegration framework

[10] First-order asymptotics states that for samples large enough, the t-statistic is approximately normal. This statement would be misleading with highly persistent regressors, especially under correlated shocks. See Elliott and Stock (1994), for example.
[11] See Cashin, Cespedes, Sahay (2004), among others.

will produce significant size distortions.[12] As stated in Stock and Watson (1996), the asymptotically efficient estimators of cointegrating coefficients are appropriate when some of the roots of the system are exactly equal to one and the others are well within the range of stationarity. However, the accuracy of these inferences depends crucially on the largest roots being exactly one, rather than near one, and the confidence sets for the coefficients of long-run relations can have coverage rates far from their nominal coverage rate if the regressors are highly serially correlated but do not have an exact unit root.

Since researchers can seldom justify on theorerical grounds that a variable has exact unit roots, local-to-unity asymptotics may therefore be the most appealing as they account for highly persistent regressors yet remain robust to the autoregressive roots being near or exactly one (see Cavanagh, Elliott, and Stock 1995, Elliott 1998, Jansson and Moreira 2006, among others.)

2.2 Estimations using the Bonferroni Method

The local-to-unity approach remains agnostic to whether the dynamics of real commodity prices contains a unit root in Eq (1) above, and models the largest autoregressive root as $\rho = 1 + c/T$, where c is a constant and T the sample size. The advantage of this setup is that we avoid the discontinuity in the asymptotic distributions when the regressor is I(1), i.e. when $c = 0$. As described in Elliott and Stock (1994), the near integration setup has the feature that the sample moments of the regressor do not converge to a constant probability limit but functionals of a diffusion process. As such, under local-to-unity, the t-statistic is not asymptotically normal, but has a distribution that depends on an unknown "nuisance parameter" c , making the test infeasible. To estimate the system, we follow the procedure described in Campbell and Yogo (2006), which relies on a Q-test that replaces the nuisance parameters with consistent estimators to arrive at a feasible statistics.[13] The procedure essentially involves first constructing a confidence interval for ρ using the DF-GLS test, and then for each possible value of ρ in the

[12] If the regressors have exact unit roots, the cointegration estimators are asymptotically efficient and the associated t and F statistics have their usual normal and chi-squared null limiting distributions. But if the roots are less than one, tests based on comparing the t and F statistics using the normal or chi-squared critical values can have size far above the normal level. Elliott (1998) shows that the size distortions are serious even when the roots are only slightly less than 1, which are specifically the cases where unit root tests have little power.

[13] The fact that the distributions of the test statistics depend on the degree of persistence of the regressor means that we need to either adjust the critical values of the test (t-test) or the value of the test statistics itself (Q-test). Cavanagh et al. (1995) describe several methods for making tests feasible. We follow Campbell and Yogo (2006) and use their modified Bonferroni procedure.

interval, a confidence interval for β is constructed. The Bonferroni interval that is independent on ρ is then the union of all such intervals conditional on ρ. Campbell and Yogo (2006) choose to use the Q-test instead of the t-test to construct the confidence interval for β given ρ, as there is some evidence that it may offer better power properties. Here we follow their procedure and refer readers to their papers for additional discussions and estimation details.[14]

Table 2 and Table 3A present estimates for the autoregressive coefficient ρ and the elasticity β using the real exchange rates relative to the US. We consider sample periods that cover the full floating-exchange rate period (till 2011Q4), as well as sub-samples before and after the adoption of inflation targeting policy. We first note that the 95% DF-GLS-based confidence intervals for the autoregressive root ρ (5th column of Table 2) indicate that real commodity prices are quite persistent in all cases; they essentially all contain a unit root in the intervals.[15] "# Lags" reports the autoregressive lag length of commodity prices chosen by the Bayesian information criterion, with the maximum lag length set at six. The column labeled $\sigma_{\mu\varepsilon} / \sigma_{\mu}\sigma_{\varepsilon}$ in Table 2 reports the correlation between innovations to real exchange rates and to real commodity prices. As discussed earlier, when the regressor is highly persistent, inference on β based on conventional t-test suffers from large size distortions when the shocks to real exchange rates and to commodity prices are highly correlated. We see that in the case of real exchange rates and real commodity prices (which is computed based on dollar-commodity prices and deflated by US-CPI) the relation of the shocks are mostly quite small. This may explain why in Table 3 we see elasticity estimates that are not only consistent across methods, but also in line with previous studies.

Tables 3A-3C report estimates for elasticity β for exchange rates relative to alternative cross currencies (the US dollar, Japanese Yen, and the British pound) using three different methods. The first two columns report point estimates and t-statistics based on OLS regressions of Eq(1). Ninety-percent Bonferroni confidence intervals based on both the t-test and the Q-test are then reported, computed as described in Campbell and Yogo (2006). Again, treating the adoption date for inflation targeting policy as a possible exogenous break, we look at whether the

[14] While Campbell and Yogo (2006) is concerned with constructing robust and efficient tests for inferences in predictive regressions with near-persistent variables, the same arguments apply to the potentially cointegrated relationship like our equation (1).

[15] The confidence interval is computed by inverting the the DF-GLS statistics and setting the size of the one-sided Bonferroni Q-test to 5%. See Campbell and Yogo (2006) for details.

commodity price-real exchange rate relation has changed before and after inflation targeting. . Entries in bold indicate the interval does not contain zero. We see that overall, estimates based on all three methods present a very consistent picture, that real exchange rates respond positively to commodity prices, with elasticity estimates generally in the range of 0.2 to 1, which is similar to the estimates reported in our earlier study (Chen and Rogoff 2003). Not only is the relationship robust to the additional years of data, which include the recent crisis period, the "commodity currency" pattern is also observed to be robust to Chile and South Africa.[16] In addition, for Canada, Chile and New Zealand, there is some evidence that the real exchange rate may be more sensitive to the commodity terms-of-trade movements after inflation targeting. This suggests likely inter-play between monetary policy and the exchange rate – terms of trade connection.

As reported in Chen and Rogoff (2003), the commodity price – exchange rate connection is empirically strong and appears robust to alternative assumption about the underlying time series properties (unit roots, cointegration or not). Our new results here based on local-to-unity asymptotics confirm this point and show that the bias from using inappropriate inference procedures (e.g. first-order asymptotics or cointegration) are not large enough to overturn the previous conclusions.

2.3. Predictive Regressions

We next test whether the strong contemporaneous exchange rate responses observed in Eq (1) extend to exchange rate predictability by commodity prices. We again use local-to-unity approach to look at how the one-quarter *changes* of real exchange rate respond to current commodity price movements, as follows:

$$\begin{aligned} &d\ln(RER_{t+1}) = \phi + \delta \ln(CP_t) + \upsilon_{t+1} \\ &\ln(CP_t) = \gamma + \rho \ln(CP_{t-1}) + \varepsilon_t \end{aligned} \tag{2}$$

Tables 4A-4C show estimates for the predictive coefficient δ under the same three alternative estimation methods (standard t-statistics, Bonferroni confidence intervals based on the t-test and the Q-test). Again, due to relatively low innovation correlations, results based on OLS and t-

[16] This is confirmed in Chen et al (2010) using nominal exchange rates.

statistics are overall consistent with findings based on local-to-unity asymptotics. As evident from these tables, commodity price movements lead to essentially no detectable dynamic responses in real exchange rates. Across base-currencies and sub-samples, commodity price shocks *alone* appear to tell us little about future exchange rate movements in the bivariate predictive regressions.

