Forecasting Commodity Currencies: The Role of Fundamentals with Short-Lived Predictive Content*

Claudia Foroni[†] Francesco Ravazzolo[‡] Pinho J. Ribeiro[§]

January 27, 2016

Abstract

Recent evidence highlights that commodity price changes exhibit a short-lived, yet robust contemporaneous effect on commodity currencies, which is mainly detectable in daily-frequency data. We use MIDAS models in a Bayesian setting to include mixed-frequency dynamics while accounting for time-variation in predictive ability. Using the random walk Metropolis-Hastings technique as a new tool to estimate our class of MIDAS regressions, we find that for most of the commodity currencies in our sample exploiting this short-lived relationship yields to statistically more precise out-of-sample exchange rate point and density forecasts relative to the no-change benchmark. Further, the usual low-frequency predictors, such as money supplies and interest rates differentials, typically receive little support from the data at monthly forecasting horizons. In contrast, models featuring daily commodity prices are highly likely.

Keywords: Exchange rate point and density forecasting; Commodity prices; MIDAS model; Bayesian model averaging; Metropolis-Hastings algorithm

JEL Classification: C53, C55, F37.

*This working paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank. We benefited from constructive comments by Raffaella Giacomini, Barbara Rossi, and seminar participants at Norges Bank. This research was conducted while Ribeiro was a Ph.D. Intern at Norges Bank. Correspondence to: Pinho Ribeiro, University of Glasgow, Adam Smith Building, Glasgow G12 8RT - United Kingdom. E-mail: p.ribeiro.1@research.gla.ac.uk

[†]Norges Bank.

[‡]Free University of Bolzano and BI Norwegian Business School.

[§]University of Glasgow, Adam Smith Business School.

1 Introduction

Exchange rate fluctuations constitute a major source of risk to several economic agents. Not surprisingly, academics, market practitioners and policymakers have long been concerned about the determinants of exchange rate movements. In their seminal paper, Meese and Rogoff (1983) examine whether exchange rate fluctuations can be predicted using macroeconomic variables. They show that forecasts based on standard models that relate exchange rates dynamics to macroeconomic variables do not outperform forecasts based on a driftless random walk. Their results triggered a large literature examining the weak predictive power of macroeconomic variables on exchange rates, and three decades later, Rossi (2013) notes that Meese and Rogoff's (1983) findings have not yet been overturned. As she points out, the main issue is that the predictive ability of macroeconomic fundamentals is ephemeral.[1] In other words, although some fundamentals exhibit predictive content at short horizons and others at long horizons, none of them have systematic forecasting power.

In a recent paper, however, Ferraro et al. (2015) suggest that the frequency of the data used in the predictive regressions for exchange rates may be important in pinning down forecasting ability. They argue that the most probable reason for the failure to uncover predictive power in fundamentals such as commodity prices is the emphasis of the literature on data sampled at low frequency. At this frequency, the predictive content of this sort of fundamental is transitory. In fact, using monthly/quarterly data on oil price changes to predict fluctuations in exchange rates at similar frequencies, Ferraro et al. (2015) hardly detect predictive content (see also Chen et al., 2010 for congruent results). When instead they regress the contemporaneous daily change in the exchange rate on the current daily fluctuation on oil prices, they find a significant and consistent relationship. The relationship is short-lived, in the sense that it can mainly be detected using high frequency data and it washes away quickly. Indeed, in a strict out-of-sample exercise, where lagged rather than contemporaneous daily price changes are used to predict future exchange rate movements, predictability is found to be time-varying and subject to large instabilities.

In this paper we employ a systematic approach to exploit the short-lived effect of commodity prices on exchange rates, in a pseudo out-of-sample context. In contrast with the existing

[1]A very limited list of other papers highlighting this conclusion includes Berge (2013), Fratzscher at al. (2015), Giacomini and Rossi (2010), Ferraro et al. (2015), Rogoff and Stavrakeva (2008) and Sarno and Valente (2009).

exchange rate studies, we allow the effect of daily fluctuations in commodity prices to carry on to the end-of-month change in the exchange rate. Using the so-called MIxed DAta Sampling (MIDAS) framework, each daily observation on price fluctuations can have a different weight or impact on the end-of-month observation on the exchange rate change. The MIDAS regression is a simple, parsimonious, and flexible modeling approach that allows the variables entering a time series regression to be sampled at different frequencies (Ghysels, 2007). For instance, fluctuations at the end of the month can have more predictive power than fluctuations further back. With our approach we can attribute more importance to these observations that are closer in time, while the literature typically would aggregate them to the lowest frequency with equal weights.

Further, the empirical literature also suggests that the predictive content of either commodity prices or the standard macroeconomic fundamentals is time-varying. Ferraro et al. (2015), for example, find that lagged daily fluctuations in oil prices were better predictors of daily changes in the Canadian/U.S. dollar exchange rate around 2006-2007, while at the monthly and quarterly frequencies predictive ability is never found.[2] Hence, in our approach, we let each of the high-frequency commodity prices we consider be potentially relevant at each point in time. More specifically, our MIDAS predictive models allow for changing sets of high and/or low frequency regressors at each period in time. In this setting, we make two additional contributions. First, we use a likelihood-based approach to shed light on whether regressors sampled at high frequency are more informative about monthly changes in exchange rates than predictors sampled at low/same frequency. Second, we equally employ the likelihood information to account for potential time-variation in the predictive content of our predictors (i.e., commodity prices and standard macroeconomic fundamentals). Therefore, we forecast with the predictors with the highest support from the data at each period in time. Alternatively, we compute the forecast as a weighted average of each model's forecast. In this methodical manner, we analyze if accounting for the time-changing predictive ability improves forecast accuracy. More generally, in our framework, we check whether the predictive content of fundamentals sampled at high and low frequency should be regarded as complementary, rather than substitute of commodity prices.

