Are the Commodity Currencies an Exception to the Rule?[*]

Yu-chin Chen
(University of Washington)

and

Kenneth Rogoff
(Harvard University)

Abstract. This paper first confirms and extends the findings in Chen and Rogoff (2003) 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. We then show that despite inducing strong contemporaneous currency responses, commodity prices tell us little about future real exchange rate movements. Using Bayesian Model Averaging as a mechanism to combine information and address model uncertainty, we examine exchange rate predictability in a broader macroeconomic context and find that macroeconomic fundamentals appear more useful in predicting exchange rate changes than commodity prices. However, no single specification emerge as the clear winner across both countries and time periods.

[*] The authors would like to thank Drew Creal, Theo Eicher, Sibel Sirakaya, Jonathan Wright, and Moto Yogo for their helpful insights and suggestions. We are also grateful to the staff of Bank of Canada, the Reserve Bank of Australia, the Reserve Bank of New Zealand, and the IMF for providing some of the data used in this paper. Part of this research was conducted when Chen was visiting the Economics Department of the Reserve Bank of New Zealand, whose hospitality is greatly acknowledged. All remaining errors are our own.
Correspondences: yuchin@u.washington.edu and rogoff@harvard.edu.
.

Introduction

The empirical literature on the major currency cross exchange rates is notorious for its enduring puzzles, particularly the near impossibility of explaining nominal exchange rate movements, even after the fact.[1] Surveying a vast literature in the Handbook of International Economics, Frankel and Rose (1995) conclude with doubts about "the value of further time-series modeling of exchange rates at high or medium frequencies using macroeconomic models." Since then, researchers have continued exploring more subtle and intricate explanations to help shed some light on the determinants of exchange rates and their dynamics, but with very limited success. Non-linearity, data aggregation, and more sophisticated market structures are examples of continuing research areas that have all yielded marginal progress, but the core anomaly remains: it is extremely difficult to find any model that systematically explains exchange rate fluctuations between the dollar, euro, yen or pound, particularly out of sample, except at very long horizons.[2] Indeed, as more countries have adopted market-based floating exchange rate systems, thereby expanding the universe of testable currencies, one tends to find the anomaly extending to other exchange rates, such as the Mexican peso or the Brazilian real.

In recent years, however, researchers have begun to note one possible exception to the rule. For Canada, Australia and New Zealand, all countries that depend heavily on commodity exports and all of which have adopted a form of inflation targeting, the world price of commodities appears to have a strong and systematic relationship to the currency. The nascent correlation was first noted by central bank researchers, including Amano and Norden (1993), Djoudad, Murray, Chan and Dow (2001), and Gruen and Kortian (1996). In Chen and Rogoff (2003), where the Australian, New Zealand and Canadian dollars are termed “commodity currencies,” we established that the world price of their commodity export basket is indeed a strong and robust driver of their real exchange rates. Later, Chen (2004) extended this work to look at commodity-price augmented monetary models for nominal exchange rate determination and out-of-sample forecasts, while Cashin, Cesedpes, and Sahay (2004) look at a broad set of

[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.
[2] See, for example, Frankel and Rose (1995), Mark (1995), and Cheung, Chinn, Pascual (2005).

developing countries and find some limited correlation, though much less robust than for the three OECD countries.[3] This latter 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. Even Canada, Australia 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. The short sample is particularly problematic given the well known persistence in shocks to real exchange rates.

In this paper, we considerably extend the data set used in our earlier work, and also consider two newcomers, Chile and South Africa, who have both adopted flexible exchange rate cum inflation targeting regimes within the last ten to fifteen 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 huge instability found in the general empirical exchange rate equations literature, it would not be surprising if the addition of a few years of data would show that the commodity currencies have vanished as another victim.[4] 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 emphasize the importance of using local-to-unity asymptotics to test for the real exchange rate responses 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. In addition, unit root tests are well known to have very low power against the alternative of a highly persistent yet mean-reverting process. We thus argue that the theoretically and empirically proper inference procedure should be based on local-to-unity asymptotics, which accounts for highly persistent regressors and remains robust to the autoregressive roots being near or exactly one (see Cavanagh, Elliott, and Stock 1995, Elliott

[3] Connecting this observation to the broader empirical exchange rate literature, Chen and Rogoff (2003), Cashin et al (2004) focus on real exchange rates and the relation of commodity terms of trade shocks and the PPP puzzle. Chen (2004) focus on the forecast performance of canonical nominal exchange rate models and show that incorporating commodity prices can substantially improve the forecast performance of these models.
[4] See Mark (1995) and subsequent work, e.g. Groen (1999), on the sensitivity of the result over sample period.

1998, among others). Empirically, as the commodity price-exchange rate connection appears very strong and robust (e.g. see Chen and Rogoff 2003), the bias from using inappropriate inference procedures tend not to overturn most of the qualitative results. Nevertheless, we feel this methodological point is an important one as it relates to the long-standing PPP puzzle, the on-going struggle to find mean-reversion in real exchange rates, and the broader real exchange rate determination analyses in general.[5]

Adopting the Bonferroni method similar to the one discussed in Campbell and Yogo (2005), we find strong evidence that commodity prices – with AR roots either near one or exactly one – is an important driving force behind real exchange rate movements for this set of countries. We also see that the approximate magnitude of the effect 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.[6] 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 in a bivariate framework, 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 prices 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 in 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. 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 provides such an apparently unique exception to the rule that structural variables cannot systematically explain exchange rates.

In the second part of the paper, we try to further explore just how unique the commodity currencies are. Are they predictable? This will not necessarily resolve our theoretical conundrums, but can perhaps shed some light on the underlying transmission mechanism.

---

[5] For the "near unit root" behavior of real exchange rate and the PPP puzzle, see Rogoff (1996), Froot and Rogoff (1995), and Chen-Wang (2006), among numerous others.

[6] See Chen and Rogoff (2003) for a brief discussion on the relevant models.

Looking at canonical nominal exchange rate models, Chen (2004) found that the inclusion of a commodity price term can improve the forecast performance of these standard models dramatically. Here we take a different approach. Because we are uncertain about the structural channel of transmission, we avoid pre-selecting a particular model but remain agnostic about the exact model specification. As the exogenous commodity price shock may be absorbed by other endogenous variables before feeding into the exchange rate dynamically, we consider a large set of potential candidate predictors to identify the relevant factors for explaining exchange rate dynamics. Put it more precisely, our predictive analysis incorporates the uncertainty in the model selection process.[7] A few 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] Both of these methods involve combining outcomes from alternative models using proper weights or relative model likelihood, be it derived from the Bayesian posterior odds or from information theoretic criterion. Aside from the conceptual justification of accounting for model uncertainty, these approaches are empirically appealing as well for out-of-sample forecasts. The forecast literature on inflation and GDP forecasts have found that judiciously combining multiple forecast outcomes tend to produce superior results than relying on a single model (see, for example, Stock and Watson 1999, Wright 2003, and references there within). The argument here is that averaging serves as a shrinkage mechanism to combine useful information from different sources, while avoiding having to estimate lots of free parameters.

Using BMA, our analysis of the in-sample predictive equations reveals several noteworthy patterns. The first is that while the current level of real exchange rate appears the most robust predictor for future exchange rate levels – a result consistent with the famous Meese-Rogoff (1983) Random Walk result, the simple autoregressive model is by and large 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

[7] As statistical inferences are sensitive to our model choice, making forecast conditioning 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] The current version of the paper only has BMA results, but we plan to implement a frequentists' bootstrap technique to based on information criterion (Buckland, Bunham, Augustin 1997) to address model uncertainty as a robustness check.

average are 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 could be absorbed by and operate through 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.

The out-of-sample forecast results show that for Australia, forecast combination under BMA produces forecasts that are surprisingly good, beating the Random Walk forecasts by a substantial amount. This finding supports the result found in Chen (2004), yet 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 a clearly something that deserves further exploration.

The rest of the paper is divided into the following sections: Section 2 first discusses the rationale behind using the local-to-unity asymptotic framework and explores whether commodity price shocks drive real exchange rates contemporaneously *and* dynamically in these five countries; Section 3 examines multivariate predictive regressions more fully and discusses using model averaging technique to potentially improve out-of-sample real exchange rate forecasts. Section 4 concludes.

2. Do Commodity Price Shocks Drive Real Exchange Rates?

It has long been recognized that if one could find a missing real shock, and if that shock were sufficiently volatile, one could potentially go a long ways towards resolving the various empirical exchange rate puzzles. For most OECD economies, it is hard to know what that shock might be, much less measure it.[9] Commodity currencies thus offer an ideal ground for

[9] Oil prices certainly have the volatility and there is some evidence that they impact the terms of trade (Backus and Crucinni, 1999), but adding these variables to standard monetary equations does not seem to do the trick.

exploration, and in this paper, we examine the commodity price and real exchange rate connection in five commodity exporting economies – Australia, Canada, Chile, New Zealand, and South Africa – where internal and external markets operate with relatively little intervention, and where floating exchange rate regimes have been implemented for a sufficiently long period of time.[10] What these countries have in common is that primary commodities constitute a very significant component of their exports, as such, world commodity price fluctuations – generally exogenous to these small countries for all but a few goods – potentially explain a major component of their terms of trade fluctuations. As we can see in Figure 1, commodity prices clearly fit the lost glass slipper in one respect: they are extremely volatile, on the same order of magnitude as exchange rates. In addition, their centralized trading in the world commodity exchanges gives us an easily observable "world price" for the product, providing a clean identification strategy for testing exchange rate responses to exogenous terms of trade shocks. If filling in the shock really works so well for the "commodity currencies," perhaps we will be motivated to look harder for the corresponding real shocks in larger economies.

To test how real exchange rates respond to terms of trade shocks – fluctuations in the world prices of their commodity exports – we consider the following regression specifications:

$$\ln RER_t = \alpha + \beta \ln CP_t + \mu_t \quad (1)$$

$$\ln CP_t = \gamma + \rho \ln CP_{t-1} + v_t \quad (2)$$

$$b(L)v_t = \varepsilon_t$$

where RER is the log of the CPI real exchange rate, and lnCP the export-share weighted real price index of country's major commodity exports, in logs (see Appendix 1 for the list of products and their relative weights for these five countries). We assume commodity price to follow an exogenous AR(p) process, and that all the roots of the lag polynomial b(L) are fixed and within the unit circle. The parameter of interest is β, the elasticity of real exchange rate response to commodity price movements.

[10] Canada began floating its currency before the collapse of Bretton Woods. Australia and New Zealand abandoned their exchange rate pegs in 1983 and 1985 respectively. All three adopted some variant of inflation targeting monetary policy in early 1990s. The Chilean central bank gained its independence in 1989 and officially dropped the exchange rate bands and adopted inflation targeting in 1999. South Africa started to move towards a market-based economy in 1994.

2.1. Local-to-Unity Asymptotics

Previous approaches to finding the determinants of real exchange rates mostly rely on first-order asymptotics, where the largest autoregressive root of the regressor is modeled as fixed within the unit circle, or on a cointegration framework, where the regressor is assumed to have a unit root. 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 such as OLS, produce severe size distortions in finite samples when the regressor is highly persistent.[11] The alternative approach in the literature is to use unit root test results to justify cointegration analyses, such as the error-correction framework of Johansen (1988) or dynamic OLS (Stock and Watson 1993).[12] 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 Stock and Watson (1996), Elliott (1998), Wright (1999) among others, if the regressors have roots that are not exactly one, the cointegration framework will produce significant size distortions.[13] 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 fully that a variable has exact unit roots, it is thus advisable to adopt a framework that is robust to the roots being slightly below one. In this paper, we emphasize that local-to-unity asymptotics may be the most appealing both theoretically and empirically, as it accounts for highly persistent regressors yet remains robust to the

[11] See Elliott and Stock (1994), Mankiw and Shapiro (1986), and Stambaugh (1999) among others.
[12] See MacDonald and Ricci (2003), Cashin, Cespedes, Sahay (2004), among others.
[13] 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 slightly 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 slightly less than 1, cases where unit root tests have little power.

autoregressive roots being near or exactly one (see Cavanagh, Elliott, and Stock 1995, Elliott 1998, among others.)

2.2. Estimations using the Bonferroni Method

In the context of our estimation, namely equations (1) and (2), the local to unity discussion above refers to remaining agnostic to whether the dynamics of real commodity prices contains a unit root. We model 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-statistics 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 (2005), which relies on a Q-test that replaces the nuisance parameters with consistent estimators to arrive at a feasible statistics.[14] 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 interval, a confidence interval for β is constructed. The Bonferroni interval that does not depend on ρ is then the union of all such intervals conditional on ρ. The authors 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.[15]

[14] 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 (2005) and use their modified Bonferroni procedure.

[15] While Campbell and Yogo (2005) is concerned with constructing robust and efficient test for inferences in predictive regressions with near-persistent variables are, the same arguments apply to the potentially cointegration relationship like our equations (1) and (2). Indeed, Hjalmarsson (2006) shows that the efficient test for inference in predictive regressions derived by Campbell and Yogo (2005) can also be seen as the natural test resulting from a generalization of fully modified estimation (Phillips and Hansen, 1990, and Phillips, 1995) to the case of near-unit-root regressors. In addition, the optimality properties of the Campbell and Yogo (2005) test-statistic can be seen as a direct analogue of the optimal inference results derived by Phillips (1991) for cointegrated unit-root systems.