This finding raises the questions of why and how terms-of-trade shocks from the world commodity markets are absorbed instantaneously (that is, within the quarter) into the real exchange rates, but have so little or no dynamic impact. As discussed in Chen and Rogoff (2003), the approximate magnitude of the *contemporaneous* exchange rate response – covering a range of 0.2 to 1 or so – is consistent with a variety of theoretical models, with the channels of transmission encompassing the Balassa-Samuelson effect, price rigidity, income effect, fixed or flexible factor mobility, and alternative monetary policies such as inflation targeting. However, these models suggest different dynamic impacts. The observation that the shocks to commodity prices, which themselves are highly persistent, tend to build immediately into real exchange rates is supported theoretically by certain special cases when commodity price shocks are perceived as permanent (e.g. the Balassa-Samuelson case of perfect factor mobility), or the case analyzed by Rogoff (1992) where factors are sector specific but utility is separable into traded and non-traded goods consumption. One might expect that in general – that is, with limited and gradual factor mobility – there would be some longer term persistence in the exchange rate response. This motivates us to look at a broader set of macroeconomic variables next, in hope of detecting consistent dynamic patterns from a more general equilibrium approach. We explore this in the next section.

3. Real Exchange Rate Predictability

Theoretical exchange rate models are notorious for their empirical failures. Most canonical models not only fail to provide sensible in-sample fits, they also offer no improvement in delivering improved out-of-sample forecast over a naïve random walk. While central banks of several commodity-exporting economies claim to have more reliable forecasting equations, their specifications are also fragile, even across time within a country. The large body of literature on various empirical exchange rate puzzles underscores the degree of *model uncertainty* in exchange rate prediction.   As such, we emphasize estimation strategies that specifically address model uncertainty.[17] The hope is to use such algorithm to establish a consistent set of variables that determine exchange rate dynamics, if possible. From there, we may understand better the transmission mechanism of various shocks, such as commodity terms-of-trade movements, and construct structural models accordingly.

Even if no consistent variables are selected across countries and time periods (as is often the case in forecasting exercises), it would be useful to examine whether pooling information from a large set of indicators may help forecast exchange rate out of sample. Most research efforts looking at exchange rate forecast tends to propose one specific setup, i.e. a fixed model, and compare its performance with a benchmark. However, given the large degree of model uncertainty in this literature, approaches such as forecast combination that explicitly acknowledge model uncertainty seem prudent. In fact, several recent work, such as Stock and Watson (2003), Timmermann (2006), and Wright (2008) have shown that judiciously combining a large set of potential predictors can lead to superior forecast performance to outcomes based on a single set of predictors. For both of the reasons above, this paper argues that in exchange rate forecasts, researchers should take into account model uncertainty and parameter uncertainty, and that using a large set of potentially useful predictors should not be ruled out a priori.

The Bayesian model averaging (BMA) framework we adopt in this paper allows us to accomplish two things. First, for different economies and different time periods, BMA allows us to identify separately the relevant models that are applicable for exchange rate prediction. In addition, the estimated posterior probabilities for each potential predictor can be used to combine forecasts, as in Wright (2008).[18]

3.1 Model Selection and Bayesian Model Averaging

Much of the motivation behind model averaging can be traced to the issues of model uncertainty analyzed by Leamer (1978).   While it has become standard practice to ignore model uncertainty and proceed to make inference, forecast, or even evaluate policy outcomes based on one single model specification as if it is the "true" model, this approach can result in biased

[17] Model uncertainty is essentially uncertainty about the composition of a regression in our context.

[18] Wright (2008) uses Bayesian posterior weights to combine exchange rate forecasts from univariate forecast and found that even though the Bayesian forecasts are slightly superior relative to single equation forecasts or the random walk, the quantitative improvements are small. Commodity prices are not covered in his analyses, however.

parameter estimates, over-confident standard errors, and misleading inference and predictions (see Doppelhofer 2005). Model averaging treats both models and their associated parameters as unobservable, and uses empirical data to estimate their distributions. This is an idea that is increasingly being acknowledged in the economics profession.[19] As discussed in Doppelhofer (2005), there are various model averaging approaches. Below we focus on Bayesian model averaging (BMA) algorithm, developed by Adrian Raftery and a series of co-authors (see Raftery, Madigan, and Hoeting 1997; Hoeting et al 1999).[20] BMA treats models themselves and the parameter values within a model both as random, and summarizes model uncertainty in terms of a probability distribution over the space of possible models. It constructs a weighted average of the posterior distribution for each parameter under all possible models, using as weights the posterior model probabilities.[21] For a detailed derivation of the BMA framework, we refer readers to Hoeting et al (1999).

3.2 In-Sample Predictive Regression

We consider the following in-sample predictive regression:

$$d\ln(RER_{t+1}) = \ln(RER_{t+1}) - \ln(RER_t) = a + b' X_t + e_{t+1} \tag{3}$$

where X_t is a set of candidate predictor variables available at time t. Drawing from standard exchange rate theories and other potential predictors, we consider a set of ten macroeconomic variables to be potential contributors to exchange rate dynamics. These include the relative real income between the two countries, the relative tradable-to-nontradable sector productivity differences (Balassa-Samuelson effect), real commodity prices, interest differentials at short and

[19] For example, model uncertainty has been addressed in the empirical growth literature (Sala-i-Martin, Doppelhofer and Miller 2004, and Fernàndez, Ley and Steel 2001b); in policy evaluations (Brock, Durlauf and West 2003); and in forecasting (Wright 2008, and Kapetanios, Labhard, and Price 2005).

[20] For background literature and new developments on BMA see the "Bayesian Model Averaging Home Page" at http://www.research.att.com/~volinsky/bma.html.

[21] The BMA algorithm here does not average *all* possible models, but first identifies a subset of "good" models based on some search and select criteria. Our particular algorithm (bicreg) uses Occam's Window (Raftery 1995) mostly, with occasionally robustness checks using Markov Chain Monte Carlo (Hoeting et al 1996). In general, the MCMC method can also identify outliers but requires large sample size relative to the regressor set. Occam's Window technique chooses a subset of models and treats all the worst-fitting models outside the subset as having zero posterior probability.

long horizons, a broad index of commodity futures prices, stock market performance differentials across countries.[22] We use the USD-based real exchange rate for the rest of our analysis.

We run the above equation in the BMA setup. Intuitively, one can interpret this exercise as the following: the predictive regression aims to estimate the partial derivative of exchange rate change with respect to a predictor x, called it β_x. A *model* would be a particular set/combination of predictors. If we have n potential predictors, there would be 2^n potential models to consider. Conditional on each model, there is a distribution of β_x under a given dataset. The posterior distribution of β_x is then the weighted average of all these individual distributions, where the weights are proportional to the likelihoods of the models.

As mentioned earlier, we hope the model selection algorithm would help uncover a consistent set of exchange rate determinants, which in turn can help establish the channel of transmission from commodity prices to real exchange rate movements. Table 5 shows the results of our BMA analyses for three of our five countries with a more complete data series. Results are reported for the sample up to 2005Q4, and also a sub-sample up to the end of 2001.[23] We first note that most of the results show that contrary to the view that exchange rates are "disconnected" from macro-fundamentals, we see that macro-variables do offer explanatory power for exchange rate movement over the next quarter. For example, differences in real output across countries and the Balassa-Samuelson tradable-non-tradable productivity differences appear especially relevant for Australia. Non-energy commodity prices appear important for Canada up to 2001, along with short-run interest differentials and inflation differentials relative to the US.