All our models are estimated with Bayesian methods, and we introduce the random walk

[2] See also an explanation for the time-variation in predictive content based on a scapegoat theory of exchange rates of Bacchetta and van Wincoop (2004, 2013) or the empirical evidence in Fratzscher et al. (2015).

chain Metropolis-Hastings algorithm as a tool for estimating MIDAS regressions. Bayesian methods are progressively being applied in MIDAS papers, owing to their advantage in terms of providing a systematic framework to incorporate model and parameter uncertainty by focusing on the full predictive density (see Pettenuzzo et al., 2015, for a recent application). These methods also allow us to systematically achieve our goals of (i) examining the degree of informativeness of predictors sampled at different frequencies and (ii) accounting for time-variation in forecasting performance.

We focus on commodity prices/currency pairs of three major commodity exporting countries: (a) Australia with emphasis on gold and copper prices; (b) Canada, concentrating on oil and copper prices, and (c) Norway with oil and gas prices. In addition, following the indication in Chen et al. (2010) that commodity price movements may induce exchange rates fluctuations for large commodity importers, we examine the case of Japan (focusing on oil prices and a commodity price index), as an example of this category of countries. Overall, while our left-hand side variable is always sampled at monthly frequency, on the right-hand-side our regressions allow for commodity prices sampled at daily or monthly frequency, or standard macroeconomic predictors sampled at monthly frequency (e.g., interest rate differentials, money supply differentials, and price differentials).

Using monthly and the corresponding daily data from September 1986 to March 2014 we recursively forecast the 1–month ahead change in the exchange rate. Our forecasts are compared to those of the driftless Random Walk, which according to Rossi (2013), is the toughest benchmark in the exchange rate literature. To assess the forecasting performance of our methods we employ the root mean squared forecast error (RMSFE) for point forecasts and log-score differentials for density forecasts. We examine the statistical significance of our forecasts using the Clark and West (2006, 2007) test-statistic.

What we find is that exploiting the properties of daily commodity prices in a MIDAS setting leads to forecast improvements. In terms of point forecasts for example, MIDAS regressions with daily copper prices improve upon the RW benchmark for the Australian dollar and the Canadian dollar. In contrast, and consistent with the existing evidence, standard regressions with commodity prices sampled at low frequency hardly improve upon our benchmark. Regarding density forecasts, our results suggest that once we account for the full forecast distribution, the RW never forecasts better than the commodity or fundamentals-based regressions. As well, when we account for time-variation in forecasting ability by combining the forecasts from our

MIDAS models and from regressions based on standard macroeconomic fundamentals we also improve upon the RW. Inspection of the data-driven weights underlying our forecast combinations approaches reveals that daily commodity prices are relatively more informative about monthly changes in exchange rates than monthly commodity prices or the typical macroeconomic variables.

The paper proceeds as follows. In Section 2 we use a small simulation example to illustrate why a MIDAS setup might be appropriate to pin down the forecasting ability of daily commodity prices. In Section 3 we detail our methodology, including our new contribution in terms of estimation of MIDAS regression using the random walk Metropolis-Hastings algorithm. Section 4 describes the essential features of our empirical exercise. In Section 5 we report our main forecasting results. Section 6 examines the empirical attributes underlying our Bayesian forecast combination methods. Robustness checks are in Section 7, while Section 8 concludes.

2 A Small Simulation Example

To visualize the importance of considering our approach, Figure 1 shows a simulation exercise based on the moments (mean and standard deviation) taken from the data we consider in our empirical section. The econometric procedure underlying the simulation is detailed in the methodological section.

In Panel A we assume a Data Generating Process (DGP) in which monthly fluctuations in the exchange rate, Δs_t, are driven by a daily-frequency variable, denoted x_{td}, where each observation is allowed to have a different effect on Δs_t. The simulated DGP is:[3]

$$\Delta s_t = -0.001 + 0.50 \times [f(\theta_1, \theta_2)(x_{td21} + x_{td20} + ... + x_{d1})] + \varepsilon_t \tag{1}$$

where ε_t is an i.i.d. error term with $\text{var}(\varepsilon_t) = 0.11$. The subscript $d()$ attached to x_t indicates the occurrence of the daily observation in a month. Essentially, we consider 22 working days within a month. Further, we assume that the previous 21 daily observations affect the value of Δs_t. The function, $f(\theta_1, \theta_2)$, is a polynomial that allows us to smooth the past daily observations on the basis of the two parameters. We set these parameters to $\theta_1 = 0.3$ and $\theta_2 = -0.1$, implying that for this DGP, observations close to the end of the month have higher impact on Δs_t than those at

[3] The DGP is a MIDAS model based on the exponential Almon lag polynomial with the parameters that determine the weights defined by θ_1 and θ_2. A complete description of this type of model is given in Section 3.

the beginning of the month. Subsequently, we simulate 160 monthly data points corresponding to 3520 daily observations and fit a MIDAS regression and a typical Linear regression. Note that the latter regression imposes equal weights on the daily observations.

The panel illustrates how well we can fit the true DGP if we use the usual constant weighting scheme, as opposed to the MIDAS approach. As depicted, imposing equal weights on the effects of the daily variable results in a relatively poor fit. There are larger mismatches between the true DGP and the line fitted with the constant weighting approach, especially in the high and low spikes. In contrast, the line fitted with the MIDAS approach recovers reasonably well the true DGP. Accordingly, the adjusted R-squared is 0.63 in the MIDAS setup, whereas in the usual weighting scheme is 0.14.

In Panel B we consider a DGP in which the monthly fluctuations in the exchange rate are driven by a daily-frequency variable where each observation has the same weight on Δs_t. Consistent with this assumption, we set $\theta_1 = \theta_2 = 0$ in Equation (1), and keep the remaining features unchanged. In the panel we inspect how well we can fit the true DGP if we use the MIDAS approach instead of the typical constant weighting scheme (Linear regression). The graph shows that the MIDAS approach is as well suited as the same weighting scheme to recover the true DGP; the two lines fitted to the data overlap, and the adjusted R-squared is 0.27 in the two setups. As it will become clearer in the next section, the line fitted under the MIDAS approach coincides with the one based on the Linear regression because the weights on the daily observations are also estimated from the data. And in this case, under the MIDAS approach the estimates of the parameters that determine these weights happened to be zero - consistent with equal weighting scheme and hence the true DGP.