Table 1 presents results for the estimated β using local-to-unity asymptotics. The upper panel for each country table shows the result from estimating equations (1) and (2). For each commodity currencies, we consider its value relative to alternative cross currencies (the US dollar, Japanese Yen, and the British pound), and also look at whether the commodity price-real exchange rate connection has changed with the adoption of inflation targeting. The table also presents the selected lag length for the commodity price process based on Bayesian Information Criterion, and the 95% confidence interval for ρ, based on DF-GLS, all fall in the "local-to-unity" range. The last column shows the confidence interval for our β estimate based on the Q-test. The shaded entries indicate the interval does not contain zero, showing mostly strictly positive estimates of β. We thus see that, consistent with our earlier findings reported in Chen and Rogoff (2003), the elasticity of real exchange rate response to commodity price shocks mostly fall in the range of 0.2 to over 1. Not only is this relationship robust to the additional four years of data (something which cannot be taken for granted in the fragile exchange rate literature), we also observe that the "commodity currency" pattern has spread to two other countries who now have enough data for our analyses. In addition, we see some evidence that the real exchange rate may be more sensitive to these terms of trade shocks after the country has adopted an inflation target. There suggests likely inter-play between monetary policy and the exchange rate-terms of trade connection.

As found in Chen and Rogoff (2003), the commodity price-exchange rate connection is very strong empirically and appears robust to alternative assumption about the underlying time series properties (unit roots, cointegration or not). So this respect, the bias from using inappropriate inference procedures (e.g. first-order asymptocics or cointegration) instead of the preferred local-to-unity asymptotics may not overturn most of the qualitative results. Nevertheless, we feel this methodological point is an important one as it relates to the long-standing PPP puzzle and the broader real exchange rate determination analyses in general.

2.3. Dynamic Responses

Despite having strong contemporaneous responses, commodity price shocks *alone* appears to tell us little about future exchange rate movements, as evident from the bivariate predictive regressions in the bottom panels of Table 1. In these estimations, we look at how the one-quarter *changes* of real exchange rate relate to current commodity price shocks. Considering the very few shaded Q-test entries, we see that aside from Chile, commodity price shocks lead to almost no detectable dynamic responses in real exchange rates.

This finding raises the questions of why and how the terms of trade shocks from the world commodity markets are absorbed instantaneously into the real exchange rates, with so little 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 encompass the Balassa-Samuelson effect, price rigidity, income effect, fixed or flexible factor mobility, and alternative monetary policy 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 prices 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 in 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, in hope of detecting consistent dynamic patterns from a more general equilibrium approach. We explore this in the next section.

3. Exchange Rate Dynamics and Predictability

Theoretical exchange rate models are notorious for their empirical failures. Most canonical models fail to provide sensible in-sample fits and offer no improvement in out-of-sample forecast performance over a naïve random walk. While central banks of several commodity exporting economies report to have more reliable forecasting equations, their specifications are also of variant, even across time within a country. The gargantuan body of literature on numerous empirical exchange rate puzzles underscore the degree of *model uncertainty* within this literature. As such, we employ an estimation method that addresses model uncertainty seriously.[16] In hope of using the algorithm to sort out a consistent sent of variables that determine exchange rate dynamics, which would help shed light on the transmission mechanism of various shocks.

In addition, we are also interested in finding whether pooling information from a large set of macroeconomic indicators may help forecast exchange rate out of sample. Most research effort looking at exchange rate dynamics tends to propose one specific setup (fixed model), and uses it to generate forecasts relative to some benchmark model, such as the random walk. However, especially in this literature with such model uncertainty, for practical purposes of generating a prediction, model uncertainty should not be ignored. In fact, several recent work, such as Stock and Watson (2003) and Wright (2003) 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 need to take into account both model uncertainty as well as parameter uncertainty, and that a large set of potentially useful models should be considered instead of ruling out a priori. The BMA framework allows us to do two things: First, given different economies and different time periods, BMA allows us to identify separately the relevant models that are pertinent to predicting exchange rate behavior, and it estimates the posterior probability of each such combination of regressors. In addition, conditional on model posterior probabilities, we can resolve the issue of model uncertainty by estimating the prosterior probabilities of all candidate predictive variables commonly considered in the exchange rate literature.

Applying the BMA framework for commodity currency forecasts is further motivated by findings in Wright (2003), and Chen (2004). Wright (2003) 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. Chen (2004) considers four canonical exchange rate

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

models and augmented them with a commodity price term, which in term leads to drastic forecast improvements for certain time periods and cross currencies. The fact it is unclear which model fits well when, seems to suggest a model averaging method would be beneficial.

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 is 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, ignoring model uncertainty generally results in biased parameter estimates, over-confident standard errors, and misleading inference and predictions (see Doppelhofer 2005). The main idea of model averaging is to treat both models and their associated parameters as unobservable, and estimate their distributions based on the data. The issue of model uncertainty has been taken more seriously in economic research, as seen in the empirical growth literature with Sala-i-Martin, Doppelhofer and Miller (2004) and Fernàndez, Ley and Steel (2001b), policy evaluations with Brock, Durlauf and West (2003), and forecasting with Wright (2003), and Kapetanios, Labhard, and Price (2005).

As discussed in Doppelhofer (2005), there are various model averaging approaches: Bayesian, Empirical Bayes, and Frequentist. In this version of the paper, we focus on a specific model averaging algorithm, Bayesian Model Averaging (BMA), developed by Adrian Raftery and a series of co-authors (see Raftery, Madigan, and Hoeting 1997; Hoeting et al 1999).[17] What BMA does is essentially treating models themselves and the parameter values within a model both as random, and aims to summarize model uncertainty in terms of a probability distribution over the space of possible models. It also constructs a weighted average of the posterior distribution for the parameters under all possible models, using as weights the posterior model probabilities. To evaluate the posterior model probability, the algorithm (Raftery et al. 1997) uses the Bayesian Information Criterion as an approximation of the Bayes factors.[18] For a

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

[18] The BMA algorithm here does not average *all* possible models, but first identify 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 Mont Carlo (Hoeting et al 1996). In general, the MCMC

detailed derivation of the BMA framework, we refer readers to Hoeting et al (1999) [i.e. this section is to be completed later.]

3.2 In-Sample Predictive Regression

Table II presents results from the in-sample predictive regression below:

$$dlnRER_{t+k} = lnRER_{t+k} - lnRER_t = \alpha + \beta' X_t + \varepsilon_{t+k}$$

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 10-12 macroeconomic variables to be potential contributor to exchange rate dynamics. These include the relative real income between the two countries, the relative tradable-to-nontradable sector productivity differences (Balassa-Sameulson effect), real commodity prices, their interest differentials at short and long horizons, a broad index of commodity futures prices, stock market performance differentials, and so on.

We run the above equation in the BMA setup, letting the data tell us the likelihood of each candidate predictor as potentially affecting exchange rate dynamics. Intuitively, one can interpretation this exercise as the following: the predictive regression aims to estimate the partial derivative of the future exchange rate with respect to a predictor x, called it β_x. A *model* would be a particular set/combination of predictors. With say 12 potential predictors, there would be 2^{12} potential models to consider. Conditional on each model, there is a distribution of β_x for a given dataset. The posterior distribution of β_x is a 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 shed light on the determinants of exchange rate dynamics and the channel of transmission of commodity price shocks into the real exchange rate. Table II show the results of our BMA analyses for three of

---

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 treat all the worst-fitting models outside the subset as having zero posterior probability.

our five countries with a more complete data series. Results are reported for the full sample up to 2005Q4, and also a sub-sample up to the end of 2001. We first note that most of the results show that these macro-fundamentals do offer explanatory power for exchange rate movement over the next quarter. For example, differences in real output, as well as the Balassa-Samuelson tradable-non-tradable productivity differences appear especially relevant for Australia. Commodity prices, especially non-energy ones, appear important for Canada, at least up to 2001.

A related observation is that despite finding relevant macro forces are associated with exchange rate responses, no single model or variable is consistently picked out by the BMA framework. Commodity prices, in most cases, do not show up as important in explaining the dynamics either, confirming our earlier puzzle as to why the shocks are so immediately absorbed. In addition, we also see that the explanatory power of none of the selected model is large, and the posterior distribution across them is quite spread out. Figure 1A in the Appendix shows the posterior distributions of each predictor variables, and a summary graph that shows the variables included in the various models selected by the BMA.

3.3 Out-of-Sample Forecast Performance

As discussed in Inoue and Kilian (2004) and Campbell and Thompson (2005), even when a variable does contain genuine predictive power with a stable coefficient in in-sample predictive regressions, it is quite likely to have poor out-of-sample performance for an extended period of time. However, previous research has also shown that forecast combination, even done with an ad hoc fashion, can often lead to superior forecast performance (e.g. Stock and Watson (2003)). We thus recognize that the macroeconomic variables identified above as important for explaining exchange rate changes may not deliver out-of-sample forecast power, yet we remain optimistic as the BMA procedure offers a parsimonious and theoretically justifiable method for combining forecasts.

From the perspective of model selection under uncertainty, it is common to assess the efficacy of the model selection mechanism by looking at its predictive performance for future observations. As discussed in Hoeting (1994), under the rationale of Bayesian model averaging, the prediction equation would be based on the posterior predictive distribution, and in this section, we take the mean from the distribution as the BMA-forecast, and compares its root mean squared errors relative to those from driftless random walk forecasts, as is commonly done in the literature. The out-of-sample forecasts are generated by a rolling process, and the Bayesian model averaging process is run for each sub-sample to generate a forecast. As the outcome of BMA tends to be sensitive to priors, we consider two alternatives: a diffuse prior, and the so-called "unit information prior" proposed by Raftery et al (1997) and others. We find the results are actually quire robust to the choice of these two priors.

Table III presents RMSEs ratios from the out-of-sample forecast exercises. We first note that the Bayesian approach of taking into model uncertainty (or using posterior probabilities as a shrinkage mechanism to combine forecasts) do 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, if anything, beyond the random walk, a result consistent with the Meese-Rogoff findings from over two decades ago, and Wright (2003) from applying a pseudo-Bayesian averaging on a few major currency pairs.

Australia, however, presents a different picture. The forecast performance of the BMA approach appears quite striking in the context of this literature and supports results reported in Chen (2004) on nominal exchange rate forecasts. Even at the 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 horizon (the ratio gets down to under 0.3). While the statistical significance of these differences remains to be assessed, we note that the comparable statistics from applying a similarly BMA framework to the major currency pairs (the Yen, British pound, and the Canadian dollar vs. USD, and the Mark/Euro rate), these ratios rarely fall below 0.9, even at 4 quarters ahead, as seen in Wright (2003). By comparison, Australia's performance clearly puts it as an "exception to the rule" to the Meese-Rogoff puzzle. Table 3B and its associated graphs demonstrate the forecast improvement more directly. The BMA generated forecasts tend to track actual exchange rate dynamics relatively well, compared to a Random Walk-based prediction of zero (the x-axis).

Despite finding Australia to be a clear "exception to the rule" in exhibiting strong out-of-sample forecast outcome, we at this point do not offer an answer to why it behaves differently from the other two countries under analyses. In additional to seeing whether the base-currency may make a difference, we are also curious to explore if the types of commodity exports make a difference in the dynamic analysis. Clearly a more thorough exploration is required on this front.

4. Conclusion

We considerably extend the data set used in our earlier work, and also consider two newcomers, Chile and South Africa, who have both adopted flexible exchange rate cum inflation targeting regimes within the last ten to fifteen 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. We find the correlation not only remains robust for our original set of commodity currencies, but it appears to extend to the newcomers as well. We also see that the approximate magnitude of the effect 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.

Exploring exchange rate dynamics in a predictive equation set-up, we find that commodity price shocks appear to have little lasting influence on exchange rate dynamics, suggesting that the shocks to commodity prices tend to build immediately into real exchange rates. This is rather surprising as one might expect that in general, given the limited and gradual factor mobility in the short run, commodity terms of trade shock would have some longer term persistence. 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 provides such an apparently unique exception to the rule that structural variables cannot systematically explain exchange rates.

Using a larger set of macroeconomic fundamentals, we examine exchange rate dynamics under Bayesian model averaging, to take into account model uncertainty especially in the context of a short sample size relative to the large number of potential explanatory variables. We find that while fundamentals do help predict future exchange rate changes, no single equation jumps out as the "true" specification. 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.

As in-sample predictability can be quite disconnected with out-of-sample forecastability, we also use the BMA algorithm to compare macro fundamental based forecasts with that of a driftless random walk. In this exercise, we uncovered another "exception to the rule" in seeing strong predictability in the Australian-US Dollar exchange rate. At this point, we do not offer any explanation for why this particular currency appears so different; it is a question that deserves further investigation.

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. Mendoza (1995) finds that terms of trade shocks explain up to 50% of output fluctuations in developing economies, and Cruccini (1999) finds that they are important for exchange rates. Therefore, in addition to its academic value of potentially helping to resolve some empirical puzzles, the commodity currency phenomenon can be quite important for a large number of the world's economies. 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

References

Amano, R., Norden, S., (1993), “A Forecasting Equation for the Canada-U.S. Dollar Exchange Rate,” The Exchange Rate and the Economy, 201-65. Bank of Canada, Ottawa.

Brock, W.A., Durlauf, S.N. and West K. 2003. Policy Evaluation in Uncertain Economic Environments. *Brookings Papers on Economic Activity* 1:2003, 235-322.

Buckland, ST, Burnham, KP, and Augustin, NH (1997), “Model selection: An integral part of inference,” Biometrics, 53:275--290.

Burnham, K.P. and Anderson, D.R. 1998. *Model Selection and Inference: A Practical Information-Theoretic Approach*. New York: Springer.

Cavanagh, C. G. Elliott, and J. Stock (1995), “Inference in Models with Nearly Integrated Regressors," Econometric Theory,” Cambridge University Press, vol. 11(5), pages 1131-47, December.

Campbell, J. and M. Yogo (2006), “Efficient Tests of Stock Return Predictability,” Journal of Financial Economics, 81(1), pp. 27–60.

Cashin, P., L. Céspedes, and R. Sahay (2004) "Commodity Currencies and the Real Exchange Rate" Journal of Development Economics, Vol. 75, pp. 239-68.

Chen, Y. (2004), “Exchange Rates and Fundamentals: Evidence from Commodity Economies,” University of Washington Work Paper.