Despite finding that various macroeconomic variables are able to predict subsequent exchange rate movements, we note that no single model (or set of variables) emerges consistently across countries and time periods under BMA. In most cases, commodity prices do not even show up as important in explaining real exchange rate dynamics, confirming our earlier puzzle as to why the shocks are so immediately absorbed. In unreported results (available upon request), we see that the explanatory power of the BMA- selected model is never large, and the

[22] We note that this list is certainly far from exhaustive, and that our approach can be extended to include a much broader set of variables, macroeconomic or financial. We leave this to future research.
[23] We consider two alternative priors: a diffuse prior and the "unit information prior" proposed by Raftery et al (1997). We find the results are quite robust to the choice of these two priors.

posterior distribution for each predictor across selected models is quite spread out. In the next section, we use an alternative variable selection algorithm to confirm these patterns.

3.3 Least Angle Regressions

We next use least angle regressions (LARS) of Efron, Hastie, Johnstone, and Tibshirani (2004) as a way to select a parsimonious and efficient set of predictors for real exchange rate changes. Similar to Lasso and forward-stagewise regressions, LARS as a model-selection algorithm is relatively fast and easy to implement, balancing goodness-of-fit and parsimony[24]. The LARS procedure provides a natural way to judge the relative importance of the variables in predicting exchange rate that is superior to the traditional stepwise regression.

LARS begins by setting the coefficients on all predictors to zero, and adds in variables step-by-step based on their correlation with the residuals of the previous model. To select the number of variables to include, we use the minimized C_p criterion, where C_p is an estimate of the prediction error.[25] As a robustness test to the BMA results, we include the set of predictors into the exchange rate prediction equation. Our goal is to see if a consistent set of predictors would be selected for inclusion in the specifications producing the minimum C_p.

Table 6 reports the regression specifications chosen by the minimized C_p statistics and the coefficient estimates for the chosen variables for Australia, Canada, and New Zealand. In addition, the cumulative R^2's for the regression after the additional inclusion of a particular variable are reported in the parentheses underneath its coefficient estimate. For example, we see that for Australia, the first variable selected is the difference in the stock market valuation *dln(Stock)*, since it has the smallest R^2 (0.012) amongst the reported R^2's. The next variable to enter is real output differential, *dln(rY),* followed by short-term interest differentials di^{SR} and so on, producing a final R^2 of 0.358.[26] Note that the real commodity price variable, *ln(rCP),* is selected under LARS as a predictor for Australian real exchange rate change. For Canada, current account differential *d(CA/Y)* is selected first, but not commodity price. We also note a generally weaker result in terms of the final R^2 (or 0.106). Result for New Zealand is yet different; inflation differential, $d\pi$, which was not important for Australia and Canada, is the first

[24] See Efron et al. (2004) for a full description of the algorithm and its relation to other alternatives
[25] See Madigan and Ridgeway (2004) for more detailed discussion.
[26] Regressions that include additional variables that have no reported coefficients deliver larger C_p statistics, hence are not selected

variable to be included. Real commodity price as well as futures price both contribute non-negligibly in terms of incremental R^2's.

For all three real exchange rates, we observe the same qualitative message under LARS as our BMA results: in-sample predictive regressions, macro fundamentals do play a role in explaining real exchange rate changes, and the random walk model is dominated by fundamental-based models. Commodity prices, while important, do not play a consistent or most important role. And while interest differentials, real GDP differentials, do show up frequently as important predictors of quarterly real exchange rate changes, we don't observe a clear model emerging across these results.

3.4. Out-of-Sample Forecast with BMA

In this section, we look at pseudo out-of-sample real exchange rate forecast using the BMA algorithm as a parsimonious method to combine forecasts. It is well-known in the forecasting literature that even when a variable contains genuine predictive power with a stable coefficient in in-sample predictive regressions, it may have poor out-of-sample performance for an extended period of time (see, e.g., Inoue and Kilian 2005, and Campbell and Thompson 2008). Previous research has also shown that forecast combinations, even done in an ad hoc fashion, can often lead to superior forecast performance (e.g. Stock and Watson 2003, and Timmermann 2006). We generate out-of-sample forecasts by a rolling process using sub-samples of different sizes to obtain 20, 30, and 40 forecasts for each real exchange rate, and the Bayesian model averaging process is run recursively for each sub-sample, and we compare the results with forecasts based on a random walk process.

Table 7 presents root-mean squared forecast error (RMSE) ratios from the out-of-sample forecast exercise. We first note that the Bayesian approach of taking into account model uncertainty – using posterior probabilities as a shrinkage mechanism to combine forecasts – does not necessarily lead to better performance than a driftless random walk. For Canada and New Zealand, it appears that forecasts based on fundamentals offer little robust improvement over the random walk at horizons shorter than one year, a result consistent with the Meese-Rogoff (1983) findings from over three decades ago, and with Wright (2008) which applies pseudo-Bayesian averaging to major OECD currency pairs.

Australia, however, presents a different picture. The forecast performance of the BMA approach appears quite striking. Even at 1-quarter ahead, the BMA-forecast offers quantitatively significant improvements (over 10% improvements over the RW forecasts). The difference is even more pronounced at longer horizons (the ratio gets down to under 0.3). Looking at comparable statistics using a similar BMA framework and major currency pairs, Wright (2008) reports ratios that rarely fall below 0.9, even at 4-quarters ahead. By comparison, Australia's performance clearly puts it as an "exception to the rule" with respect to the Meese-Rogoff (1983) puzzle. We do not offer an explanation here as to why Australia behaves differently from the other countries under analysis, but suspect market structure, the types of commodity products a country specializes in, or even central bank's reserve management policy responses may all make a difference.[27] Clearly a more thorough exploration is required on this front, which we leave to future research.

4. Conclusion

Understanding the effects of commodity price shocks on exchange rates is of broad interest, particularly as more developing countries open up their capital markets and adopt more flexible exchange rates. If commodity prices can indeed be shown to be a consistent and empirically reliable factor in empirical exchange rate equations, the finding would have important implications across a variety of policy issues, not least concerning issues such as how to implement inflation-targeting in developing countries. To further our understanding of the commodity currency phenomenon, this paper considerably extends the data set used in our earlier work and also refines the econometric technique to reflect the local-to-unit root behavior exhibited in these time series data. We find the correlation between real exchange rates and real commodity prices not only remains robust for our original set of commodity currencies, it extends to the newcomers – Chile and South Africa – as well. The approximate magnitude of the effect is consistent with a variety of theoretical models.

Exploring exchange rate dynamics in a predictive equation set-up, we find that commodity price movements have little lasting influence on exchange rate dynamics, suggesting that the shocks to commodity prices tend to build immediately within the quarter into real

[27] See Chen and Lee (2012), for example.

exchange rates. This is rather surprising as one might expect that, in general, commodity terms-of-trade shock would have some longer term persistence given the limited and gradual factor mobility in the short run. We do not resolve this question here, though it may have important ramifications for understanding flexible exchange rates more broadly, especially as the commodity currencies provide such an apparently unique exception to the rule that structural variables cannot systematically explain exchange rates.

Using a broader set of macroeconomic fundamentals, we examine exchange rate prediction more broadly using Bayesian model averaging and least angle regressions, taking into account model uncertainty. We also use the BMA algorithm to compare macro fundamental-based forecasts with that of a driftless random walk. In doing so, we uncover an "exception to the rule" and find strong out-of-sample predictability in the Australian-US Dollar exchange rate. The overall results across countries suggest that while fundamentals do help predict future exchange rate changes, no single equation jumps out as the winning specification that is robust across countries and over time. This finding cautions against relying on a single forecast equation religiously, and raises the question on whether the quest for "one equation to rule them all" may be too much of a fantasy.