All in all, our simulation suggests that, at least in-sample, the MIDAS approach is well-suited to capture the properties of the unknown true DGP. Whether the better in-sample fit will translate into a better out-of-sample forecast depends on the existence of predictive content of daily commodity prices on monthly exchange rates. Our first aim is to use the MIDAS approach to examine if accounting for the properties of commodity prices at daily-frequency yield better monthly out-of-sample exchange rate forecasts.

3 Methodology

3.1 Predictive MIDAS Model

In our empirical analysis, we are firstly interested in forecasting the h-month-ahead change in the exchange rate, using a predictor sampled daily. The usual procedure would be to aggregate the data on the daily-frequency variable to match the frequency of the low-sampled one. As shown in Section 2, this aggregation might result in a poor fit, as well as loss of the properties of the data, and econometric estimation issues related to inconsistent estimators (see Andreou et al., 2010). To potentially avoid these issues, a MIDAS regression allows mixing variables sampled at different frequencies. A simple MIDAS regression for our forecasting problem is:

$$\Delta s_{t+h} = \beta_0 + \beta_1 B_1(L^{1/m}; \theta_1) x_t^{(m)} + \varepsilon_{t+h}; \quad \varepsilon_{t+h} \sim N(0, \sigma^2), \tag{2}$$

where

$$\beta_1 B_1(L^{1/m}; \theta_1) \equiv B(L^{1/m}; \theta) = \sum_{k=0}^{K-1} B(k; \theta) L^{k/m}, \tag{3}$$

for $t = 1, ..., T - h$, and $h = 1$ (a similar model is used by Pettenuzzo et al., 2015).

In Equation (2), Δs_{t+h} is the period-ahead change in the exchange rate at monthly frequency. Our daily regressor, denoted $x_t^{(m)}$, is sampled m times between t and $t+1$, and $m = 22$ assuming that there are always 22 observations within a month.[4] The key ingredient in the MIDAS model is the polynomial function, $B(L^{1/m}; \theta)$, which allows to smooth K past observations of $x_t^{(m)}$ on the basis of a few number of parameters $\theta = (\theta_0, \theta_1, ..., \theta_p)$, where $p + 1 << K$. In this function, $L^{k/m}$ is a lag operator such that $L^{1/m} x_t^{(m)} = x_{t-1/m}^{(m)}$, i.e., we denote lags of $x_t^{(m)}$ by $x_{t-j/m}^{(m)}$. Once the parameters of this function are obtained, the effect of past values of $x_t^{(m)}$ on Δs_{t+h} is captured by β_1.

To gain insights on these concepts, consider for instance that a time t monthly change in the exchange rate is affected by the previous 21 daily observations of $x_t^{(m)}$. Without using a smoothing function or restricting the parameters in $B(L^{1/m}; \theta)$, we would have to include $K = 21$ daily lags in Equation (2) and estimate $21 + 2$ parameters. Instead, in a MIDAS

[4] To create balanced monthly observations we assume the following. First, for months with less than 22 observations, we consider that the observation in the last working day of the previous month extends to one day before the first working day of the current month. If this does not complete 22 days, we further posit that the last observation of the current month is valid for one extra day. Second, for months with more than 22 days, typically 23, we average the first two daily observations.

regression the smoothing function, $B(L^{1/m};\theta)$, uses fewer parameters (two in our application).

We can extend the model in (2) to include n other regressors, $\mathbf{z}_t = (z_{1t}, ..., z_{nt})'$, sampled at the same frequency as Δs_{t+h}:

$$\Delta s_{t+h} = \beta_0 + \beta_1 B(L^{1/m};\theta_1)x_t^{(m)} + \delta'\mathbf{z}_t + \varepsilon_{t+h}, \tag{4}$$

where δ is a vector of n coefficients associated with $\mathbf{z}_t$. The model in (4) nests two specifications that we consider in our empirical work: (i) a MIDAS model if we exclude the predictors in $\mathbf{z}_t$ and (ii) a typical Linear regression, if we exclude the daily ($x_t^{(m)}$) variables and forecast the monthly change in the exchange only with commodity prices or macroeconomic fundamentals sampled at the same frequency as Δs_{t+h}.

To complete the specification of the MIDAS regression we need to define the functional form of the polynomial $B(L^{1/m};\theta)$. While several alternatives exist, and the adoption of any particular depends on the application at hand, we employ the exponential Almon lag polynomial following Ghysels et al. (2007):[5]

$$B(k;\theta) = \frac{e^{(\theta_1 k + \theta_2 k^2)}}{\sum_{i=1}^{K} e^{\theta_1 i + \theta_2 i^2}}, \tag{5}$$

with $\theta = (\theta_1, \theta_2)$. This polynomial is flexible enough to take various shapes for different values of its parameters, (θ_1, θ_2), and Ghysels et al. (2005) have found it to work well in practice. If we consider that only the past 21 trading days affect the value of Δs_{t+h}, then under this polynomial Equation (2) is a compact representation of:

$$\Delta s_{t+h} = \beta_0 + \beta_1 \left(\frac{e^{(\theta_1 \times 1 + \theta_2 \times 1^2)}}{\sum_{i=1}^{K} e^{\theta_1 i + \theta_2 i^2}} x_{td21} + \frac{e^{(\theta_1 \times 2 + \theta_2 \times 2^2)}}{\sum_{i=1}^{K} e^{\theta_1 i + \theta_2 i^2}} x_{td20} + ... + \frac{e^{(\theta_1 \times 21 + \theta_2 \times 21^2)}}{\sum_{i=1}^{K} e^{\theta_1 i + \theta_2 i^2}} x_{td1} \right) + \varepsilon_{t+h}. \tag{6}$$

This MIDAS regression is non-linear, requiring non-linear methods for estimation. We focus on an appropriate algorithm to implement in the next subsection.