Chen, Y. and B. Wang (2006), “The Search for Stationarity in Real Exchange Rates: An Unobserved Component Regime-Switching Approach,” University of Washington Work Paper.

Cheung, Y., M. Chinn, and A. Pascual (2005), "Empirical exchange rate models of the nineties: Are any fit to survive?," Journal of International Money and Finance, Elsevier, vol. 24(7), pages 1150-1175, November.

Djoudad, R., Murray, J., Chan, T., Daw, J., (2001), “The Role of Chartists and Fundamentalists in Currency Markets: the Experience of Australia, Canada, and New Zealand,” *Revisiting the Case for Flexible Exchange Rates*, proceedings of a conference held at the Bank of Canada.

Doppelhofer, G. (2005), “Model Averaging”, Survey for *New Palgrave Dictionary in Economics,* 2nd edition.

Elliott, G., (1998), “The Robustness of Cointegration Methods When Regressors Almost Have Unit Roots,” Econometrica, 66, 149-58.

Elliott, G. & Rothenberg, T. & Stock, J. (1996), "Efficient Tests for an Autoregressive Unit Root," Econometrica, Econometric Society, vol. 64(4), pages 813-36, July.

Elliott, G. and Stock, J., (2001), "Confidence Intervals for Autoregressive Coefficients Near One," Journal of Econometrics, Elsevier, vol. 103(1-2), pages 155-181, July.

Faust, J., J. Rogers, and J. Wright (2003), "Exchange rate forecasting: the errors we've really made," Journal of International Economics, Elsevier, vol. 60(1), pages 35-59, May.

Fernandez, C., Ley, E., and Steel, M. F. (2001a). "Benchmark Priors for Bayesian Model Averaging," Journal of Econometrics, 100:381-427.

Fernandez, C., Ley, E., and Steel, M. F. (2001b), "Model Uncertainty in Cross-Country Growth Regressions," Journal of Applied Econometrics, 16(5):563-76.

Groen, J.J. 1999. "Long horizon predictability of exchange rates: Is it for real?," Empirical Economics, Springer, vol. 24(3), pages 451-469

Gruen, D., Kortian, T., 1996. Why does the Australian dollar move so closely with the terms of trade. Reserve Bank of Australia Research Discussion Paper No. 9601.

Hjalmarsson, Erik, 2005. "On the Predictability of Global Stock Returns," Working Papers in Economics 161, Göteborg University, Department of Economics.

Hjalmarsson, Erik, (2006), "*Fully Modified Estimation With Nearly Integrated Regressors*," International Finance Discussion Papers 854. Washington: Board of Governors of the Federal Reserve System.

Hoeting, J. A. (1994), "Accounting for Model Uncertainty in Linear Regression," Ph.D. Dissertation, University of Washington.

Hoeting, J. A. (2002), "Methodology for Bayesian Model Averaging: An Update," Proceedings - Manuscripts of invited paper presentations, International Biometric Conference, Freiburg, Germany, 231-240.

Hoeting, J. A., Madigan, D., Raftery, A. E., and Volinsky, C. T. (1999). Bayesian model averaging: A tutorial with discussion. Statistical Science, 14:382{417. Printing errors corrected in version available at http://www.stat.washington.edu/www/research/online/hoeting1999.pdf.

Inoue, A. and L. Kilian, (2005). "In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use?," Econometric Reviews, Taylor and Francis Journals, vol. 23(4), pages 371-402, January.

Kapetanios, G., V. Labhard, and S. Price (2005), "Forecasting using Bayesian and Information Theoretic Model Averaging: An Application to UK Inflation", Bank of England Quarterly Bulletin.

Kilian, L. (1999), "Exchange Rates and Monetary Fundamentals: What Do We Learn from Long-Horizon Regressions?," Journal of Applied Econometrics, John Wiley & Sons, Ltd., vol. 14(5), pages 491-510, Sept.-Oct.

Kilian, Lutz & Taylor, Mark P. (2003), "Why is it so difficult to beat the random walk forecast of exchange rates?," Journal of International Economics, Elsevier, vol. 60(1), pages 85-107, May.

Koop, G. and S. Potter (2003), "Forecasting in large macroeconomic panels using Bayesian Model Averaging," Staff Reports 163, Federal Reserve Bank of New York.

Leamer, E. (1978), *Specification Searches,* New York Wiley.

Meese, Richard A. & Rogoff, Kenneth, 1983. "Empirical exchange rate models of the seventies : Do they fit out of sample?," Journal of International Economics, Elsevier, vol. 14(1-2), pages 3-24, February.

Raftery, A., D. Madigan, and J. Hoeting (1997), "Bayesian Model Averaging for Linear Regression Models," *Journal of the American Statistical Association, 92, 179-191.*

Sala-i-Martin, X., G. Doppelhofer and R.I. Miller. (2004), "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach," American Economic Review 94, 813-835.

Stambaugh, R. (1999), "Predictive regressions," Journal of Financial Economics, vol. 54(3), pages 375-421, December.

Stock, J. and M. Watson. (2003). "Forecasting Output and Inflation: The Role of Asset Prices," Journal of Economic Literature, American Economic Association, vol. 41(3), pages 788-829, September.

Stock, J. and M. Watson. (2005), "“‘An Empirical Comparison of Methods for Forecasting Using Many Predictors," manuscript.

Wasserman, L. (2000). "Bayesian Model Selection and Bayesian Model Averaging." *Journal of Mathematical Psychology* 44(1): 97–112.

Wright, J. (1999), "A Simple Approach to Robust Inference in a Cointegrating System," No 654, International Finance Discussion Papers from Board of Governors.

Wright, J. (2003), "Bayesian Model Averaging and exchange rate forecasts," International Finance Discussion Papers 779, Board of Governors of the Federal Reserve System

TABLE 1: Exchange Rates and Commodity Prices

Country: Australia

Dep Var:Log CPI-Real Exchange Rate

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

(1984Q1 - 2005Q4; IT = 1993)

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	β-hat	t-stat	90% CI: β t-test	90% CI: β Q-test
vs.USD	88	Full Sample	2	0.034	-1.013	[0.916,1.044]	[-7.217,3.809]	0.462	8.677	[0.376,0.552]	[0.357,0.534]
	36	- Pre-IT	1	-0.12	-1.117	[0.767,1.108]	[-7.933,3.657]	0.543	2.896	[0.198,0.838]	[0.243,0.875]
	52	- Post-IT	2	0.05	-0.606	[0.904,1.085]	[-4.786,4.253]	0.818	11.704	[0.705,0.938]	[0.719,0.951]
vs.UKP	88	Full Sample	2	-0.135	-1.013	[0.916,1.044]	[-7.217,3.809]	0.534	11.436	[0.448,0.608]	[0.457,0.616]
	36	- Pre-IT	1	-0.195	-1.117	[0.767,1.108]	[-7.933,3.657]	0.581	3.077	[0.212,0.872]	[0.381,1.029]
	52	- Post-IT	2	-0.111	-0.606	[0.904,1.085]	[-4.786,4.253]	0.658	9.766	[0.537,0.766]	[0.583,0.809]
vs.JPY	88	Full Sample	2	-0.086	-1.013	[0.916,1.044]	[-7.217,3.809]	0.462	5.729	[0.320,0.591]	[0.327,0.598]
	36	- Pre-IT	1	-0.277	-1.117	[0.767,1.108]	[-7.933,3.657]	0.475	1.722	[-0.095,0.889]	[0.253,1.211]
	52	- Post-IT	2	0.089	-0.606	[0.904,1.085]	[-4.786,4.253]	0.393	2.748	[0.165,0.651]	[0.121,0.600]

Dep Var: First-Differenced Log CPI-Real Exchange Rate

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

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	β-hat	t-stat	90% CI: β t-test	90% CI: β Q-test
vs.USD	87	Full Sample	2	0.188	-1.001	[0.916,1.045]	[-7.131,3.826]	-0.006	-0.266	[-0.043,0.040]	[-0.052,0.031]
	36	- Pre-IT	1	0.189	-1.117	[0.767,1.108]	[-7.933,3.657]	0.046	0.518	[-0.091,0.222]	[-0.144,0.162]
	51	- Post-IT	2	0.159	-0.753	[0.887,1.084]	[-5.533,4.116]	-0.02	-0.494	[-0.085,0.057]	[-0.098,0.042]
vs.UKP	87	Full Sample	2	0.117	-1.001	[0.916,1.045]	[-7.131,3.826]	-0.018	-0.56	[-0.068,0.041]	[-0.076,0.032]
	36	- Pre-IT	1	0.072	-1.117	[0.767,1.108]	[-7.933,3.657]	0.019	0.134	[-0.202,0.262]	[-0.247,0.214]
	51	- Post-IT	2	0.152	-0.753	[0.887,1.084]	[-5.533,4.116]	-0.009	-0.197	[-0.078,0.074]	[-0.093,0.057]
vs.JPY	87	Full Sample	2	0.175	-1.001	[0.916,1.045]	[-7.131,3.826]	-0.012	-0.312	[-0.069,0.059]	[-0.085,0.043]
	36	- Pre-IT	1	0.21	-1.117	[0.767,1.108]	[-7.933,3.657]	0.269	2.152	[0.077,0.513]	[0.009,0.437]
	51	- Post-IT	2	0.064	-0.753	[0.887,1.084]	[-5.533,4.116]	0.061	0.963	[-0.040,0.171]	[-0.055,0.155]

Table 1 reports estimates of model parameters using modified Bonferroni method discribed in Campbell and Yogo (2006).
p is the estimated autoregressive lag length for ln(Commodity Price)
δ is the estimated correlation between μt and shocks to ln(Commodity Price)
The DF-GLS statistics, 95% Confidence Interval for the largest AR root (ρ) and the associated local-to-unity parameter (c) are for the ln(Commodity Price) series.
the point estimate β-hat and the t-statistics are from an OLS regression of ln(RER) on ln(CP).
The last two columns report the 90% Bonferroni confidence intervals for β using the t-test and Q-test.
Confidence intervals that reject the null of β = 0 are shaded

Country: Canada

Dep Var:Log CPI-Real Exchange Rate

(1973Q1 - 2005Q4; IT = 1991)

$$Q_t = \alpha + \beta CP_t + \mu_t$$
$$CP_t = \gamma + \rho CP_{t-1} + \varepsilon_t$$

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	β-hat	t-stat	90% CI: β t-test	90% CI: β Q-test
vs.USD	132	Full Sample	2	-0.045	-1.186	[0.935,1.027]	[-8.411,3.553]	0.312	10.69	[0.261,0.359]	[0.262,0.360]
	68	- Pre-IT	1	0.197	-0.551	[0.933,1.064]	[-4.500,4.286]	0.172	3.232	[0.089,0.276]	[0.056,0.243]
	64	- Post-IT	2	-0.151	-1.157	[0.868,1.058]	[-8.198,3.597]	0.546	6.26	[0.382,0.683]	[0.473,0.767]
vs.UKP	132	Full Sample	2	-0.168	-1.186	[0.935,1.027]	[-8.411,3.553]	0.435	8.844	[0.341,0.512]	[0.365,0.537]
	68	- Pre-IT	1	-0.077	-0.551	[0.933,1.064]	[-4.500,4.286]	0.018	0.149	[-0.192,0.209]	[-0.166,0.235]
	64	- Post-IT	2	-0.179	-1.157	[0.868,1.058]	[-8.198,3.597]	0.268	3.011	[0.097,0.407]	[0.196,0.497]
vs.JPY	132	Full Sample	2	-0.168	-1.186	[0.935,1.027]	[-8.411,3.553]	0.821	16.078	[0.723,0.901]	[0.745,0.923]
	68	- Pre-IT	1	-0.175	-0.551	[0.933,1.064]	[-4.500,4.286]	0.806	6.869	[0.581,0.989]	[0.631,1.042]
	64	- Post-IT	2	-0.063	-1.157	[0.868,1.058]	[-8.198,3.597]	0.529	3.896	[0.290,0.747]	[0.373,0.825]

Dep Var: First-Differenced Log CPI-Real Exchange Rate

$$dQ_t = \alpha + \beta CP_{t-1} + \mu_t$$
$$CP_t = \gamma + \rho CP_{t-1} + \varepsilon_t$$

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	β-hat	t-stat	90% CI: β t-test	90% CI: β Q-test
vs.USD	131	Full Sample	2	0.076	-1.175	[0.935,1.028]	[-8.332,3.569]	-0.003	-0.358	[-0.016,0.012]	[-0.019,0.009]
	68	- Pre-IT	1	0.033	-0.551	[0.933,1.064]	[-4.500,4.286]	-0.029	-1.956	[-0.053,-0.004]	[-0.054,-0.005]
	63	- Post-IT	2	0.132	-1.271	[0.850,1.056]	[-9.140,3.407]	0.013	0.407	[-0.036,0.070]	[-0.054,0.050]
vs.UKP	131	Full Sample	2	0.058	-1.175	[0.935,1.028]	[-8.332,3.569]	0.008	0.445	[-0.021,0.039]	[-0.024,0.035]
	68	- Pre-IT	1	0.082	-0.551	[0.933,1.064]	[-4.500,4.286]	0.023	0.56	[-0.043,0.095]	[-0.053,0.086]
	63	- Post-IT	2	-0.045	-1.271	[0.850,1.056]	[-9.140,3.407]	0.065	1.268	[-0.023,0.148]	[-0.031,0.139]
vs.JPY	131	Full Sample	2	0.092	-1.175	[0.935,1.028]	[-8.332,3.569]	0.006	0.296	[-0.027,0.044]	[-0.034,0.038]
	68	- Pre-IT	1	0.167	-0.551	[0.933,1.064]	[-4.500,4.286]	0.022	0.496	[-0.048,0.109]	[-0.072,0.087]
	63	- Post-IT	2	-0.037	-1.271	[0.850,1.056]	[-9.140,3.407]	0.101	1.535	[-0.010,0.208]	[-0.009,0.209]