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Tables

Table 1: Main Sample Coverage and Inflation Targeting Dates

(quarterly frequency)

Australia		
	full sample	1984Q1-2011Q4
	break date	1993Q1
Canada		
	full sample	1973Q1-2011Q4
	break date	1991Q1
Chile		
	full sample	1989Q3-2011Q2
	break date	1999Q3
New Zealand		
	full sample	1987Q1-2011Q4
	break date	1990Q1
South Africa		
	full sample	1994Q1-2011Q4
	break date	2000Q1

Note: Break dates correspond roughly to the start of inflation-targeting policy in the respective countries; they are not exact.

Table 2: Local-to-Unity Parameter Estimates

$$\ln(RER_t) = \alpha + \beta \ln(CP_t) + \mu_t$$
$$\ln(CP_t) = \gamma + \rho \ln(CP_{t-1}) + \varepsilon_t$$

		# Lags	$\sigma_{\mu\varepsilon}/\sigma_{\mu}\sigma_{\varepsilon}$	DF-GLS Stats	95% CI for ρ	# Obs.
Australia						
	Full Sample	2	0.233	-1.133	[0.927,1.033]	112
	- Pre-IT	1	0.017	-1.003	[0.790,1.112]	36
	- Post-IT	3	0.229	0.053	[0.968,1.063]	76
Canada						
	Full Sample	2	0.002	-0.475	[0.973,1.028]	156
	- Pre-IT	1	-0.368	-0.205	[0.953,1.067]	68
	- Post-IT	3	0.1	-1.27	[0.893,1.040]	88
Chile						
	Full Sample	1	-0.068	-1.061	[0.914,1.043]	88
	- Pre-IT	1	0.058	-0.543	[0.885,1.110]	40
	- Post-IT	1	-0.02	-0.487	[0.910,1.092]	48
New Zealand						
	Full Sample	2	0.162	-2.181	[0.811,1.002]	100
	- Pre-IT	1	0.062	-2.859	[-1.529,0.629]	12
	- Post-IT	2	0.169	-2.454	[0.744,0.985]	88
South Africa						
	Full Sample	1	-0.073	0.702	[0.985,1.069]	72
	- Pre-IT	4	-0.314	-1.833	[0.274,1.090]	24
	- Post-IT	1	0.11	0.557	[0.973,1.103]	48

Note: Parameter estimates based on the Campbell and Yogo (2006) local-to-unity estimation are reported for the full sample and sub-samples before and after the inflation targeting break date (see Table 1). "# Lags" indicates the number of lagged regressor selected by the Bayesian information criterion; $\sigma_{\mu\varepsilon}/\sigma_{\mu}\sigma_{\varepsilon}$ is the correlation between the shocks (for USD-based *lnRER*); the 95% confidence intervals for ρ is computed based on the DF-GLS statistics reported. See text for details.

Table 3: Do Commodity Prices Drive Real Exchange Rates?

$$\ln(RER_t) = \alpha + \beta \ln(CP_t) + \mu_t$$
$$\ln(CP_t) = \gamma + \rho \ln(CP_{t-1}) + \varepsilon_t$$

3A) USD-based Exchange Rates

			90% CI: $\hat{\beta}$		
	$\hat{\beta}$	**t-stats**	**t-test**	**Q-test**	**Obs.**
Australia					
Full Sample	0.441	14.071	**[0.393,0.504]**	**[0.383,0.492]**	112
- Pre-IT	0.493	2.445	**[0.166,0.833]**	**[0.130,0.796]**	36
- Post-IT	0.446	14.238	**[0.397,0.509]**	**[0.392,0.500]**	76
Canada					
Full Sample	0.79	17.862	**[0.718,0.864]**	**[0.697,0.842]**	156
- Pre-IT	0.682	11.906	**[0.556,0.759]**	**[0.583,0.800]**	68
- Post-IT	1.009	6.617	**[0.768,1.284]**	**[0.624,1.138]**	88
Chile					
Full Sample	0.132	4.893	**[0.084,0.175]**	**[0.088,0.178]**	88
- Pre-IT	-0.114	-1.833	**[-0.214,-0.007]**	**[-0.214,-0.008]**	40
- Post-IT	0.209	10.592	**[0.176,0.241]**	**[0.169,0.234]**	48
New Zealand					
Full Sample	0.815	11.762	**[0.706,0.945]**	**[0.670,0.907]**	100
- Pre-IT	-0.039	-0.036	[-1.802,1.835]	**[-4.091,-0.408]**	12
- Post-IT	0.873	11.261	**[0.751,1.021]**	**[0.717,0.984]**	88
South Africa					
Full Sample	0.158	2.828	**[0.060,0.248]**	**[0.073,0.261]**	72
- Pre-IT	0.808	9.305	**[0.622,0.932]**	**[0.367,0.645]**	24
- Post-IT	0.355	6.848	**[0.272,0.448]**	**[0.262,0.437]**	48

Note: Local-to-unity estimations are conducted for the full sample as well as subsamples before and after inflation targeting. Point estimates and t-statistics for β based on OLS regressions are reported along with the 90% Bonferroni confidence intervals for β using the t-test and the Q-test. Confidence intervals that reject the null of $\beta = 0$ are in bold.

3B) JPY-based Exchange Rates

		$\hat{\beta}$	t-stats	90% CI: $\hat{\beta}$ t-test	90% CI: $\hat{\beta}$ Q-test	Obs.
Australia						
	Full Sample	0.493	10.962	**[0.423,0.580]**	**[0.419,0.573]**	112
	- Pre-IT	0.628	2.403	**[0.097,1.023]**	**[0.395,1.296]**	36
	- Post-IT	0.481	10.441	**[0.409,0.574]**	**[0.395,0.555]**	76
Canada						
	Full Sample	0.79	17.862	**[0.718,0.864]**	**[0.697,0.842]**	156
	- Pre-IT	0.682	11.906	**[0.556,0.759]**	**[0.583,0.800]**	68
	- Post-IT	1.009	6.617	**[0.768,1.284]**	**[0.624,1.138]**	88
Chile						
	Full Sample	0.175	5.961	**[0.126,0.223]**	**[0.124,0.221]**	88
	- Pre-IT	-0.287	-3.465	**[-0.427,-0.153]**	**[-0.396,-0.122]**	40
	- Post-IT	0.233	12.417	**[0.201,0.263]**	**[0.194,0.256]**	48
New Zealand						
	Full Sample	0.757	7.092	**[0.587,0.954]**	**[0.552,0.913]**	100
	- Pre-IT	0.177	0.188	[-1.356,1.761]	[-1.985,1.129]	12
	- Post-IT	0.851	7.128	**[0.662,1.075]**	**[0.622,1.030]**	88
South Africa						
	Full Sample	0.203	4.678	**[0.133,0.276]**	**[0.134,0.277]**	72
	- Pre-IT	0.061	0.344	[-0.366,0.282]	**[-1.039,-0.514]**	24
	- Post-IT	0.292	5.29	**[0.206,0.398]**	**[0.190,0.380]**	48

Note: Local-to-unity estimations are conducted for the full sample as well as subsamples before and after inflation targeting. Point estimates and t-statistics for β based on OLS regressions are reported along with the 90% Bonferroni confidence intervals for β using the t-test and the Q-test. Confidence intervals that reject the null of $\beta = 0$ are in bold.