[5] In our empirical exercise we also experimented with the unrestricted MIDAS approach of Foroni et al. (2013). In unreported results we find that forecasts based on this approach were generally less precise than the RW benchmark. A possible explanation for this weak performance might be the loss of precision in parameter estimates, since in this approach and given our daily-frequency predictors, a relatively large number of parameters have to be estimated.

3.2 Bayesian Estimation and Forecasting

We use Bayesian methods to estimate the parameters of our regressions. These methods are increasingly being applied in MIDAS studies (see, e.g., Pettenuzzo et al., 2015 and references there in). The major advantage of Bayesian techniques over the typical frequentist methods is to account for model and parameter uncertainty. This is achieved by obtaining the full predictive density, rather than solely a point forecast underlying the frequentist approach. As we elaborate next, in a Bayesian setup we can also combine forecasts in a more methodical fashion.

To describe the mechanics of our novel MIDAS estimation techniques with a simple notation, first express Equation (6) in the following functional form:

$$S = f(X, \gamma) + \varepsilon, \qquad \varepsilon \sim N(0, \frac{1}{\eta}), \text{ and } \qquad \frac{1}{\eta} = \sigma^2; \tag{7}$$

where we have suppressed, for notational simplicity, the dependence on the forecast horizon h and time t. Moreover, $f(.)$ indicates that our function of interest depends on the data (X) and parameters in γ, where X contains our daily predictors (x_{td}), and γ includes the parameters $\beta_0, \beta_1, \theta_1, \theta_2$.

Bayesian estimation involves the definition of prior distributions, the likelihood function, and the posterior distribution. We use independent Normal-Gamma priors. As such, the prior for γ is independent of the prior for η and is defined as:

$$\gamma \sim N(\underline{\gamma}, \underline{V}). \tag{8}$$

For the error precision, η, the prior is:

$$\eta \sim G(\underline{s}^{-2}, \underline{\nu}). \tag{9}$$

We set $\underline{\gamma} = (0,0,0,0)'$, $\underline{V} = 0.35I$, $\underline{\nu} = 1$, and $\underline{s}^{-2}$ is based on OLS estimate of Equation (2) assuming that the data is aggregated to the monthly frequency under the constant weighting scheme. All these choice of priors are sensible but relatively diffuse. For instance, the elements of the prior mean in $\underline{\gamma}$ incorporate the view that the driftless Random Walk model provides better exchange rate forecasts. At the same time, the prior variance, $\underline{V}$, allows the coefficients estimates to wander in the region $[-1.2, 1.2]$ with 95% prior probability assuming normality. We further note that only data available up to the beginning of our first forecast are used to estimate any data-based quantity such as $\underline{s}^{-2}$.

If we combine these priors with the likelihood we obtain the following conditional posterior for η (see Appendix A for details):

$$p(\eta|S,\gamma) \sim G(\overline{s}^{-2},\overline{\nu}), \tag{10}$$

where $\overline{s}^2 = \frac{[S-f(X,\gamma)]'[S-f(X,\gamma)]+\underline{\nu}\underline{s}^2}{\overline{\nu}}$ and $\overline{\nu} = \underline{\nu} + T$. As shown in Koop (2003, Ch. 5), the conditional posterior distribution of γ is:

$$\begin{aligned} p(\gamma|S,\eta) \propto \exp & \left[-\frac{\eta}{2}\left\{S - f(X,\gamma)\right\}'\left\{S - f(X,\gamma)\right\}\right] \\ \exp & \left[(-\frac{1}{2}(\gamma-\underline{\gamma})'\underline{V}^{-1}(\gamma-\underline{\gamma}))\right]. \end{aligned} \tag{11}$$

This latter conditional posterior ($p(\gamma|S,\eta)$) does not suggest any density from which to directly sample from. We propose the random walk chain Metropolis-Hasting (RW-MH) posterior simulator to sequentially draw parameters from a suitable candidate generating density, in the spirit of Koop (2003, Ch. 5). Essentially, candidate draws of γ, denoted by γ^*, are generated according to a random walk. Following a typical procedure, we choose the multivariate Normal distribution as the candidate generating density:

$$q(\gamma^{(dr-1)},\gamma) \sim fN(\gamma|\gamma^{(dr-1)},\Sigma), \tag{12}$$

where $\gamma^{(dr-1)}$ denotes the last accepted draw of γ, and Σ is a pre-selected covariance matrix which guarantees that the acceptance probability is within a reasonable range, typically $[0.2, 0.5]$. Using data available up to the beginning of our first forecast we set this covariance matrix to the maximum likelihood variance estimate, $\Sigma = var(\widehat{\gamma}_{ML})$. The acceptance probability of the candidate draw is calculated as:

$$a(\gamma^{(dr-1)},\gamma^*) = \min\left[\frac{p(\gamma = \gamma^*|S,\eta)}{p(\gamma = \gamma^{(dr-1)}|S,\eta)}, 1\right]. \tag{13}$$

with $p()$ at the current and previous draw evaluated using Equation (11).

The RW-MH algorithm simulates draws for $p(\gamma|S,\eta)$, but we also require draws from $p(\eta|S,\gamma)$. Since we know the form of this density (see Equation (10)), we can easily combine the RW-MH step with the Gibbs sampler. Such Metropolis-within-Gibbs algorithm allows us to sequentially draw η conditional on γ. Refer to Appendix A for further details and exact steps.