Country: Chile

Dep Var:Log CPI-Real Exchange Rate

$$Q_t = \alpha + \beta CP_t + \mu_t$$
$$CP_t = \gamma + \rho CP_{t-1} + \varepsilon_t$$

(1989Q3 - 2005Q4; IT = 1999Q3)

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	t-stat	β-hat	90% CI: β t-test	90% CI: β Q-test
vs.USD	66	Full Sample	2	-0.16	-1.357	[0.846,1.051]	[-9.846,3.243]	3.537	0.179	[0.084,0.258]	[0.111,0.284]
	40	- Pre-IT	1	0.064	-0.497	[0.890,1.111]	[-4.278,4.318]	-2.002	-0.121	[-0.218,-0.015]	[-0.220,-0.019]
	26	- Post-IT	1	-0.139	0.399	[0.938,1.191]	[-1.562,4.765]	4.197	0.219	[0.121,0.302]	[0.162,0.339]
vs.UKP	66	Full Sample	2	-0.146	-1.357	[0.846,1.051]	[-9.846,3.243]	1.056	0.068	[-0.053,0.167]	[-0.009,0.210]
	40	- Pre-IT	1	0.055	-0.497	[0.890,1.111]	[-4.278,4.318]	-1.921	-0.158	[-0.290,-0.016]	[-0.291,-0.018]
	26	- Post-IT	1	-0.147	0.399	[0.938,1.191]	[-1.562,4.765]	-0.18	-0.015	[-0.166,0.113]	[-0.123,0.151]
vs.JPY	66	Full Sample	2	-0.003	-1.357	[0.846,1.051]	[-9.846,3.243]	-0.008	0	[-0.088,0.084]	[-0.075,0.096]
	40	- Pre-IT	1	-0.041	-0.497	[0.890,1.111]	[-4.278,4.318]	-3.357	-0.268	[-0.406,-0.139]	[-0.375,-0.110]
	26	- Post-IT	1	-0.062	0.399	[0.938,1.191]	[-1.562,4.765]	4.155	0.204	[0.119,0.283]	[0.141,0.305]

Dep Var: First-Differenced Log CPI-Real Exchange Rate

$$dQ_t = \alpha + \beta CP_{t-1} + \mu_t$$
$$CP_t = \gamma + \rho CP_{t-1} + \varepsilon_t$$

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	t-stat	β-hat	90% CI: β t-test	90% CI: β Q-test
vs.USD	65	Full Sample	2	0.002	-1.431	[0.833,1.048]	[-10.494,3.052]	1.806	0.031	[0.003,0.060]	[-0.001,0.055]
	40	- Pre-IT	1	0.053	-0.497	[0.890,1.111]	[-4.278,4.318]	2.456	0.046	[0.016,0.078]	[0.010,0.071]
	25	- Post-IT	1	-0.063	-0.016	[0.893,1.191]	[-2.578,4.580]	0.87	0.036	[-0.037,0.103]	[-0.027,0.112]
vs.UKP	65	Full Sample	2	-0.213	-1.431	[0.833,1.048]	[-10.494,3.052]	1.676	0.042	[-0.008,0.081]	[0.003,0.091]
	40	- Pre-IT	1	-0.114	-0.497	[0.890,1.111]	[-4.278,4.318]	1.043	0.041	[-0.031,0.103]	[-0.020,0.113]
	25	- Post-IT	1	-0.324	-0.016	[0.893,1.191]	[-2.578,4.580]	1.729	0.074	[-0.018,0.138]	[0.032,0.185]
vs.JPY	65	Full Sample	2	-0.235	-1.431	[0.833,1.048]	[-10.494,3.052]	1.119	0.033	[-0.026,0.079]	[-0.008,0.097]
	40	- Pre-IT	1	-0.323	-0.497	[0.890,1.111]	[-4.278,4.318]	1.429	0.065	[-0.032,0.129]	[0.009,0.169]
	25	- Post-IT	1	-0.267	-0.016	[0.893,1.191]	[-2.578,4.580]	1.391	0.075	[-0.036,0.158]	[0.015,0.204]

Country: New Zealand

Dep Var:Log CPI-Real Exchange Rate

(1987Q1 - 2005Q4; IT = 1990Q1)

$$Q_t = \alpha + \beta CP_t + \mu_t$$
$$CP_t = \gamma + \rho CP_{t-1} + \varepsilon_t$$

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	β-hat	t-stat	90% CI: β t-test	90% CI: β Q-test
vs.USD	76	Full Sample	2	0.049	-0.98	[0.906,1.052]	[-6.967,3.855]	0.709	8.219	[0.570,0.857]	[0.540,0.827]
	12	- Pre-IT	1	0.217	-1.866	[-0.352,1.152]	[-14.871,1.674]	1.162	2.066	[0.307,2.282]	[-1.337,0.694]
	64	- Post-IT	2	0.036	-1.358	[0.841,1.052]	[-9.857,3.239]	1.128	8.789	[0.920,1.344]	[0.855,1.280]
vs.UKP	76	Full Sample	2	0.009	-0.98	[0.906,1.052]	[-6.967,3.855]	0.664	8.966	[0.544,0.789]	[0.520,0.764]
	12	- Pre-IT	1	0.113	-1.866	[-0.352,1.152]	[-14.871,1.674]	0.259	0.491	[-0.572,1.232]	[-1.203,0.617]
	64	- Post-IT	2	-0.013	-1.358	[0.841,1.052]	[-9.857,3.239]	0.902	7.602	[0.702,1.094]	[0.665,1.056]
vs.JPY	76	Full Sample	2	-0.132	-0.98	[0.906,1.052]	[-6.967,3.855]	0.39	3.277	[0.171,0.577]	[0.194,0.599]
	12	- Pre-IT	1	0.127	-1.866	[-0.352,1.152]	[-14.871,1.674]	-0.197	-0.335	[-1.122,0.886]	[-1.620,0.416]
	64	- Post-IT	2	-0.1	-1.358	[0.841,1.052]	[-9.857,3.239]	0.437	2.182	[0.076,0.755]	[0.119,0.794]
vs.AUS*	76	Full Sample	2	-0.237	-1.217	[0.882,1.047]	[-8.769,3.507]	0.232	2.026	[0.004,0.407]	[0.143,0.531]
	12	- Pre-IT	4	-0.621	-1.525	[-0.035,1.255]	[-11.384,2.803]	1.232	3.375	[0.299,1.689]	[0.656,2.879]
	64	- Post-IT	2	-0.1	-1.358	[0.841,1.052]	[-9.857,3.239]	0.437	2.182	[0.076,0.755]	[0.119,0.794]

Dep Var: First-Differenced Log CPI-Real Exchange Rate

$$dQ_t = \alpha + \beta CP_{t-1} + \mu_t$$
$$CP_t = \gamma + \rho CP_{t-1} + \varepsilon_t$$

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	β-hat	t-stat	90% CI: β t-test	90% CI: β Q-test
vs.USD	75	Full Sample	2	0.096	-1.001	[0.902,1.052]	[-7.130,3.826]	-0.027	-0.745	[-0.083,0.038]	[-0.087,0.034]
	12	- Pre-IT	1	-0.087	-1.866	[-0.352,1.152]	[-14.871,1.674]	-1.398	-2.667	[-2.322,-0.561]	[-1.209,0.572]
	63	- Post-IT	2	0.248	-1.356	[0.839,1.053]	[-9.838,3.246]	-0.041	-0.72	[-0.129,0.075]	[-0.149,0.053]
vs.UKP	75	Full Sample	2	0.166	-1.001	[0.902,1.052]	[-7.130,3.826]	-0.033	-0.778	[-0.097,0.048]	[-0.105,0.039]
	12	- Pre-IT	1	0.023	-1.866	[-0.352,1.152]	[-14.871,1.674]	-0.302	-0.359	[-1.666,1.114]	[-1.660,1.126]
	63	- Post-IT	2	0.155	-1.356	[0.839,1.053]	[-9.838,3.246]	0.007	0.101	[-0.096,0.130]	[-0.110,0.115]
vs.JPY	75	Full Sample	2	0.129	-1.001	[0.902,1.052]	[-7.130,3.826]	0.012	0.249	[-0.064,0.101]	[-0.077,0.088]
	12	- Pre-IT	1	0.038	-1.866	[-0.352,1.152]	[-14.871,1.674]	-0.999	-1.219	[-2.319,0.412]	[-2.025,0.708]
	63	- Post-IT	2	0.102	-1.356	[0.839,1.053]	[-9.838,3.246]	0.037	0.482	[-0.086,0.177]	[-0.112,0.150]
vs.AUS*	75	Full Sample	2	0.17	-1.565	[0.839,1.037]	[-11.767,2.687]	0.061	0.846	[-0.051,0.200]	[-0.094,0.152]
	12	- Pre-IT	4	0.471	-1.525	[-0.035,1.255]	[-11.384,2.803]	0.395	1.466	[0.040,1.029]	[-0.847,0.577]
	63	- Post-IT	2	0.102	-1.356	[0.839,1.053]	[-9.838,3.246]	0.037	0.482	[-0.086,0.177]	[-0.112,0.150]

* ln(Real Commodity Prices) for exchange rate between Australia and New Zealand is the difference between their country-specific real commodity price series.

Country: South Africa

Dep Var:Log CPI-Real Exchange Rate

(1994Q1 - 2005Q4; Break = 2000Q1)

$$Q_t = \alpha + \beta CP_t + \mu_t$$
$$CP_t = \gamma + \rho CP_{t-1} + \varepsilon_t$$

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	β-hat	t-stat	90% CI: β t-test	90% CI: β Q-test
vs.USD	48	Full Sample	1	-0.34	-0.451	[0.913,1.092]	[-4.083,4.345]	0.665	3.609	[0.264,0.921]	[0.472,1.139]
	24	- Pre-2000	2	-0.465	-0.711	[0.768,1.181]	[-5.341,4.156]	0.808	11.463	[0.643,0.891]	[0.652,0.958]
	24	- Post-2000	1	-0.322	-0.028	[0.886,1.199]	[-2.613,4.574]	1.205	9.072	[0.921,1.398]	[1.015,1.500]
vs.UKP	48	Full Sample	1	-0.351	-0.451	[0.913,1.092]	[-4.083,4.345]	0.445	2.486	[0.055,0.693]	[0.264,0.912]
	24	- Pre-2000	1	-0.46	-0.711	[0.768,1.181]	[-5.341,4.156]	1	12.957	[0.821,1.093]	[0.823,1.156]
	24	- Post-2000	1	-0.228	-0.028	[0.886,1.199]	[-2.613,4.574]	0.654	4.886	[0.387,0.863]	[0.455,0.929]
vs.JPY	48	Full Sample	1	-0.357	-0.451	[0.913,1.092]	[-4.083,4.345]	0.528	3.929	[0.235,0.714]	[0.392,0.878]
	24	- Pre-2000	1	-0.577	-0.711	[0.768,1.181]	[-5.341,4.156]	-0.015	-0.097	[-0.388,0.159]	[-0.242,0.451]
	24	- Post-2000	1	-0.451	-0.028	[0.886,1.199]	[-2.613,4.574]	1.178	12.428	[0.958,1.298]	[1.047,1.409]

Dep Var: First-Differenced Log CPI-Real Exchange Rate

$$dQ_t = \alpha + \beta CP_{t-1} + \mu_t$$
$$CP_t = \gamma + \rho CP_{t-1} + \varepsilon_t$$

	N	Time Period	p (BIC lag length)	δ (innovation correl)	DF-GLS stats	95% CI: ρ	95% CI: c	β-hat	t-stat	90% CI: β t-test	90% CI: β Q-test
vs.USD	47	Full Sample	1	0.256	-0.662	[0.890,1.091]	[-5.055,4.201]	0.074	1.000	[-0.039,0.223]	[-0.102,0.160]
	24	- Pre-2000	2	-0.207	-0.711	[0.768,1.181]	[-5.341,4.156]	0.046	0.684	[-0.086,0.152]	[-0.061,0.188]
	23	- Post-2000	1	0.426	-0.298	[0.843,1.202]	[-3.457,4.436]	0.066	0.468	[-0.116,0.386]	[-0.293,0.250]
vs.UKP	47	Full Sample	1	0.234	-0.662	[0.890,1.091]	[-5.055,4.201]	0.07	0.989	[-0.039,0.212]	[-0.095,0.157]
	24	- Pre-2000	1	-0.01	-0.711	[0.768,1.181]	[-5.341,4.156]	0.026	0.31	[-0.114,0.160]	[-0.112,0.162]
	23	- Post-2000	1	0.33	-0.298	[0.843,1.202]	[-3.457,4.436]	0.093	0.734	[-0.091,0.364]	[-0.206,0.265]
vs.JPY	47	Full Sample	1	0.247	-0.662	[0.890,1.091]	[-5.055,4.201]	0.145	2.044	[0.037,0.289]	[-0.025,0.228]
	24	- Pre-2000	1	0.126	-0.711	[0.768,1.181]	[-5.341,4.156]	0.202	1.952	[0.038,0.393]	[-0.009,0.355]
	23	- Post-2000	1	0.339	-0.298	[0.843,1.202]	[-3.457,4.436]	0.071	0.639	[-0.083,0.313]	[-0.193,0.223]

Table II.
Predictive Analysis using Bayesian Model Averaging

$\mathbf{lnRER_{t+1} - lnRER_t = \alpha + \beta' X_t + \varepsilon_{t+1}}$
Country: Australia
Full Sampe

85 models were selected
Best 80 models (cumulative posterior probability = 0.9999):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	**Posterior Mean of Coeff**	**Posterior Std Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
Intercept	100	-2.46E-01	0.1988626	-2.90E-01	-2.40E-01	-3.89E-01	-2.87E-01	-3.30E-01
lnRER	40.1	-2.96E-02	0.0432168	-7.02E-02	.	.	.	-8.32E-02
d.Short.Rate.	6.7	-5.36E-05	0.0009419	.	.	.	.	.
d.Long.Rate.	18.7	1.34E-03	0.003594	.	.	.	.	.
d.Inflation.	6.7	-5.51E-05	0.0005498	.	.	.	.	.
dCApY	6.5	-6.46E-05	0.001032	.	.	.	.	.
dGpY	7.2	-1.04E-04	0.0005744	.	.	.	.	.
dlnRY	99.8	1.89E+00	0.4624811	2.08E+00	2.03E+00	1.68E+00	2.14E+00	1.79E+00
lnRCP	33.5	-3.08E-02	0.0523295	.	.	-1.10E-01	-5.66E-02	.
lnCPFutures	9.5	-8.44E-03	0.0332729	.	.	.	.	.
dlnProd	97.2	2.76E-01	0.0923633	3.17E-01	2.89E-01	2.85E-01	3.60E-01	2.46E-01
dlnStock	35.7	2.34E-02	0.0385519	.	.	7.37E-02	.	3.96E-02
nVar				3	2	4	3	4
r2				0.318	0.276	0.346	0.302	0.336
BIC				-1.88E+01	-1.83E+01	-1.79E+01	-1.69E+01	-1.67E+01
post prob				0.149	0.112	0.095	0.057	0.05

Exclude 2001-2005.