3C) GBP-based Exchange Rates

		$\hat{\beta}$	t-stats	90% CI: $\hat{\beta}$ t-test	Q-test	Obs.
Australia						
	Full Sample	0.364	10.396	**[0.307,0.423]**	**[0.326,0.442]**	110
	- Pre-IT	0.67	3.857	**[0.350,0.943]**	**[0.470,1.055]**	36
	- Post-IT	0.341	9.384	**[0.282,0.404]**	**[0.293,0.414]**	74
Canada						
	Full Sample	0.356	7.614	**[0.268,0.429]**	**[0.286,0.447]**	154
	- Pre-IT	0.043	0.39	[-0.147,0.221]	[-0.132,0.236]	68
	- Post-IT	0.183	3.492	**[0.086,0.265]**	**[0.115,0.294]**	86
Chile						
	Full Sample	0.021	0.605	[-0.039,0.078]	[-0.032,0.085]	88
	- Pre-IT	-0.145	-1.704	[-0.283,0.002]	**[-0.284,-0.001]**	40
	- Post-IT	0.089	2.558	**[0.030,0.145]**	**[0.029,0.144]**	48
New Zealand						
	Full Sample	0.675	9.782	**[0.565,0.797]**	**[0.572,0.801]**	98
	- Pre-IT	-0.026	-0.03	[-1.416,1.411]	[-1.886,0.940]	12
	- Post-IT	0.661	8.21	**[0.533,0.803]**	**[0.550,0.819]**	86
South Africa						
	Full Sample	0.067	1.09	[-0.046,0.164]	[-0.022,0.186]	70
	- Pre-IT	0.984	10.1	**[0.778,1.124]**	**[0.495,0.808]**	24
	- Post-IT	0.25	4.536	**[0.161,0.343]**	**[0.158,0.340]**	46

Note: Local-to-unity estimations are conducted for the full sample as well as subsamples before and after inflation targeting. Point estimates and t-statistics for β based on OLS regressions are reported along with the 90% Bonferroni confidence intervals for β using the t-test and the Q-test. Confidence intervals that reject the null of $\beta = 0$ are in bold.

Table 4: Do Commodity Prices Predict Real Exchange Rates?

$$d\ln(RER_{t+1}) = \ln(RER_{t+1}) - \ln(RER_t) = \phi + \delta \ln(CP_t) + \upsilon_{t+1}$$
$$\ln(CP_t) = \gamma + \rho \ln(CP_{t-1}) + \varepsilon_t$$

4A) USD-based Exchange Rates

				90% CI: $\hat{\delta}$		
		$\hat{\delta}$	**t-stats**	**t-test**	**Q-test**	**Obs.**
Australia						
	Full Sample	0.001	0.069	[-0.030,0.030]	[-0.025,0.035]	111
	- Pre-IT	-0.019	-0.192	[-0.196,0.141]	[-0.208,0.128]	36
	- Post-IT	0.002	0.117	[-0.029,0.035]	[-0.024,0.039]	75
Canada						
	Full Sample	-0.025	-1.302	[-0.054,0.012]	[-0.056,0.009]	155
	- Pre-IT	0.034	1.781	[0.004,0.071]	[-0.003,0.065]	68
	- Post-IT	-0.118	-1.773	[-0.216,0.022]	**[-0.281,-0.043]**	87
Chile						
	Full Sample	0.008	0.712	[-0.013,0.027]	[-0.008,0.031]	87
	- Pre-IT	0.049	2.319	**[0.015,0.084]**	**[0.010,0.079]**	40
	- Post-IT	0.002	0.14	[-0.028,0.027]	[-0.021,0.033]	47
New Zealand						
	Full Sample	-0.038	-1.069	[-0.093,0.029]	[-0.098,0.022]	99
	- Pre-IT	-1.879	-2.027	**[-3.439,-0.368**]	[-0.694,2.397]	12
	- Post-IT	-0.038	-0.952	[-0.099,0.040]	[-0.112,0.024]	87
South Africa						
	Full Sample	0.007	0.268	[-0.032,0.054]	[-0.044,0.041]	71
	- Pre-IT	0.008	0.103	[-0.130,0.130]	[-0.201,0.051]	24
	- Post-IT	-0.013	-0.376	[-0.068,0.054]	[-0.077,0.042]	47

Note: Local-to-unity estimations for the predictive regression are conducted for the full sample as well as subsamples before and after inflation targeting. Point estimates and t-statistics for δ based on OLS regressions are reported along with the 90% Bonferroni confidence intervals for δ using the t-test and the Q-test. Confidence intervals that reject the null of $\delta = 0$ are in bold.

4B) JPY-based Exchange Rates

		$\hat{\delta}$	t-stats	90% CI: $\hat{\delta}$ t-test	90% CI: $\hat{\delta}$ Q-test	Obs.
Australia						
	Full Sample	-0.012	-0.483	[-0.057,0.029]	[-0.052,0.033]	111
	- Pre-IT	0.194	1.474	[-0.018,0.420]	[-0.063,0.373]	36
	- Post-IT	-0.015	-0.563	[-0.062,0.028]	[-0.052,0.037]	75
Canada						
	Full Sample	-0.025	-1.302	[-0.054,0.012]	[-0.056,0.009]	155
	- Pre-IT	0.034	1.781	**[0.004,0.071]**	[-0.003,0.065]	68
	- Post-IT	-0.118	-1.773	[-0.216,0.022]	**[-0.281,-0.043]**	87
Chile						
	Full Sample	0	-0.014	[-0.034,0.028]	[-0.023,0.038]	87
	- Pre-IT	0.067	1.417	[-0.036,0.132]	**[0.011,0.179]**	40
	- Post-IT	-0.014	-0.658	[-0.050,0.020]	[-0.046,0.024]	47
New Zealand						
	Full Sample	-0.044	-0.923	[-0.122,0.040]	[-0.123,0.038]	99
	- Pre-IT	-0.805	-0.582	[-3.133,1.449]	[-1.978,2.587]	12
	- Post-IT	-0.055	-1.013	[-0.141,0.040]	[-0.144,0.036]	87
South Africa						
	Full Sample	-0.012	-0.437	[-0.056,0.044]	[-0.072,0.025]	71
	- Pre-IT	0.25	2.196	**[0.075,0.473]**	**[0.234,0.607]**	24
	- Post-IT	-0.044	-1.188	[-0.101,0.027]	[-0.111,0.015]	47

Note: Local-to-unity estimations for the predictive regression are conducted for the full sample as well as subsamples before and after inflation targeting. Point estimates and t-statistics for δ based on OLS regressions are reported along with the 90% Bonferroni confidence intervals for δ using the t-test and the Q-test. Confidence intervals that reject the null of $\delta = 0$ are in bold.