To forecast with our model we need the predictive density. This is given by:

$$p(S^*|S,\gamma) = t(S^*|f(X^*,\gamma), \bar{s}^2 I_T, T), \tag{14}$$

where $\bar{s}^2 = (S-f)'(S-f)/T$. Using the Gibbs sampler we can obtain draws from this predictive density, from which we can compute point and density forecasts. In our empirical exercise, we generate 31000 draws from which we discard the first 1000 and keep every third draw for inference. Details about the convergence measures are relegated to Appendix C.[6]

3.3 Bayesian Model Averaging or Selection and Optimal Predictive Pool

So far we have focused on estimating and forecasting with a model defined according to the predictors it includes. Since we estimate and obtain predictive densities for several alternative models at each point in time, we can optimally exploit the predictive content of each predictor. For example, we compute forecast combinations based on each model's relative importance over time. Alternatively, we forecast with the model that yields the highest weight (i.e., probability) at each point in time or compute the optimal predictive pool of Geweke and Amisano (2011). The first two approaches assume that the true model is in the model set and the selection or combination converges asymptotically to it. The optimal predictive pool, on the contrary, allows for model incompleteness, meaning the true model might not be present in the model set, see Mitchell and Hall (2007) and Geweke and Amisano (2011). Moreover, apart from allowing to account for instabilities in the model's forecasting performance, the weights permit to make inference about which predictors are more informative about exchange rate fluctuations.

To visualize these weighting and forecasting schemes, let M_i identify a specific model from the set of M^N models, such that the predictive density in (14) is now also model-specific, $p(S^*|S,\gamma,M_i)$. Bayesian Model Selection (BMS) uses weights derived from the realized likelihood of the model's prediction to select a single model. Bayesian Model Averaging (BMA) employs the weights to average results over all models.

The starting point is to assign prior probabilities to each model, and subsequently obtaining

[6] We checked the convergence and adequacy of the number of draws using standard procedures, such as Geweke's (1992) numerical standard errors (NSE) and acceptance rates in the RW-MH algorithm. Overall results indicate an acceptable degree of efficiency of the algorithm.

posterior probabilities (weights) based on the model's realized likelihood. We assume a priori that each model has the same chance of becoming probable, hence, the prior is: $\Pr(M_i) = 1/M^N$. The posterior probability of model i, defined by $\Pr(M_i|D^t)$, is given by:

$$\Pr(M_i|D^t) = \frac{\Pr(D^t|M_i)\Pr(M_i)}{\sum_{j=1}^{M^N}\Pr(D^t|M_j)\Pr(M_j)}, \tag{15}$$

where $\Pr(D^t|M_i)$ is the marginal likelihood of the ith model. We compute this likelihood using the method of Gelfand and Dey (1994), see Appendix A for details. Note that the posterior model probability also allows us to infer about which predictor receive more support from the data.

The forecasts from BMA are computed by weighting each model's forecast by the model's posterior probability:

$$p(S^*|S,\gamma) = \sum_{i=1}^{M^N}\Pr(M_i|D^t)p(S^*|S,\gamma,M_i). \tag{16}$$

In BMS, instead, the forecasts are based on the model with the highest posterior probability. Finally, the optimal predictive pool combines the forecasts of the M^N models according to weights related to the model's past predictive performance:

$$p(S^*|S,\gamma) = \sum_{i=1}^{M^N}\mathbf{w}_i^*(S^*|S,\gamma,M_i), \tag{17}$$

with $\mathbf{w}_i^*$ denoting an $(M^N \times 1)$ vector of weights obtained by solving a maximization problem conditional on information available at the time the forecast is made:

$$\mathbf{w}_i^* = \arg\max_w \log\left[\sum_{i=1}^{M^N} w_i^* \times \exp(LS_i)\right]. \tag{18}$$

where $\mathbf{w}_i^* \in [\mathbf{0},\mathbf{1}]$ and LS_i is the log score for model i computed using information available up to time t. In the next section we describe our predictors, and hence the set of models contained in M^N.

4 Forecasting Exercise

4.1 Choice of Regressors

While our left-hand side variable is always sampled at monthly frequency, on the right-hand-side our regressions allow for commodity prices sampled at daily or monthly frequency, or standard macroeconomic predictors at monthly frequency. The menu of commodity-related regressors includes changes in prices of oil, gold, gas, and copper and a commodity price index. These choices reflect the main commodities exported by the countries we focus upon and are in line with recent studies on the commodity price - exchange rate relationship, such as Chen et al. (2010) and Ferraro et al. (2015).

The selection of the macroeconomic variables is guided by the standard models of exchange rate determination (see, among others, Engel and West (2005), Molodtsova and Papell (2009), and Rossi (2013)). In addition to commodity prices changes at monthly frequency, in $\mathbf{z}_t$ we equally include predictors derived from:

- The Monetary Model (MM):

$$\mathbf{z}_{t,MM} \equiv (m_t - m_t^*) - (y_t - y_t^*) - s_t, \tag{19}$$

  where m_t is the log of money supply, y_t is the log of income, and asterisks denote foreign country variables;[7]

- Purchasing Power Parity (PPP) condition:

$$\mathbf{z}_{t,PPP} \equiv p_t - p_t^* - s_t, \tag{20}$$

  where p_t is the log of price level;

- Uncovered Interest Rate Parity (UIP) condition:

$$\mathbf{z}_{t,UIP} \equiv i_t - i_t^*, \tag{21}$$

  with i_t denoting the short-term nominal interest rate;

[7] Note that we have assumed an income elasticity of one in the monetary model ($\mathbf{z}_{t,MM}$), following Mark (1995) and Engel and West (2005).

- A symmetric and an asymmetric Taylor rule (TRsy and TRasy, respectively):

$$\mathbf{z}_{t,TRsy} \equiv 1.5(\pi_t - \pi_t^*) + 0.5(\overline{y}_t - \overline{y}_t^*), \tag{22}$$

$$\mathbf{z}_{t,TRasy} \equiv 1.5(\pi_t - \pi_t^*) + 0.1(\overline{y}_t - \overline{y}_t^*) + 0.1(s_t + p_t^* - p), \tag{23}$$

where π_t is the inflation rate, and $\overline{y}_t$ the output gap.[8]

4.2 Data and Forecasting Mechanics

The data consists of exchange rates of the following (home) countries relative to the U.S. dollar: Australia (AUD), Canada (CAD), Norway (NOK) and Japan (YEN). The first three countries can be currently categorized as net commodity exporters, while Japan is a net oil importer. We include the latter to examine the hypothesis in Chen et al. (2010) that commodity price movements may induce exchange rates fluctuations for large commodity importers. The exchange rate is the end-of-month value of the national currency per U.S. dollar. Our effective sample period runs from 1986M9 to 2014M3 for all countries, except Norway. Due to unavailability of data on daily gas prices fluctuations, the sample period for Norway comprises 1997M1 - 2014M3. Further details on exact data sources, definitions, and descriptive statistics are provided in Appendix (B).