97 models were selected
Best 80 models (cumulative posterior probability = 0.9994):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	**Posterior Mean of Coeff**	**Posterior Std Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
Intercept	100	-2.01E-01	0.3989687	-4.66E-01	-3.12E-01	-2.54E-01	-3.28E-01	8.88E-01
lnRER	40.8	-4.44E-02	0.0660773	.	-8.20E-02	.	.	.
d.Short.Rate.	6.8	9.74E-05	0.0010343	.	.	.	.	.
d.Long.Rate.	24	1.90E-03	0.004263	.	.	.	.	.
d.Inflation.	17.5	-5.87E-04	0.0015443	.	.	.	.	.
dCApY	4.3	1.34E-04	0.0010351	.	.	.	.	.
dGpY	3.6	1.10E-05	0.0003621	.	.	.	.	.
dlnRY	99.6	2.18E+00	0.5582422	2.27E+00	2.22E+00	2.08E+00	2.19E+00	2.15E+00
lnRCP	39.4	-4.70E-02	0.0695326	-1.38E-01	.	.	-7.90E-02	.
lnCPFutures	19.1	-2.97E-02	0.0752419	.	.	.	.	-2.35E-01
dlnProd	85.2	2.51E-01	0.1444194	3.05E-01	3.40E-01	3.05E-01	4.11E-01	.
dlnStock	55	6.38E-02	0.0717459	1.05E-01	.	.	.	1.71E-01
nVar				4	3	2	3	3
r2				0.364	0.321	0.276	0.316	0.306
BIC				-1.27E+01	-1.27E+01	-1.26E+01	-1.22E+01	-1.13E+01
post prob				0.088	0.085	0.083	0.066	0.042

(Cont.) Table II.
Predictive Analysis using Bayesian Model Averaging

$\ln RER_{t+1} - \ln RER_t = \alpha + \beta' X_t + \varepsilon_{t+1}$
Country: Canada
Full Sampe

75 models were selected
Best 40 models (cumulative posterior probability = 0.9677):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	Posterior Mean of Coeff	Posterior Std Dev of Coeff	model 1	model 2	model 3	model 4	model 5
Intercept	100	-9.51E-03	0.0233856	-0.00095	-0.01031	-0.01476	-0.00614	-0.00606
lnRER	20.3	-1.03E-02	0.0244043	.	.	.	.	.
d.Short.Rate.	19.1	5.44E-04	0.0013701	.	.	.	0.003138	.
d.Long.Rate.	40.1	3.40E-03	0.0049271	.	0.008315	0.008077	.	.
d.Inflation.	3.3	2.24E-05	0.0002339	.	.	.	.	.
dCApY	63	1.26E-03	0.0011866	.	0.001806	0.00241	0.001743	0.001818
dlnRY	34.6	5.56E-02	0.0916372	.	.	0.152573	.	0.157219
lnRCP	8.6	3.04E-04	0.0067609	.	.	.	.	.
lnRCP_NE	11.3	1.45E-03	0.0086617	.	.	.	.	.
dlnStock	5.1	2.88E-04	0.0029418	.	.	.	.	.
lnCPFutures	2.7	-2.73E-04	0.0037206	.	.	.	.	.
nVar				0	2	3	2	2
r2				0	0.067	0.101	0.067	0.066
BIC				0	0.619192	0.655869	0.731509	0.773603
post prob				0.105	0.077	0.076	0.073	0.071

Exclude 2001-2005.

88 models were selected
Best 40 models (cumulative posterior probability = 0.892):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	Posterior Mean of Coeff	Posterior Std Dev of Coeff	model 1	model 2	model 3	model 4	model 5
Intercept	100	2.91E-02	0.1063303	0.1895	-0.00373	-0.05626	-0.00747	-0.05889
lnRER	57.2	-6.39E-02	0.0651094	-0.12694	.	-0.11792	.	-0.12684
d.Short.Rate.	64.6	3.15E-03	0.0028754	0.005757	.	0.00598	0.002264	0.006076
d.Long.Rate.	9.2	4.26E-04	0.0018713	.	.	.	.	.
d.Inflation.	15.6	2.26E-04	0.0006587	.	.	.	.	0.001774
dCApY	5.2	2.47E-05	0.0002898	.	.	.	.	.
dlnRY	15.8	1.92E-02	0.0682479	.	.	.	.	.
lnRCP	29.3	-1.45E-02	0.0277587	.	.	-0.04508	.	-0.05745
lnRCP_NE	55.3	3.45E-02	0.0395897	0.046309	.	0.084316	.	0.096225
dlnStock	12.2	1.83E-03	0.0070539	.	.	.	.	.
lnCPFutures	30.2	-1.22E-02	0.0221412	-0.04566	.	.	.	.
nVar				4	0	4	1	5
r2				0.155	0	0.149	0.034	0.178
BIC				-0.04192	0	0.807511	0.873239	1.629289
post prob				0.104	0.102	0.068	0.066	0.045

(Cont.) Table II.

Predictive Analysis using Bayesian Model Averaging
$\ln RER_{t+1} - \ln RER_t = \alpha + \beta' X_t + \varepsilon_{t+1}$
Country: New Zealand
Full Sampe

77 models were selected
Best 77 models (cumulative posterior probability = 1):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	**Posterior Mean of Coeff**	**Posterior Std Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
Intercept	100	9.22E-01	0.6619199	1.38E+00	-5.35E-02	9.47E-01	1.46E+00	1.17E+00
lnRER	38.8	-3.79E-02	0.0586895	.	-1.07E-01	-6.97E-02	.	.
d.Short.Rate.	7	-5.79E-05	0.0010808	.	.	.	.	.
d.Long.Rate.	16.2	-8.63E-04	0.0027628	.	.	.	-4.64E-03	.
d.Inflation.	10.3	1.80E-04	0.0009068	.	.	.	.	.
dCApY	5.1	-1.72E-05	0.0007238	.	.	.	.	.
dlrY	5.3	4.93E-03	0.0707959	.	.	.	.	.
lnRCP	30.6	-4.83E-02	0.0893064	.	-1.92E-01	.	.	-8.19E-02
dlnProd	82	-1.59E-01	0.093702	-2.21E-01	.	-1.89E-01	-2.20E-01	-1.74E-01
lnFuture	75.4	-1.65E-01	0.114023	-2.42E-01	.	-1.73E-01	-2.57E-01	-2.05E-01
dlnStock	99.9	1.20E-01	0.0267356	1.12E-01	1.35E-01	1.16E-01	1.31E-01	1.27E-01
nVar				3	3	4	4	4
r2				0.338	0.318	0.355	0.35	0.348
BIC				-1.80E+01	-1.58E+01	-1.56E+01	-1.51E+01	-1.48E+01
post prob				0.262	0.084	0.077	0.059	0.053

Exclude 2001-2005.

81 models were selected
Best 80 models (cumulative posterior probability = 1):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	**Posterior Mean of Coeff**	**Posterior Std Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
Intercept	100	6.03E-01	0.6625867	1.02E+00	5.08E-03	1.22E+00	-9.57E-02	-2.81E-02
lnRER	17.9	-1.63E-02	0.0444509	.	.	.	-1.14E-01	.
d.Short.Rate.	8.8	-9.79E-05	0.001176	.	.	.	.	.
d.Long.Rate.	11.1	-5.06E-04	0.0021636	.	.	.	.	.
d.Inflation.	20.8	7.04E-04	0.0017904	.	.	.	.	.
dCApY	5	-9.28E-05	0.0008905	.	.	.	.	.
dlrY	3.4	-3.20E-03	0.0762548	.	.	.	.	.
lnRCP	22.6	-3.17E-02	0.0744852	.	-1.78E-01	.	.	.
dlnProd	24.5	-2.94E-02	0.0660704	.	.	-1.35E-01	.	.
lnFuture	58	-1.15E-01	0.1206581	-1.96E-01	.	-2.21E-01	.	.
dlnStock	94.9	7.45E-02	0.0366761	6.03E-02	1.08E-01	9.13E-02	6.81E-02	4.46E-02
nVar				2	2	3	2	1
r2				0.232	0.221	0.274	0.215	0.154
BIC				-6.75E+00	-5.96E+00	-5.88E+00	-5.53E+00	-5.37E+00
post prob				0.121	0.082	0.079	0.066	0.061

Table III. Australia

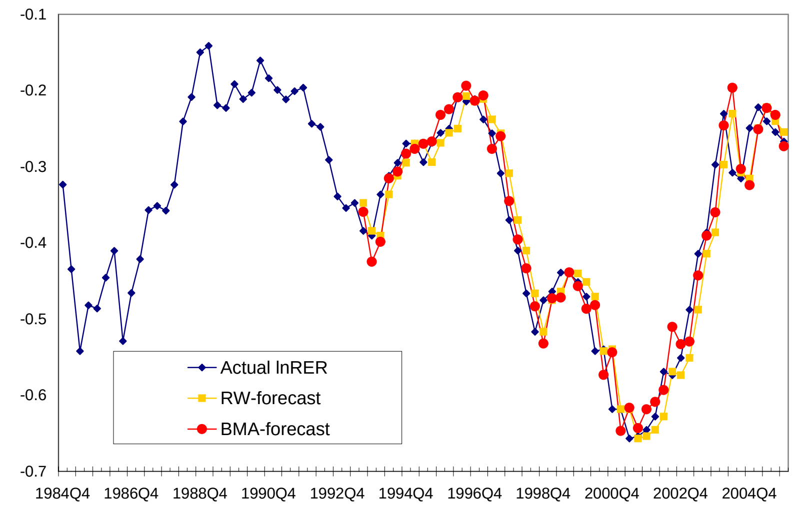
Root Mean Squared Errors Ratios of BMA Forecasts over Random Walk

$d(\ln RER_{t+k}) = \alpha + \beta' X_t + \varepsilon_{t+k}$

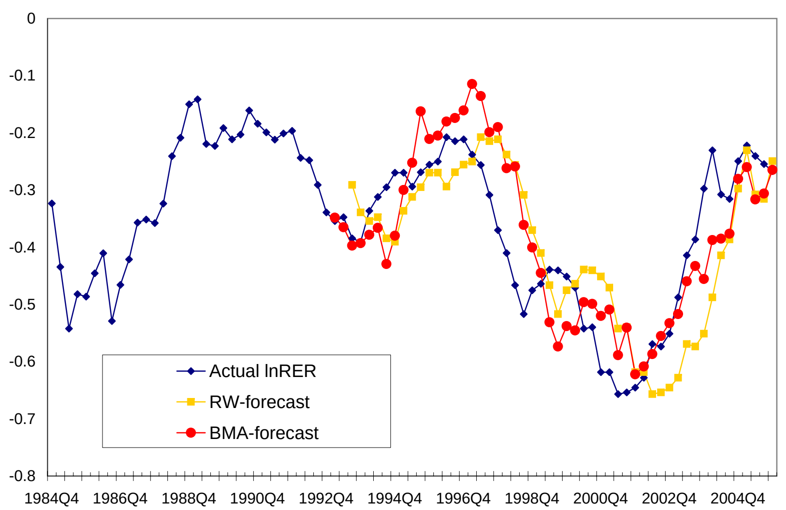
(Australian-USD; Full Sample Size = 85)

1-quarter ahead forecasts	RMSE Ratio
Ratio of forecasts for the last 20 quarters	0.857
Ratio of forecasts for the last 30 quarters	0.896
Ratio of forecasts for the last 40 quarters	0.801
4-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	0.301
Ratio of forecasts for the last 30 quarters	0.418
Ratio of forecasts for the last 40 quarters	0.594
8-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	0.290
Ratio of forecasts for the last 30 quarters	0.366
Ratio of forecasts for the last 40 quarters	0.520