4C) GBP-based Exchange Rates

		$\hat{\delta}$	t-stats	90% CI: $\hat{\delta}$ t-test	Q-test	Obs.
Australia						
	Full Sample	0.019	0.9	[-0.016,0.053]	[-0.016,0.054]	109
	- Pre-IT	-0.055	-0.377	[-0.313,0.179]	[-0.323,0.166]	36
	- Post-IT	0.025	1.411	[-0.006,0.055]	[-0.001,0.058]	73
Canada						
	Full Sample	0.009	0.561	[-0.017,0.038]	[-0.022,0.033]	153
	- Pre-IT	0.012	0.327	[-0.049,0.079]	[-0.056,0.072]	68
	- Post-IT	0.036	1.405	[-0.005,0.080]	[-0.017,0.068]	85
Chile						
	Full Sample	0.014	0.973	[-0.017,0.035]	**[0.003,0.056]**	87
	- Pre-IT	0.042	0.993	[-0.039,0.107]	[-0.020,0.123]	40
	- Post-IT	0.011	0.66	[-0.028,0.031]	[-0.007,0.055]	47
New Zealand						
	Full Sample	-0.002	-0.049	[-0.064,0.073]	[-0.072,0.062]	97
	- Pre-IT	-0.299	-0.222	[-2.565,1.896]	[-2.051,2.387]	12
	- Post-IT	0.026	0.59	[-0.043,0.107]	[-0.049,0.100]	85
South Africa						
	Full Sample	0.029	1.202	[-0.013,0.069]	[-0.008,0.073]	69
	- Pre-IT	-0.006	-0.067	[-0.175,0.147]	[-0.242,0.074]	24
	- Post-IT	0.021	0.637	[-0.038,0.075]	[-0.033,0.080]	45

Note: Local-to-unity estimations for the predictive regression are conducted for the full sample as well as subsamples before and after inflation targeting. Point estimates and t-statistics for δ based on OLS regressions are reported along with the 90% Bonferroni confidence intervals for δ using the t-test and the Q-test. Confidence intervals that reject the null of $\delta = 0$ are in bold.

Table 5. Predicting Real Exchange Rate In-Sample: Bayesian Model Averaging

$$d\ln(RER_{t+1}) = a + b' X_t + e_{t+1}$$

5A) Australia

	1983Q4-2005Q4			1983Q1-2000Q4		
	Posterior Prob	**Posterior Mean**	**Posterior Std. Dev.**	**Posterior Prob**	**Posterior Mean**	**Posterior Std. Dev.**
Intercept	100	-0.246	0.199	100	-0.2013	0.39897
$\ln(RER)$	40.1	-0.030	0.043	40.8	-0.0444	0.06608
di^{SR}	6.7	0.000	0.001	6.8	0.0001	0.00103
di^{LR}	18.7	**0.001**	**0.004**	24	**0.0019**	**0.00426**
$d\pi$	6.7	0.000	0.001	17.5	-0.0006	0.00154
$d(CA/Y)$	6.5	0.000	0.001	4.3	0.0001	0.00104
$d(G/Y)$	7.2	0.000	0.001	3.6	0.0000	0.00036
$d\ln(rY)$	99.8	**1.889**	**0.462**	99.6	**2.1840**	**0.55824**
$\ln(rCP)$	33.5	-0.031	0.052	39.4	-0.0470	0.06953
$\ln(Future)$	9.5	-0.008	0.033	19.1	-0.0297	0.07524
$d\ln(A_{T/NT})$	97.2	**0.276**	**0.092**	85.2	**0.2508**	**0.14442**
$d\ln(Stock)$	35.7	**0.023**	**0.039**	55	**0.0638**	**0.07175**

Note: This table reports posterior probabilities, means, and standard deviations for each of the variables used to predict real exchange rate under Bayesian Model Averaging over two different sample periods. Posterior coefficient estimates in bold font represent variables with post. Mean/ St. Dev. > 1.3.

5B) Canada

	1973Q1-2005Q4			1973Q1-2000Q4		
	Posterior Prob	**Posterior Mean**	**Posterior Std. Dev.**	**Posterior Prob**	**Posterior Mean**	**Posterior Std. Dev.**
Intercept	100	-0.0095	0.0234	100	0.0291	0.1063
$\ln(RER)$	20.3	-0.0103	0.0244	57.2	-0.0639	0.0651
di^{SR}	19.1	**0.0005**	**0.0014**	64.6	**0.0032**	**0.0029**
di^{LR}	40.1	**0.0034**	**0.0049**	9.2	0.0004	0.0019
$d\pi$	3.3	0.0000	0.0002	15.6	**0.0002**	**0.0007**
$d(CA/Y)$	63	**0.0013**	**0.0012**	5.2	0.0000	0.0003
$d\ln(rY)$	34.6	**0.0556**	**0.0916**	15.8	0.0192	0.0682
$\ln(rCP)$	8.6	0.0003	0.0068	29.3	-0.0145	0.0278
$\ln(rCPne)$	11.3	0.0014	0.0087	55.3	**0.0345**	**0.0396**
$d\ln(Stock)$	5.1	0.0003	0.0029	12.2	0.0018	0.0071
$\ln(Future)$	2.7	-0.0003	0.0037	30.2	-0.0122	0.0221

Note: This table reports posterior probabilities, means, and standard deviations for each of the variables used to predict real exchange rate under Bayesian Model Averaging over two different sample periods. Posterior coefficient estimates in bold font represent variables with post. Mean/ St. Dev. > 1.3.

5C) New Zealand

	1987Q1-2005Q4			1987Q1-2000Q4		
	Posterior Prob	**Posterior Mean**	**Posterior Std. Dev.**	**Posterior Prob**	**Posterior Mean**	**Posterior Std. Dev.**
Intercept	100	**0.9215**	**0.6619**	100	**0.6032**	**0.6626**
$\ln(RER)$	38.8	-0.0379	0.0587	17.9	-0.0163	0.0445
di^{SR}	7	-0.0001	0.0011	8.8	-0.0001	0.0012
di^{LR}	16.2	-0.0009	0.0028	11.1	-0.0005	0.0022
$d\pi$	10.3	0.0002	0.0009	20.8	**0.0007**	**0.0018**
$d(CA/Y)$	5.1	0.0000	0.0007	5	-0.0001	0.0009
$d\ln(rY)$	5.3	0.0049	0.0708	3.4	-0.0032	0.0763
$\ln(rCP)$	30.6	-0.0483	0.0893	22.6	-0.0317	0.0745
$\ln(Future)$	82	-0.1591	0.0937	24.5	-0.0294	0.0661
$d\ln(A_{T/NT})$	75.4	-0.1652	0.1140	58	-0.1153	0.1207
$d\ln(Stock)$	99.9	**0.1202**	**0.0267**	94.9	**0.0745**	**0.0367**

Note: This table reports posterior probabilities, means, and standard deviations for each of the variables used to predict real exchange rate under Bayesian Model Averaging over two different sample periods. Posterior coefficient estimates in bold font represent variables with post. Mean/ St. Dev. > 1.3.

Table 6: Predicting Real Exchange Rates using Least Angle Regressions
Coefficient Values Based on Minimum Cp Statistics

$$d\ln(RER_{t+1}) = a + b' X_t + e_{t+1}$$

	Australia	Canada	New Zealand
$\ln(RER)$			
di^{SR}	-0.0016 (0.130)	0.0002 (0.022)	
di^{LR}	0.0084 (0.172)	0.0068 (0.024)	-0.0037 (0.364)
$d\pi$			0.0021 (0.036)
$d(CA/Y)$		0.0024 (0.015)	
$d(G/Y)$	-0.0008 (0.272)		
$d\ln(rY)$	1.3352 (0.037)	0.1483 (0.089)	0.1003 (0.079)
$\ln(rCP)$	-0.0731 (0.294)		-0.0582 (0.333)
$\ln(Future)$	-0.0342 (0.245)	-0.0122 (0.106)	-0.2002 (0.277)
$d\ln(A_{T/NT})$	0.1462 (0.358)		-0.1551 (0.113)
$d\ln(Stock)$	0.0629 (0.012)		0.1157 (0.044)
$\ln(rCPne)$			

Note: The table reports coefficient estimates for regressors chosen based on the minimum *Cp* statistic under least angle regressions. Numbers in the parentheses represent the total R^2 when the particular regressor is added.