We employ a recursive forecasting scheme, while generating direct forecasts at 1-month horizon.[9] In Diagram 1 we exemplify the mechanics of our forecasting procedure with our MIDAS regression. We use data from 1986:M9:D22 to 1998:M9:D22 to estimate parameters of our MIDAS regression (as in Equation (2)). Data from 1998:M10:D1 to 1998:M10:D21 is used to forecast the period ahead change in the exchange rate ($s_{1998:M12} - s_{1998:M11}$). In this sense, we use information up to one day before the end-of-the month to generate the forecast. We then add one month worth of daily data and repeat, until the end of the sample. This procedure provide us with a long series of P out-of-sample forecasts, where $P = 167$ for all currencies except for the Norwegian Kroner, whose $P = 102$.

[8] The proxy for the output is monthly industrial production (IP). In line with the standard practice in exchange rate economics, the output gap is obtained by applying the Hodrick and Prescott (1997) filter recursively to the output series. We also use the conventional smoothing parameter for monthly data - 14400. To correct for the uncertainty about these estimates at the recursive sample end-points, we follow Watson's (2007) method. We estimate bivariate VAR(ℓ) regressions on the first difference of inflation and the change in the log IP, with the lag length in the VAR determined by AIC. These regressions are then used to forecast and backcast three years worth of monthly data on IP, and the filter is applied to the resulting extended series.

[9] The MIDAS approach is a direct forecasting tool. Marcellino et al. (2006) compare direct and iterated forecasting approaches and according to Wright (2008), direct and iterated forecasting approaches yield qualitatively similar conclusions.

Diagram 1: Example of Data Timing Scheme in the Forecasting Regression, $h = 1$

...	1998:M9:D22	1998:M10:D1	1998:M10:D2	...	1998:M10:D21	1998:M10:D22	...	1998:M11:D22
...	1998:M10					1998:M11		1998:M12

4.3 Measures of Forecasting Performance

We employ the root mean squared forecast error (RMSFE) as a statistical measure of out-of-sample point forecast accuracy. The benchmark model is the driftless random walk (RW).[10] To be precise, we compute the ratio of the RMSFE of our commodity or fundamentals-based models relative to the RMSFE of the RW:

$$\text{Relative RMSFE} = \frac{\sqrt{\frac{1}{P}\sum_{\overline{p}=1}^{P} fe_{i,\overline{p}}^2}}{\sqrt{\frac{1}{P}\sum_{\overline{p}=1}^{P} fe_{RW,\overline{p}}^2}}, \tag{24}$$

where P is the number of out-of-sample forecasts, fe_i^2 and fe_{RW}^2 are the squared forecast errors of our model i and the RW, respectively. Values of the relative RMSFE below one are consistent with a more accurate point forecast of model i against the RW. To evaluate whether the differences in the RMSFE between our models and the RW are significant we use the Clark and West (2006, 2007) test, hereafter CW-test. To examine the forecasting performance of our models over time in terms of point forecast, we compute the relative RMSFE recursively over the out-of-sample period.

Our use of Bayesian methods allow us to fully exploit the information in the predictive density, rather than focusing only on point forecast. In this regard, we first compute the mean log-score differentials (MLSD):

$$MLSD = P^{-1}\sum_{\overline{p}=1}^{P}(LS_{i,\overline{p}} - LS_{RW,\overline{p}}), \tag{25}$$

where $LS_{i,\overline{p}}$ and $LS_{RW,\overline{p}}$ are the log-scores of our model i and the RW, respectively. Positive values of $MLSD$ are consistent with more accurate density forecasts of model i relative to the RW. Finally, we calculate the cumulative log-score differentials (CLSD) of our regressions relative to those of the RW over the out-of-sample period. Positive values of the CLSD indicate that our commodity or fundamentals-based regressions produce more accurate density forecasts than the RW benchmark.

[10] According to Rossi (2013), the forecasts from this naive benchmark are the hardest to improve upon.

5 Forecasting Performance: Empirical Results

5.1 Single Predictor Models

In Table 1 we assess the forecasting performance of models conditioned on each of the regressors we consider. While in the left panel we focus on the relative RMSFE to examine performance in terms of point forecast, in the right panel we look at log-score differentials to inspect density forecast improvements. Focusing on point forecasts, models conditioned on daily regressors, i.e. the MIDAS models, yield a lower RMSFE than the RW benchmark for some commodity-currency pairs. This is the case for the Australian and Canadian dollar MIDAS regressions with copper prices. For instance, for the Australian dollar and changes in copper prices the MIDAS regression reduces the RMSFE by 1.1% relative to the benchmark. An improvement of the same magnitude is also patent in the non-commodity currency we examine - the Japanese Yen. While these reductions in the RMSFE are seemingly low, our tests of equal predictive ability suggest that the differences in the RMSFE we detect are statistically significant. Later, we will examine other metrics to gain more insights on the consistence of these gains over the out-of-sample period.

Also using the RMSFE metric, regressions with monthly commodity prices fail to forecast better than the RW benchmark, as in these cases the relative RMSFE are all above one. Hence, in line with Ferraro et al. (2015) and Chen et al. (2010), we affirm the lack of predictive content of commodity prices sampled at low frequency for monthly variations in exchange rates. As well, our results support the prevalent view in the literature regarding the predictive ability of fundamentals derived from Taylor rules. See, for instance, Molodtsova and Papell (2009) and Rossi (2013). As shown in the table, among the standard macroeconomic fundamentals we use, only those from the Taylor rule display a significant predictive content for at least one currency - the Canadian dollar. In contrast, fundamentals from the Monetary Model (MM), PPP, and UIP yield a relative RMSFE above one, with MM exhibiting the weakest performance for most currency pairs.