AUS-USD RER and 1 Quarter-Ahead Forecasts



AUS-USD RER and 4 Quarter-Ahead Forecasts



AUS-USD RER and 8 Quarter-Ahead Forecasts

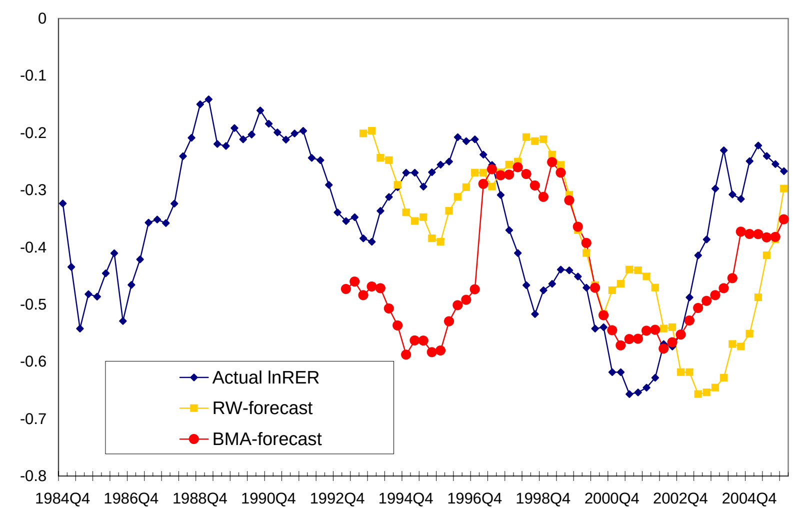
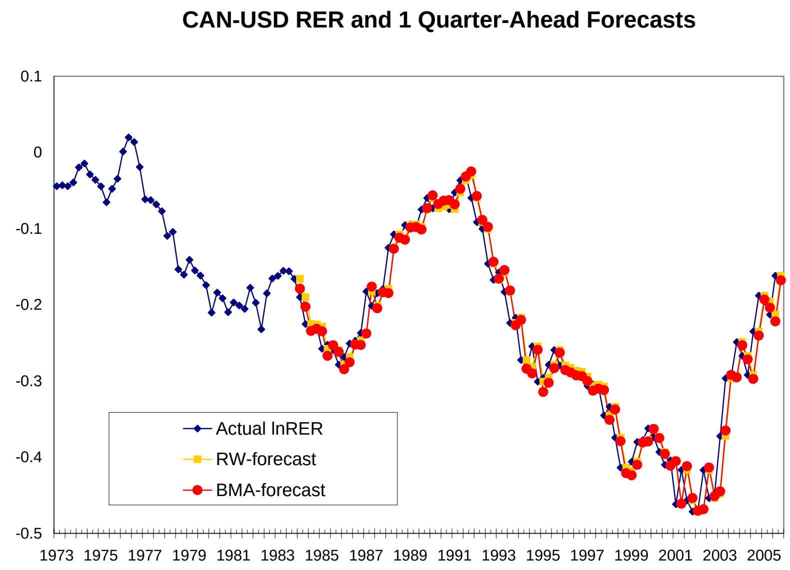
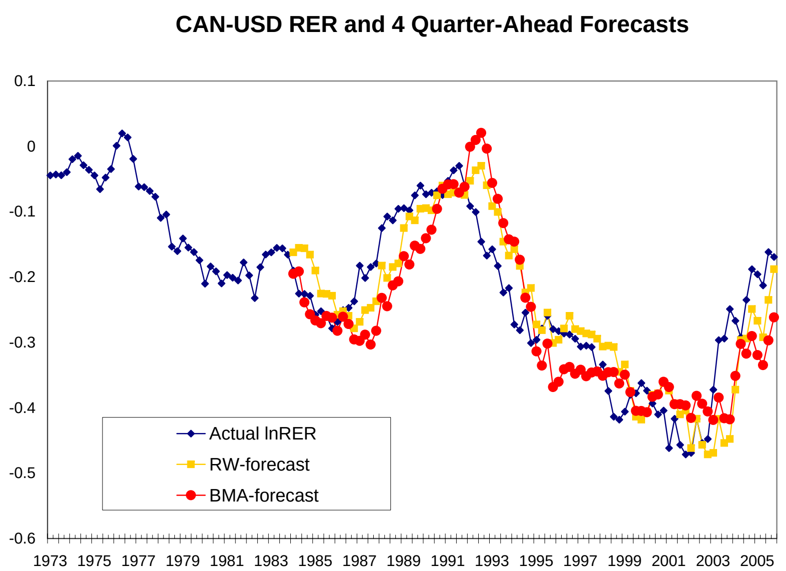


Table III (cont.) Canada

Root Mean Squared Errors Ratios of
Posterior Probability Weighted Forecasts over Random Walk
(CAN-USD; Full Sample Size = 133)

1-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	1.018
Ratio of forecasts for the last 30 quarters	1.015
Ratio of forecasts for the last 40 quarters	1.001
4-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	1.164
Ratio of forecasts for the last 30 quarters	1.059
Ratio of forecasts for the last 40 quarters	1.110
8-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	0.718
Ratio of forecasts for the last 30 quarters	0.760
Ratio of forecasts for the last 40 quarters	1.079





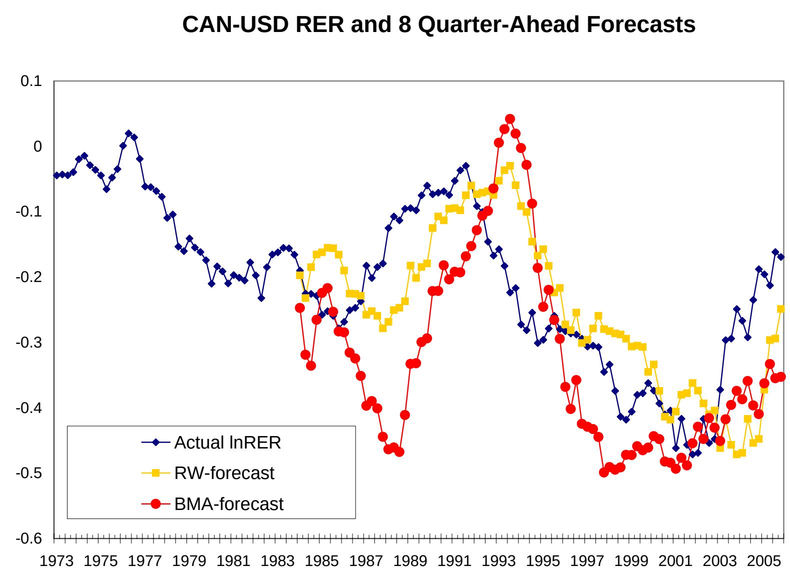
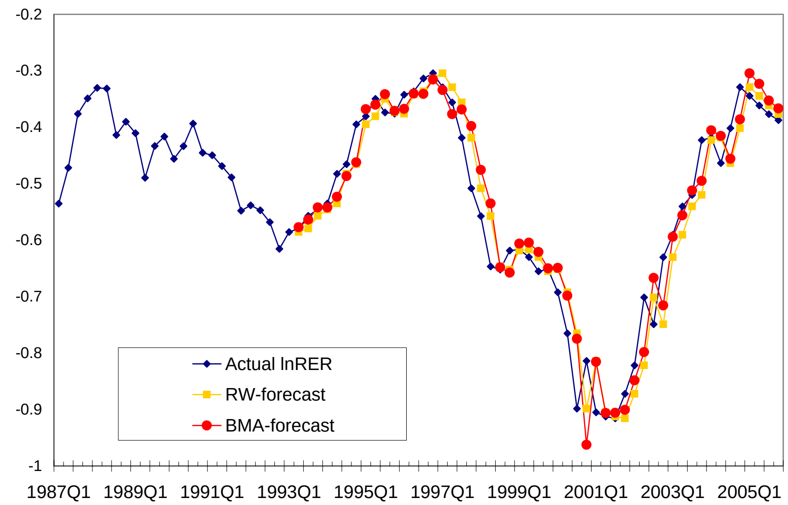


Table III (cont.) New Zealand

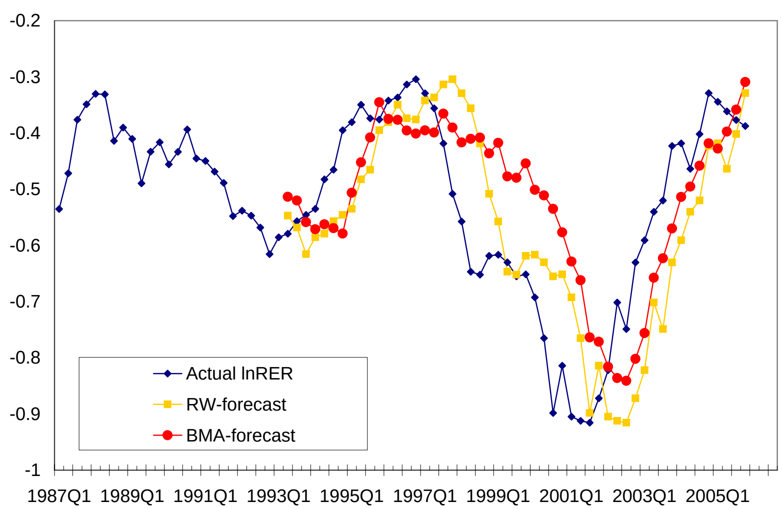
Root Mean Squared Errors Ratios of
Posterior Probability Weighted Forecasts over Random Walk
(NZD USD; Full Sample Size = 76)

1-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	0.736
Ratio of forecasts for the last 30 quarters	0.951
Ratio of forecasts for the last 40 quarters	1.042
4-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	0.732
Ratio of forecasts for the last 30 quarters	1.327
Ratio of forecasts for the last 40 quarters	1.151
8-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	0.949
Ratio of forecasts for the last 30 quarters	0.834
Ratio of forecasts for the last 40 quarters	0.840

NZ-USD RER and 1 Quarter-Ahead Forecasts



NZ-USD RER and 4 Quarter-Ahead Forecasts



NZ-USD RER and 8 Quarter-Ahead Forecasts

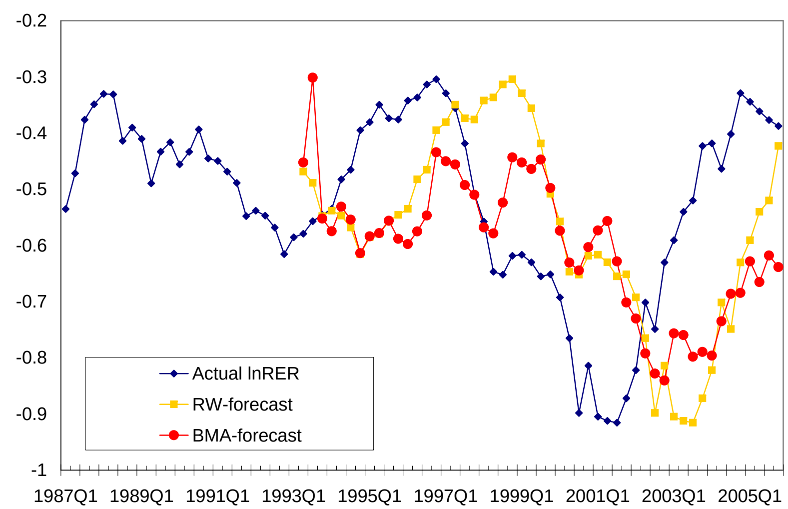


TABLE 3B. Australia (w/ Graphs of Differenced lnRER)

Root Mean Squared Errors Ratios of
BMA Forecasts over Random Walk
$d(\ln RER_{t+k}) = \alpha + \beta' X_t + \varepsilon_{t+k}$

(Australian-USD; Full Sample Size = 85)

1-quarter ahead forecasts	RMSE Ratio
Ratio of forecasts for the last 20 quarters	0.857
Ratio of forecasts for the last 30 quarters	0.896
Ratio of forecasts for the last 40 quarters	0.801
4-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	0.301
Ratio of forecasts for the last 30 quarters	0.418
Ratio of forecasts for the last 40 quarters	0.594
8-quarter ahead forecasts	
Ratio of forecasts for the last 20 quarters	0.290
Ratio of forecasts for the last 30 quarters	0.366
Ratio of forecasts for the last 40 quarters	0.520

Figure 2a. BMA Forecast of 1-Quarter-Ahead Real Exchange Rate Change

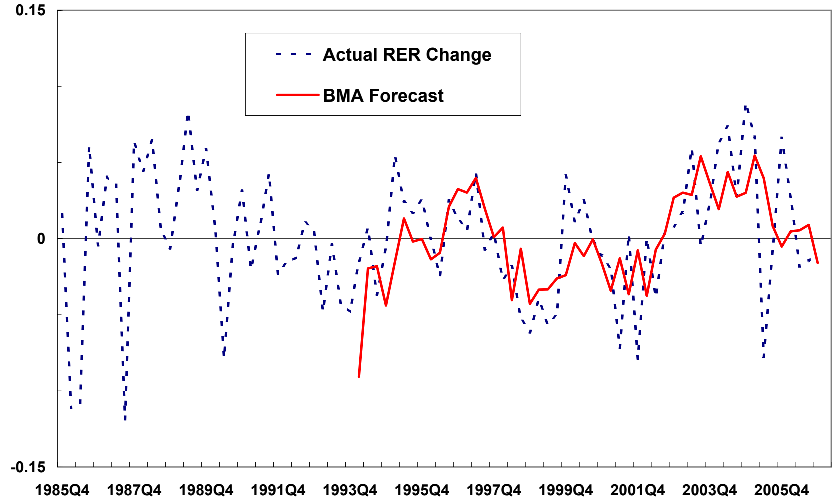


Figure 2b. BMA Forecast of 1-Year-Ahead Real Exchange Rate Change

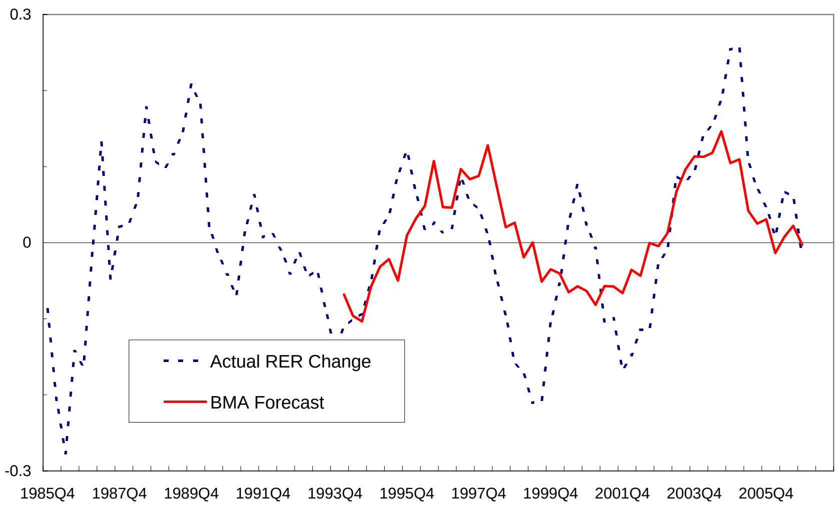


Figure 2c. BMA Forecast of 2-Year-Ahead Real Exchange Rate Change

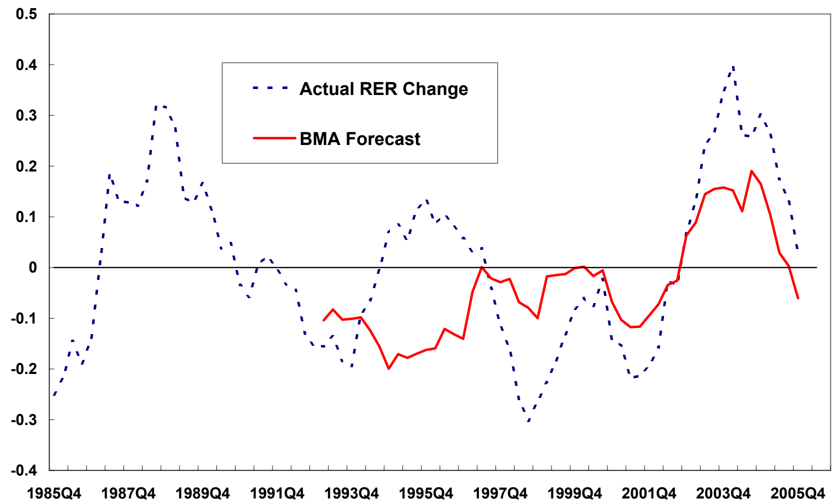


Figure I.