Table 7: Forecasting Real Exchange Rates Out-of-Sample: RMSE Ratio Comparison

(BMA Posterior Probability-Weighted Forecasts over Random Walk)

		Australia	**Canada**	**New Zealand**
Full Sample Size		N = 85	N = 133	N = 76
		1-quarter ahead forecasts		
# of forecasts	20	0.873	1.009	0.736
	30	0.899	1.005	0.951
	40	0.814	0.994	1.042
		4-quarters ahead forecasts		
# of forecasts	20	0.341	1.163	0.692
	30	0.447	1.060	1.250
	40	0.616	1.077	1.101
		8-quarters ahead forecasts		
# of forecasts	20	0.273	0.704	0.949
	30	0.354	0.703	0.834
	40	0.604	0.875	0.840

Note: The table reports the ratios of root mean squared errors between forecasts generated by Bayesian Model Averaging using the variables presented in Table 5 versus the random walk forecasts. Full sample ends in 2005Q4, and we report forecasts using different window sizes, resulting in 20, 30, and 40 out-of-sample forecasts for horizons 1, 4, and 8 quarters ahead.

Appendix Table

Table A.1: Representative Major Commodity Exports by Country

Australia	Canada	New Zealand	Chile	South Africa
Coking coal	Crude Oil	Lamb	Copper	Gold
Steaming coal	Lumber	Wholemeal MP	Lumber	Platinum
Gold	Pulp	Beef	Fruits	Coal
Iron ore	Nat. Gas	Aluminum	Fish	
Wheat	Beef	Cheese		
Aluminum	Newsprint	Wool		
Beef	Aluminum	Casein		
Alumina	Wheat	Fish		
LNG	Nickel	Butter		
Wool	Gold	Sawn Timber		
Cotton	Zinc	Kiwi		
Copper	Copper	Skim Milk Product		
Nickel	Coal	Logs		
Sugar	Hogs	Apples		
Barley	Potash	Pulp		
Zinc	Fish	Skins		
Canola	Canola			
Lead	Corn			
Rice	Silver			

Source: Reserve Bank of Australia, Statistics Canada, Reserve Bank of New Zealand , and authors' calculations