Turning to density forecasts in the right panel, results reveal that once we account for the entire forecast distribution, the RW never outperforms our commodity or fundamentals-based regressions. In all cases, the log-score differentials are significantly positive, with MIDAS models on certain commodity-currency pairs exhibiting the largest values. For example, the MIDAS model with daily gold prices changes displays the largest log-score differentials among all the forecasting models for the Australian dollar. A similar assertion holds for daily copper prices and the Canadian dollar, as well as daily oil prices and the Norwegian Kroner.

On balance, we find that when we exploit the full predictive density, all the commodity or fundamentals-based models provide more accurate forecasts than the RW benchmark. In terms of point forecasts, daily commodity prices and Taylor rule fundamentals improve forecast accuracy relative to the RW benchmark in several cases.[11]

5.2 Forecast Combinations

The results in the previous section are based on individual model performance and therefore do not exploit the possibility that one regressor might have forecasted well in parts of the out-of-sample period and poorly in other parts. To exploit this possibility and account for time-variation in forecasting performance, we now turn to forecast combinations methods.

Table 2 reports results for forecast combinations under BMA, BMS, the optimal predictive pool, and a simple average of all individual model's forecasts. This latter case is equivalent to assigning constant weights of $1/M^N$ to each model's forecast. We notice immediately the benefits of forecast combinations, since in most cases we improve upon the benchmark. In the case of the Australian dollar, for instance, either combining forecasts from daily regressors or, both, daily and monthly predictors leads to better performance with all Bayesian combination methods. For the Yen, instead, combining only daily regressors produces the best outcomes, while for the Australian dollar the best results are achieved with monthly commodity prices and macroeconomic fundamentals. In the case of the Norwegian Kroner/USD exchange rate, we note the inability of either method to improve upon the RW, consistent with results from the single predictor forecast evaluation.

Whilst the results show that combination methods based on time-varying weights are superior to the constant weighting scheme, among the former methods there is no clear ranking in terms of the overall best method across currencies. When the forecasts from monthly regressors are combined, the optimal predictive pool delivers the largest reduction in the relative RMSFE for the Canadian dollar. But for Australian dollar and combination of daily regressors, BMS achieves the best performance. In some instances, such as for the Yen with daily regressors, both BMA and BMS perform equally well.

[11] In Appendix D we experiment with a 3-months forecasting horizon. Results are less favorable to either daily or monthly commodity prices in terms of point forecasts. Results for density forecasts are comparable to those we find for 1-month horizon.

5.3 Forecasting Performance Over Time

All our results so far are based on measures of global performance since they are based on averages over the out-of-sample (OOS) period. These metrics leave open the question of whether they are influenced by a few data-points in the OOS period and if the performance we obtain is consistent over the entire OOS period. To shed light on these questions, we next examine metrics of local relative performance, namely the recursive relative RMSFE and the cumulative log-score differentials.

Figure 2 depicts the recursive relative RMSFE for a representative selection of single-predictor regressions. In general, the figure suggests that the improvements we obtain are consistent for the most part of the OOS period. In the case of the Australian dollar and copper prices for example, the relative RMSFE is below one for the most part of the forecast window except around the 2008 financial crisis. A similar pattern holds for the recursive relative RMSFE of the Canadian dollar and copper prices, excluding the period between 2003 and 2007. As anticipated, the consistency is stronger with forecast combination methods, particularly the Bayesian Model Selection (BMS). We further note that the poor forecasting performance of our regressions for the Norwegian Kroner is essentially a phenomenon of the entire OOS forecast window.

Figure 3 shows cumulative log-score differentials from regressions with individual predictors. A key observation from the graphs is that all the commodity or fundamentals-based models improve upon the RW over the OOS period. However, among them, there are generally variations over time in terms of the model with the best forecasting performance. Looking at the Australian dollar case, regressions with fundamentals from MM provided the best density forecasts up to 2010 and among all the regressions considered. From this period onwards, MIDAS models based on gold price changes turned to be the best. An analogous shift occurred between models with MM fundamentals and daily oil prices for Norway. Overall, our metrics of local relative performance indicate that our results are not influenced by a few data-points in the OOS. Rather, they prevail over the entire path of the forecasting period. In the following section we take a closer look at some of the characteristics of the Bayesian combination methods.

6 Looking Inside the Bayesian Forecast Combination

The previous results hint at the usefulness of the MIDAS regression in forecasting commodity currencies. But mostly, they reveal the benefits of Bayesian approaches to forecast combinations. Since the forecasts from our Bayesian methods emanate from a combination of several individual models, here we study some of their embedded characteristics, in an effort to pin down the degree of informativeness of predictors sampled at the different frequencies.

6.1 Predictors' Weights in the BMA and Optimal Predictive Pool

The forecasts from the BMA method in Table 2 are generated by weighting each model's forecast by the model's posterior probability. Therefore, the larger is the model posterior probability, the greater is the weight attached to the model's forecast in the BMA method. Figure 4 plots the posterior probabilities associated with each model, defined according to the predictor it includes. At a glance, MIDAS models with daily commodity prices exhibit the largest posterior probabilities regardless of their ability to improve upon the RW. In the case of Norway for example, the model with daily oil prices displays large weights for the most part of the OOS period, but the BMA method failed to improve upon the RW benchmark for the NOK. This suggests that although daily oil prices are highly likely to determine the current change in the NOK exchange rate, they do not help in terms of predicting future changes. For the other currencies on the other hand, daily commodity prices attract high weights while BMA outforecasts the RW. This is the case for MIDAS regressions for (i) Australia with daily prices of copper and gold, (ii) Canada and daily copper prices, and (iii) Japan with daily oil prices. In contrast, models based on low frequency predictors typically exhibit low posterior probabilities.