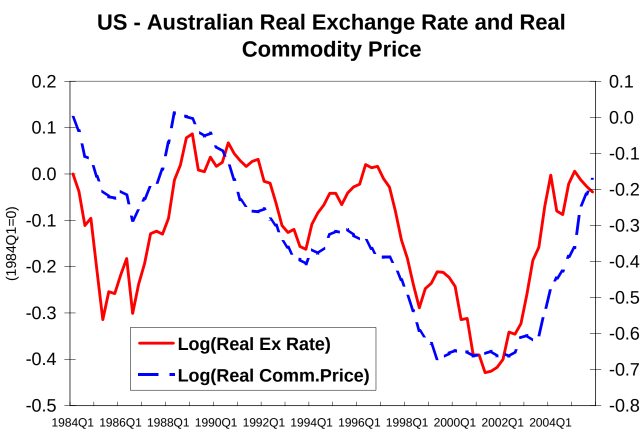


Figure I.

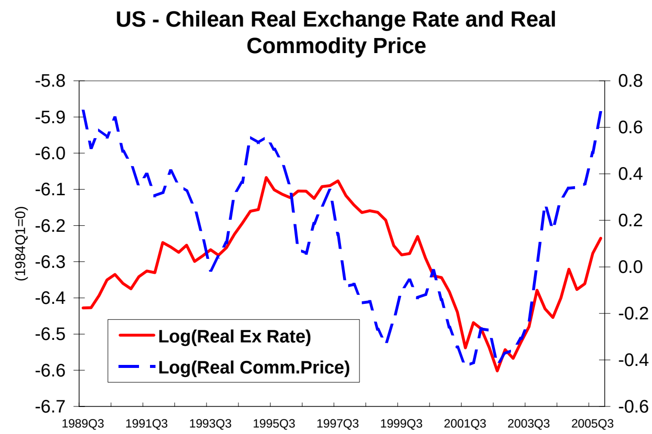


Figure I.

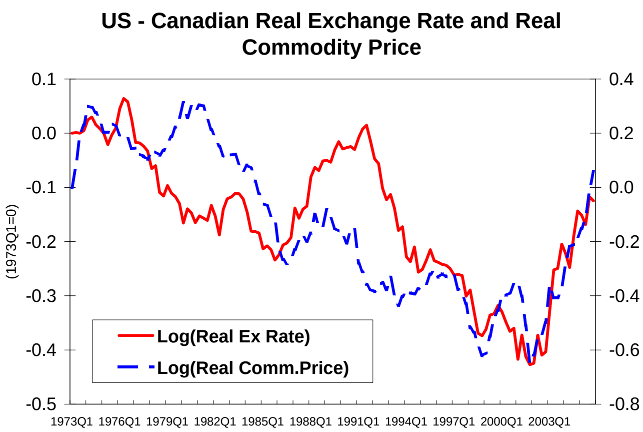


Figure I.

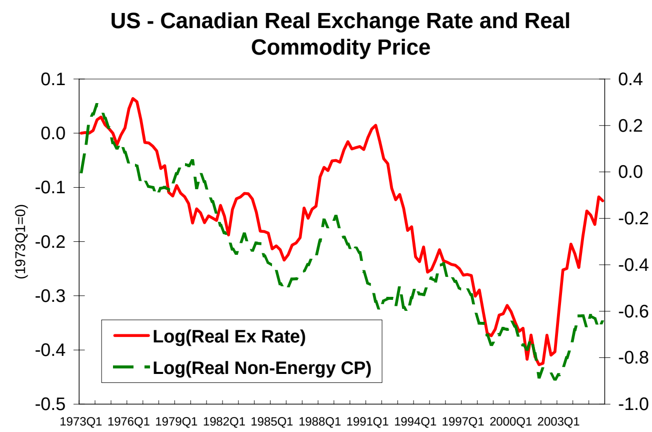


Figure I.

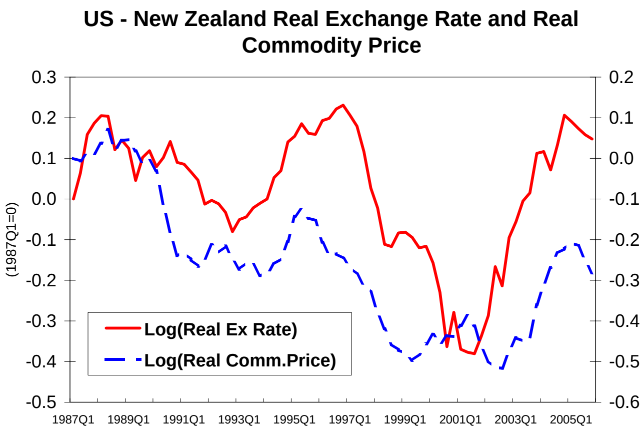
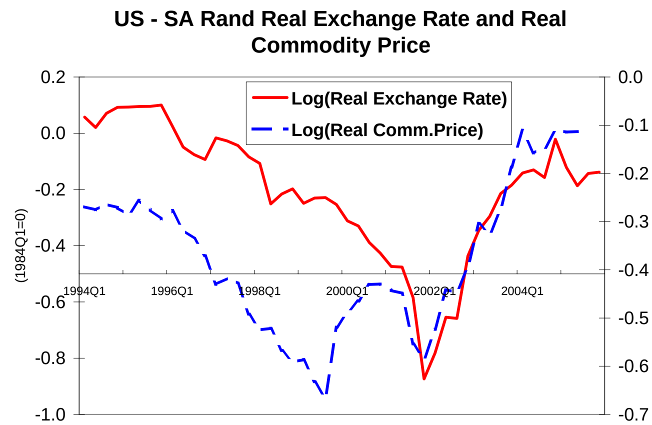


Figure I.



Appendix: Table 1A. Composition of Commodity Price Index

World Market Price in U.S. Dollar

Australia*		Canada **		New Zealand		South Africa	
1983Q1 – 2005Q4		1972Q1 - 2005Q4		1986Q1 - 2005Q4		1994Q1 – 2005Q4	
Product	Wt.	Product	Wt.	Product	Wt.	Product	Wt.
Wheat	8.3	Aluminum	4.8%	Aluminum	8.3%	Coal	22%
Beef	7.9	Beef	9.8%	Apples	3.1%	Gold	48%
Wool	4.1	Canola	2.1%	Beef	9.4%	Platinum	30%
Cotton	2.8	Copper	4.7%	Butter	6.5%		
Sugar	2.5	Corn	1.3%	Casein	6.7%		
Barley	1.9	Gold	4.5%	Cheese	8.3%		
Canola	1.0	Hogs	5.1%	Fish	6.7%		
Rice	0.5	Lumber	14.4%	Kiwi	3.7%		
Aluminium	8.1	Newsprint	13.4%	Lamb	12.5%		
Copper	2.8	Nickel	3.9%	Logs	3.5%		
Nickel	2.6	Potash	2.1%	Pulp	3.1%		
Zinc	1.5	Pulp	19.7%	Sawn Timber	4.6%		
Lead	0.7	Silver	0.9%	Skim MP	3.7%		
Coking coal	14.7	Wheat	8.9%	Skins	1.6%		
Steaming coal	9.7	Zinc	4.4%	Wholemeal MP	10.6%		
Gold	9.4			Wool	7.7%		
Iron ore	9.3						
Alumina	7.4						
LNG	4.8						

* Source: Reserve Bank of Australia Bulletin, Oct. 2003, “Changes to the Reserve Bank of Australia’s Index of Commodity Prices”; Statistics Canada; Reserve Bank of New Zealand.

Note: the commodity price for Chile is the price of copper.

Appendix Table A2.

Predictive Analysis using Bayesian Model Averaging

$\ln RER_{t+1} = \alpha + \beta' X_t + \varepsilon_{t+1}$

Country: Australia

Full Sampe

18 models were selected
Best 18 models (cumulative posterior probability = 1):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	**Posterior Mean of Coeff**	**Posterior Std Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
Intercept	100	-0.2890	0.107	-2.90E-01	-3.30E-01	-2.41E-01	-2.86E-01	-3.05E-01
lRER	100	0.9263	0.036	9.30E-01	9.17E-01	9.26E-01	9.32E-01	9.21E-01
d(short rate)	6.1	-0.0001	0.001	.	.	.	.	.
d(long rate)	17.2	0.0011	0.003	.	.	5.25E-03	.	.
d(inflation)	8.5	-0.0001	0.001	.	.	.	.	-8.78E-04
dCApY	6.3	-0.0001	0.001	.	.	.	.	.
dGpY	9.8	-0.0001	0.001	.	.	.	-1.50E-03	.
dlrY	100	1.9800	0.407	2.08E+00	1.79E+00	1.86E+00	2.12E+00	2.13E+00
lRCP	7.2	-0.0030	0.020	.	.	.	.	.
lFuture	5.7	-0.0011	0.016	.	.	.	.	.
dlProd	100	0.2885	0.078	3.17E-01	2.46E-01	2.45E-01	3.16E-01	3.32E-01
dlStock	24.5	0.0112	0.025	.	3.96E-02	.	.	.
nVar				3	4	4	4	4
r2				0.93	0.932	0.931	0.931	0.93
BIC				-2.10E+02	-2.08E+02	-2.07E+02	-2.06E+02	-2.06E+02
Posterior Prob of Model				0.342	0.114	0.089	0.061	0.044

Exclude 2001-2005.

30 models were selected
Best 20 models (cumulative posterior probability = 0.8782):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	**Posterior Mean of Coeff**	**Posterior Std Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
Intercept	100	-1.83E-01	0.394	-3.12E-01	-3.85E-01	5.69E-01	-4.67E-01	-3.52E-01
lnRER	100	8.96E-01	0.058	9.18E-01	8.93E-01	9.14E-01	8.45E-01	8.91E-01
d.Short.Rate.	6.9	-9.80E-05	0.001	.	.	.	.	.
d.Long.Rate.	26.4	2.17E-03	0.005	.	.	.	.	.
d.Inflation.	31.9	-1.07E-03	0.002	.	.	.	-3.01E-03	-2.04E-03
dCApY	2.4	4.16E-05	0.001	.	.	.	.	.
dGpY	2.2	-6.69E-06	0.000	.	.	.	.	.
dlnRY	100	2.23E+00	0.536	2.22E+00	2.26E+00	2.21E+00	2.45E+00	2.34E+00
lnRCP	10.2	-8.29E-03	0.033	.	.	.	.	.
lnCPFutures	23.6	-3.53E-02	0.078	.	.	-1.88E-01	.	.
dlnProd	75.7	2.20E-01	0.155	3.40E-01	2.29E-01	.	2.48E-01	3.77E-01
dlnStock	54.6	6.80E-02	0.077	.	6.91E-02	1.86E-01	9.17E-02	.
nVar				3	4	4	5	4
r2				0.917	0.92	0.92	0.924	0.918
BIC				-1.49E+02	-1.47E+02	-1.47E+02	-1.46E+02	-1.46E+02
Posterior Prob of Model				0.177	0.078	0.073	0.051	0.048

(Cont.) Appendix Table A2.

Predictive Analysis using Bayesian Model Averaging

$lnRER_{t+1} = \alpha + \beta' X_t + \varepsilon_{t+1}$

Country: Canada
Full Sampe

37 models were selected
Best 20 models (cumulative posterior probability = 0.8453):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	Posterior Mean of Coeff	Posterior Std Dev of Coeff	model 1	model 2	model 3	model 4	model 5
Intercept	100	-1.80E-02	0.0281659	-6.50E-03	-1.61E-02	-2.83E-02	-1.45E-02	-1.83E-02
lnRER	100	9.54E-01	0.0312074	9.73E-01	9.49E-01	9.31E-01	9.56E-01	9.55E-01
d.Short.Rate.	23	7.71E-04	0.0016402	.	.	.	2.95E-03	.
d.Long.Rate.	43.9	4.12E-03	0.0054769	.	.	7.72E-03	.	7.59E-03
d.Inflation.	1.5	1.51E-05	0.0001761	.	.	.	.	.
dCApY	36.2	6.90E-04	0.0011084	.	.	.	.	.
dlnRY	38.7	6.71E-02	0.1007	.	1.62E-01	1.65E-01	.	.
lnRCP	14.4	2.47E-03	0.0090936	.	.	.	.	.
lnRCP_NE	12.9	3.73E-03	0.0115063	.	.	.	.	.
dlnStock	5.8	-1.66E-04	0.0040245	.	.	.	.	.
lnCPFutures	3.6	-3.90E-04	0.0043258	.	.	.	.	.
nVar				1	2	3	2	2
r2				0.958	0.959	0.961	0.959	0.959
BIC				-4.10E+02	-4.10E+02	-4.09E+02	-4.09E+02	-4.09E+02
Posterior Prob of Model				0.104	0.099	0.079	0.076	0.072

Exclude 2001-2005.