Figure 1

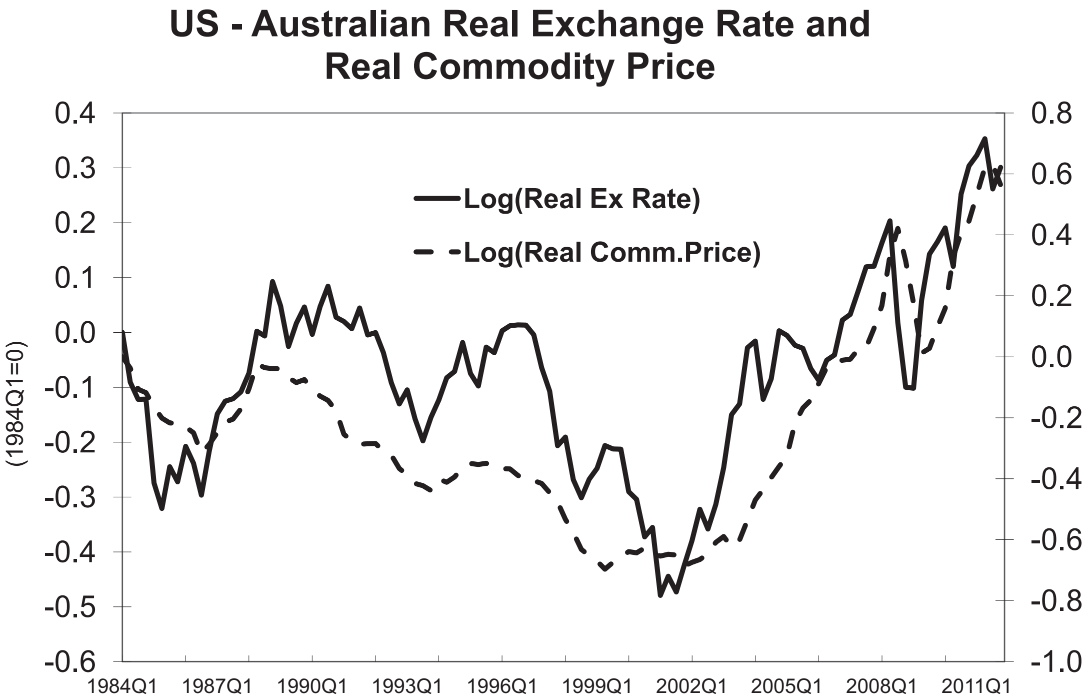

Figure 2

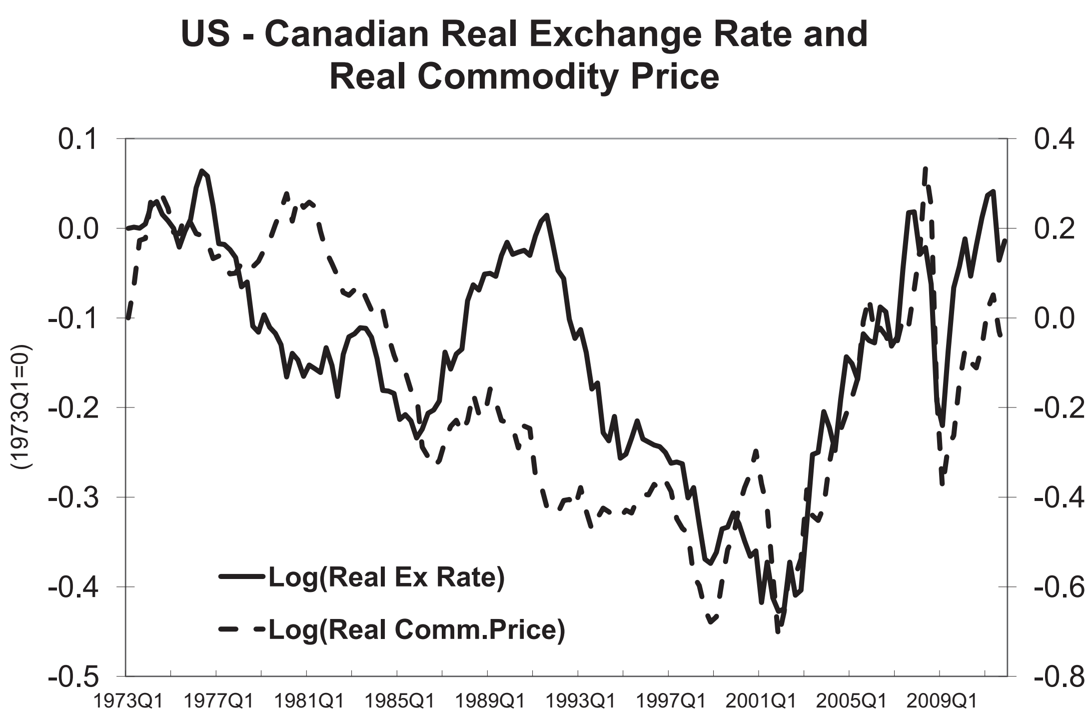

Figure 3

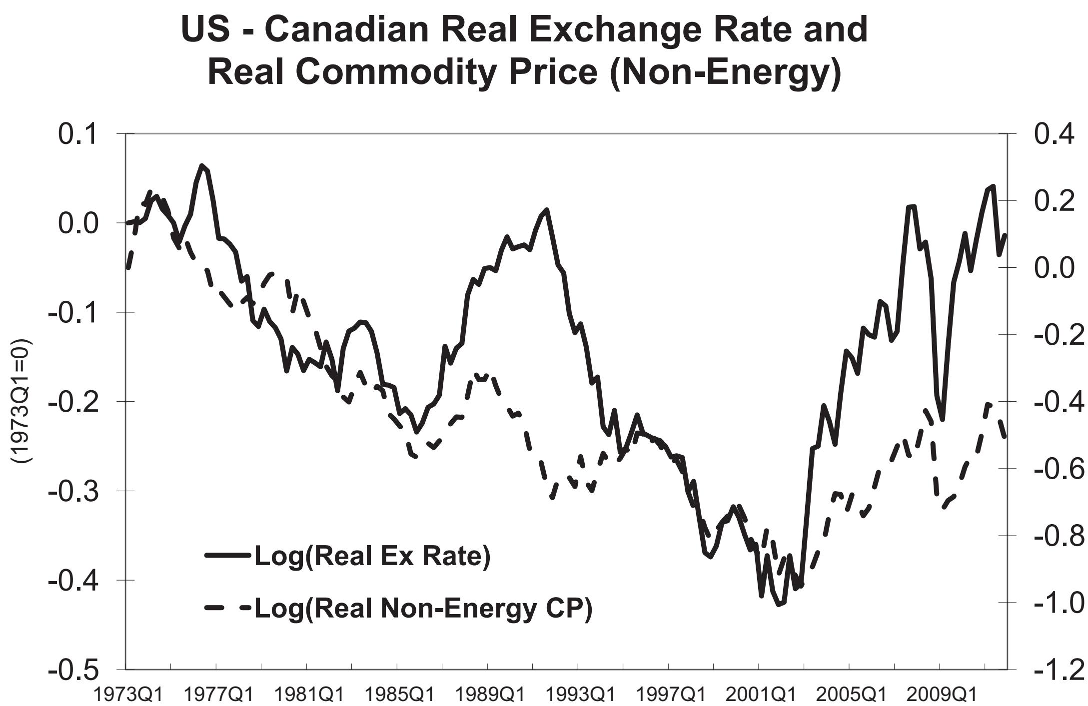

Figure 4

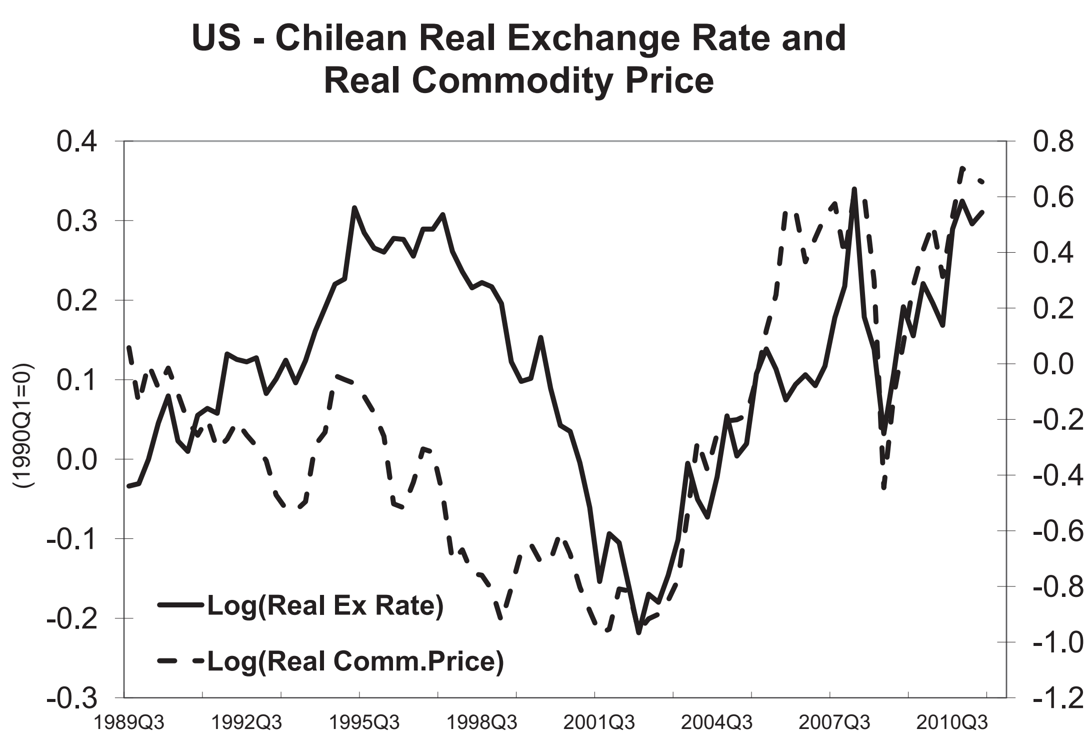

Figure 5

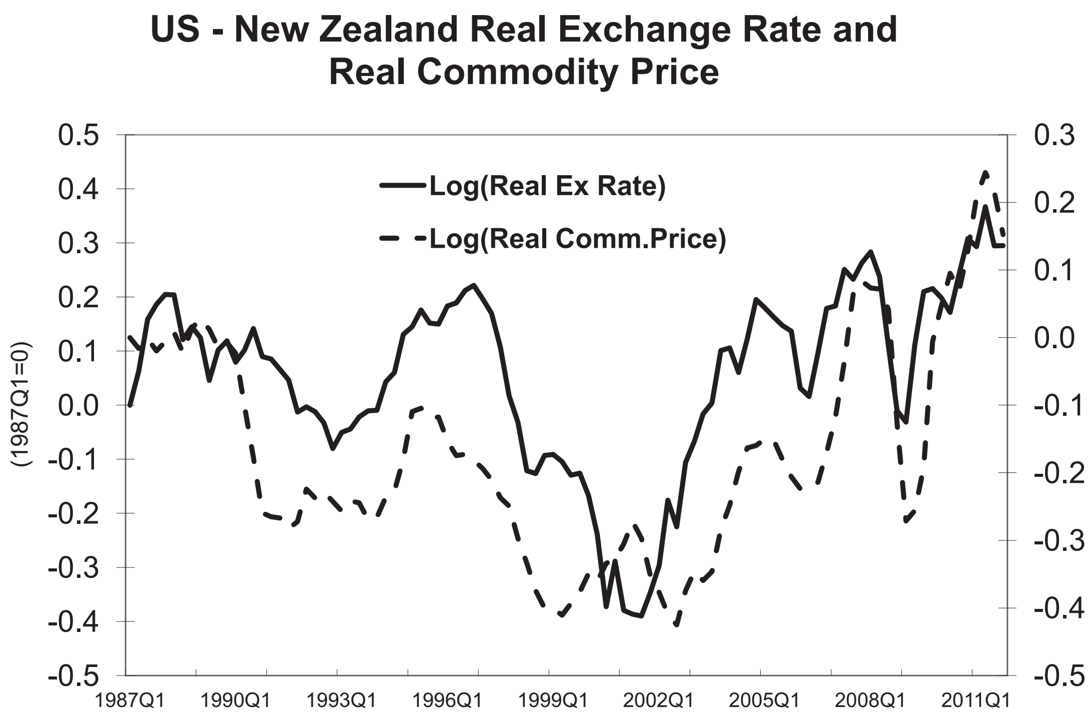

Figure 6