27 models were selected
Best 20 models (cumulative posterior probability = 0.9144):

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob of Coeff β≠ 0	Posterior Mean of Coeff	Posterior Std Dev of Coeff	model 1	model 2	model 3	model 4	model 5
Intercept	100	5.12E-02	0.1332262	1.90E-01	-5.63E-02	-5.89E-02	-4.32E-02	1.19E-01
lnRER	100	8.86E-01	0.0443068	8.73E-01	8.82E-01	8.73E-01	9.12E-01	8.64E-01
d.Short.Rate.	95.2	5.25E-03	0.0020362	5.76E-03	5.98E-03	6.08E-03	4.43E-03	6.42E-03
d.Long.Rate.	6.8	3.85E-04	0.001863	.	.	.	.	.
d.Inflation.	19.2	2.93E-04	0.0007484	.	.	1.77E-03	.	.
dCApY	4.9	3.19E-05	0.0002935	.	.	.	.	.
dlnRY	7.4	5.11E-03	0.0455612	.	.	.	.	.
lnRCP	44.2	-2.32E-02	0.0311952	.	-4.51E-02	-5.75E-02	.	-2.97E-02
lnRCP_NE	93.6	6.02E-02	0.0336884	4.63E-02	8.43E-02	9.62E-02	3.44E-02	7.60E-02
dlnStock	13.9	2.31E-03	0.0082909	.	.	.	.	.
lnCPFutures	46.2	-2.03E-02	0.0259277	-4.57E-02	.	.	.	-3.35E-02
nVar				4	4	5	3	5
r2				0.969	0.969	0.97	0.968	0.97
BIC				-3.72E+02	-3.71E+02	-3.70E+02	-3.70E+02	-3.69E+02
Posterior Prob of Model				0.207	0.136	0.089	0.089	0.055

(Cont.) Appendix Table A2.

Predictive Analysis using Bayesian Model Averaging

$$\mathbf{lnRER_{t+1} = \alpha + \beta' X_t + \varepsilon_{t+1}}$$

Country: New Zealand
Full Sampe

21 models were selected

The Top 5 selected models:
(Coeff = OLS estimates)

	Posterior Prob	**Posterior Mean**	**Posterior Std**					
Best 20 models	**of Coeff β≠ 0**	**of Coeff**	**Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
Intercept	100	0.321507	0.5609184	-5.35E-02	9.47E-01	-6.73E-02	9.54E-01	-4.67E-02
lnRER	100	0.895843	0.0552558	8.93E-01	9.30E-01	8.49E-01	9.15E-01	8.80E-01
d.Short.Rate.	6.1	-0.000144	0.0009165	.	.	.	.	.
d.Long.Rate.	15.2	-0.000824	0.0025849	.	.	.	-6.01E-03	.
d.Inflation.	8.3	0.000130	0.0007791	.	.	.	.	.
dCApY	5.4	-0.000102	0.00083	.	.	.	.	.
dIrY	5.4	0.008604	0.0722529	.	.	.	.	.
lnRCP	49	-0.083599	0.0992219	-1.92E-01	.	.	.	-1.30E-01
dlnProd	60.5	-0.090805	0.0895609	.	-1.89E-01	-1.12E-01	-1.80E-01	-6.30E-02
lnFuture	40.5	-0.065734	0.096308	.	-1.73E-01	.	-1.77E-01	.
dlnStock	100	0.125339	0.0286895	1.35E-01	1.16E-01	1.01E-01	1.42E-01	1.30E-01
nVar				3	4	3	5	4
r2				0.935	0.939	0.934	0.941	0.937
BIC				-1.92E+02	-1.92E+02	-1.91E+02	-1.90E+02	-1.90E+02
Posterior Prob of Model				0.195	0.178	0.105	0.063	0.061

Exclude 2001-2005.

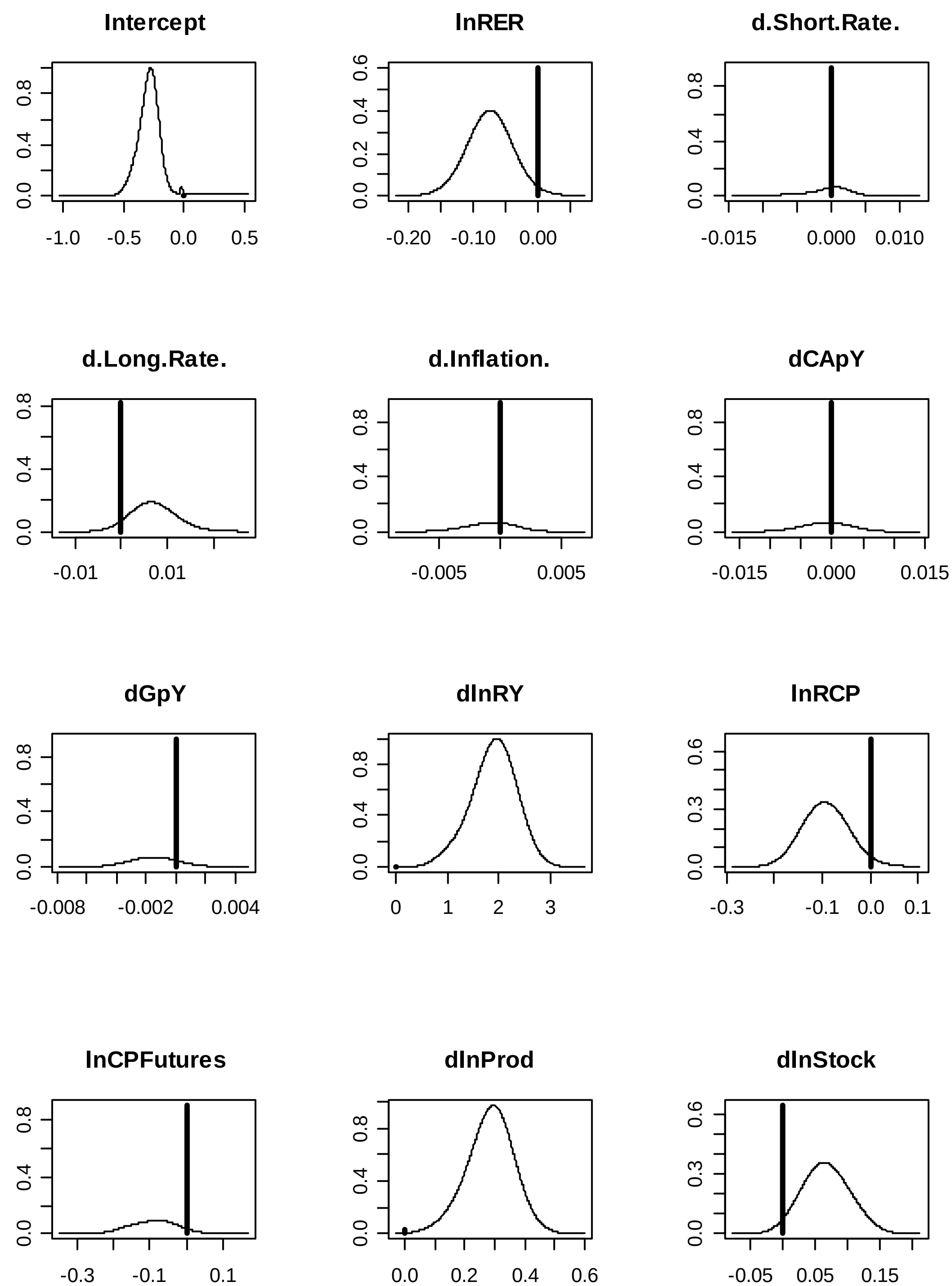
21 models were selected
Best 20 models (cumulative posterior probability = 0.9884):

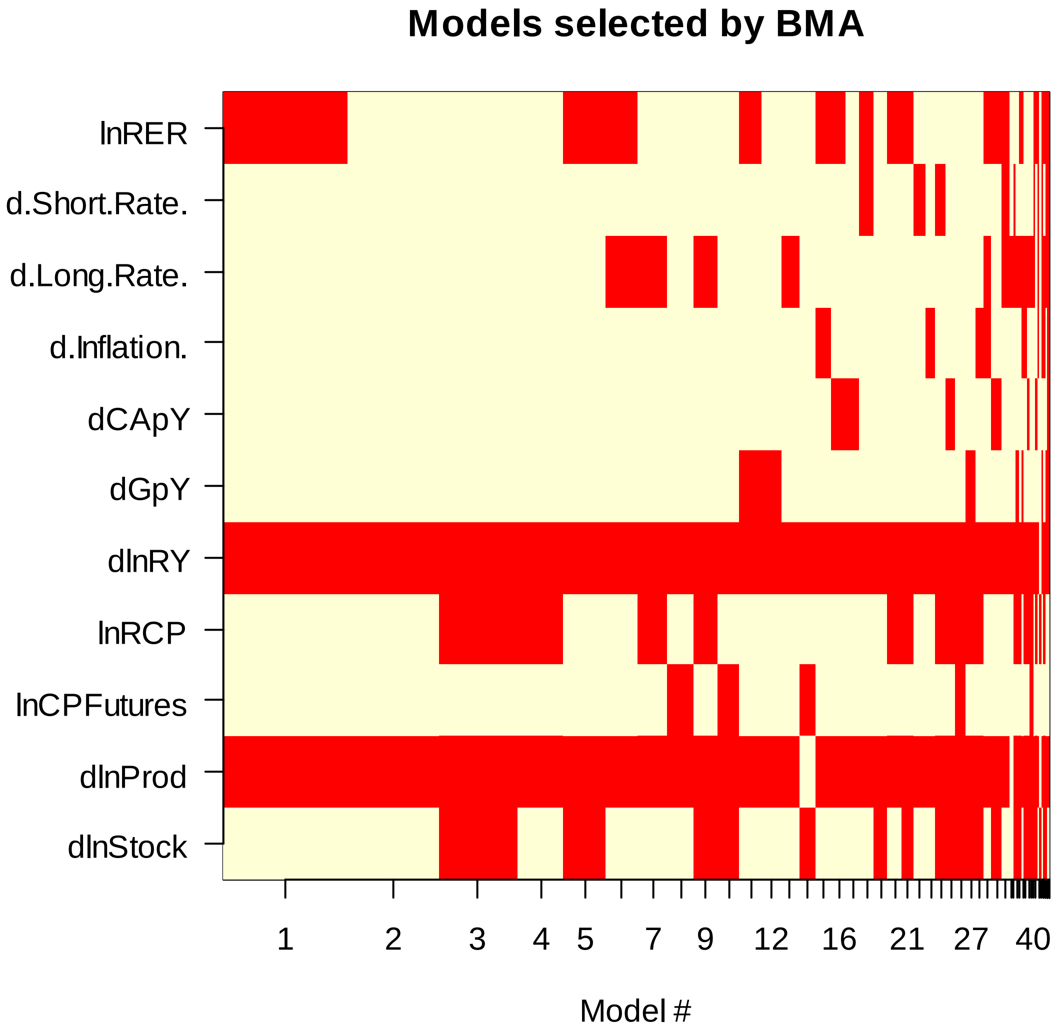
The Top 5 selected models:
(Coeff = OLS estimates)

Intercept								
	Posterior Prob	**Posterior Mean**	**Posterior Std**					
lnRER	**of Coeff β≠ 0**	**of Coeff**	**Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
d.Short.Rate.	100	0.1632356	0.495903	-9.57E-02	-5.29E-02	7.10E-01	-4.99E-02	-1.05E-01
d.Long.Rate.	100	0.9052092	0.065766	8.86E-01	9.14E-01	9.37E-01	8.85E-01	8.68E-01
d.Inflation.	8	-0.0001899	0.001072	.	.	.	.	.
dCApY	13.6	-0.0006803	0.00236	.	.	.	.	-5.04E-03
dIrY	10	0.0002385	0.001069	.	.	.	.	.
lnRCP	6.7	-0.0002068	0.001141	.	.	.	.	.
dlnProd	3	-0.001915	0.059261	.	.	.	.	.
lnFuture	22.7	-0.029805	0.06933	.	-1.39E-01	.	.	.
dlnStock	15.8	-0.0167921	0.050556	.	.	.	-1.01E-01	.
	28.4	-0.0436127	0.088234	.	.	-1.44E-01	.	.
nVar	100	0.0856988	0.032183	6.81E-02	1.12E-01	6.92E-02	8.98E-02	9.24E-02
r2								
BIC				2	3	3	3	3
Posterior Prob of Model				0.916	0.92	0.919	0.918	0.918
				-1.31E+02	-1.29E+02	-1.29E+02	-1.28E+02	-1.28E+02
				0.223	0.115	0.089	0.072	0.061

Appendix Figure 1A. BMA Posterior Distributions for Coefficients From Predictive Regression: $dln(RER)_{t+1} = \beta'X_t + \varepsilon_{t+1}$ (These plots correspond to Tabl II)

Australia (Full Sample)




Models selected by BMA
lnRER
d.Short.Rate.
d.Long.Rate.
d.Inflation.
dCApY
dGpY
dlnRY
lnRCP
lnCPFutures
dlnProd
dlnStock
1
2
3
4
5
7
9
12
16
21
27
40
Model #