In Figure 6 we look at similar features for the optimal predictive pool. With the exception of the Australian case, where daily prices of gold and copper attract large weights in extended parts of the OOS, regressions based on low-frequency predictors exhibit high weights in most parts of the OOS period. For instance, the weight placed on the monetary model for Canada is above 0.6 over the entire OOS period and 0.4 for Norway in a large portion of this OOS period. By contrast, the weight to daily prices of copper (Canada) and oil (Norway) never exceeds 0.4. Note thought that the forecasting performance of the optimal predictive pool among daily and monthly regressors is poor for the Nok and the Yen, whereas in the Australian dollar case, it exhibited the greatest improvement over the RW benchmark.

6.2 Predictors with the Largest Weights in the BMS Method

Contrary to the BMA method, where forecasts from all models are averaged, in the BMS method only forecasts from the model with the highest posterior probability are considered. Figure 5 shows which model exhibits the highest posterior probability over the OOS period. As shown, the pattern is mixed for Canada and Norway with models featuring commodity prices and macro variables having the largest posterior probability in parts of the OOS period. In the case of Japan, the switches occur between models with daily oil prices and monthly oil prices. For the Australian dollar, the MIDAS model with copper prices displays the highest posterior probability. And we recall that BMS produced the largest reduction in the relative RMSFE for this currency (1.3%).

Overall, given that the weights in the Bayesian combination methods are computed from the model's realized likelihood, our results suggest that daily commodity prices are relatively more informative about monthly changes in exchange rates. In contrast, monthly commodity prices and traditional macroeconomic fundamentals, such as those from the Taylor rules, MM, PPP, and UIP are less likely at this horizon. Our findings regarding the predictive content of daily commodity prices are novel and open up new venue for improving exchange rate forecasts.

7 Robustness Checks

We verify the robustness of our findings to two situations. First, to the choice of priors in our Bayesian estimation methods. Second, we inspect if our results thus far are driven by our particular selection of the polynomial function in the MIDAS models. In essence, our previous results hold up strongly.

7.1 Sensitivity to Change in Priors

Our baseline priors are sensible but relatively diffuse. One may question the role of these priors in driving the results we obtain. To address this potential concern, we focus on a setting that assigns equal weights to the prior and the data in the posterior covariance matrix. In particular, we redefine the prior for the coefficients vector (γ) to conform with a g-prior type:

$$\gamma \sim N\left(0_{(n\times1)}, \eta\left[gX'X\right]^{-1}\right). \quad (26)$$

Consistent with our objective we set $g = 1$ (see Koop, 2003, Ch. 11). Point forecast results from models estimated with this prior setting are presented in the left panel of Table 3. If anything, the baseline line results for the MIDAS models are stronger. We detect statistically significant improvements over the RW for the Australian and Canadian dollars with daily copper prices; and for the Japanese Yen with daily oil prices. As before, when we combine both, daily and monthly regressors, our results highlight the gains from such combinations in terms of relative forecast accuracy improvements.

7.2 Sensitivity to the Choice of the Polynomial Function

The MIDAS regressions that generated our main results employ the exponential Almon lag polynomial. To examine whether the results are sensitive to this choice we experimented with the non-normalized Almon lag polynomial (with three degrees):

$$B(k;\theta) = \sum_{i=0}^{p} \theta_i k^i, \tag{27}$$

Using this polynomial, we can rewrite (2) as:

$$\Delta s_{t+h} = \beta_0 + \sum_{k=0}^{K-1} \sum_{i=0}^{p} \theta_i k^i L^{k/m} x_t^{(m)} + \varepsilon_{t+h}, \tag{28}$$

and estimate the model via a two-blocks Gibbs Sampling as in Pettenuzzo et al. (2015). We use the same g-type prior as in the previous robustness check. As shown in the right panel of Table 3, our conclusion that MIDAS models with daily commodity prices help in forecast accuracy remain largely unaffected.

8 Conclusions

In this paper we exploit the properties of daily commodity price changes to predict commodity currencies. Using MIDAS models in a Bayesian setting, we regress monthly changes in exchange rates on daily fluctuations of commodity prices. Essentially, we use a smoothing function that allows for each daily fluctuation to affect the end-of-month exchange rate change with a possibly different weight. We put forward the random walk Metropolis-Hasting algorithm, as a new technique to estimate MIDAS models with the particular smoothing function we employ - the exponential Almon lag polynomial. Our use of Bayesian methods also allow us to account for potential instabilities in forecasting performance and examine the degree of informativeness of the daily commodity price changes, as opposed to the monthly commodity prices and standard macroeconomic fundamentals.

Focusing on data for Australia, Canada, Norway, and Japan we first find evidence favouring daily commodity prices fluctuations in terms of providing more accurate forecasts than the naive no-change benchmark. In particular, daily changes in copper prices yield point forecast improvements for the Australian and Canadian dollar at the 1-month horizon we consider. In addition, we detect significant predictive content of daily oil prices changes for the non-commodity currency we examine, the Japanese Yen. In contrast and as reported in other studies, we identify rare instances in which monthly commodity prices changes lead to systematic point forecast improvements. However, consistent with the existing evidence, macroeconomic fundamentals derived from Taylor rules do exhibit predictive power for some commodity currencies.

We then proceed and combine forecasts from regressions based on daily and monthly commodity prices and monthly traditional macroeconomic fundamentals, in an effort to account for time-variation in forecasting ability of our predictors. Here our empirical findings reveal the usefulness of such combinations in terms of forecast accuracy improvements relative to our benchmark. Our results also hint at the importance of accounting for the full forecast distribution, since in terms of density forecasts, our predictions are always better than those from the RW. Finally, when we inspect the weights underlying our forecast combinations approaches we find that daily commodity prices are relatively more informative about 1-month changes in the exchange rate than monthly commodity prices or the typical macroeconomic variables.

Overall, we interpret our results as endorsing the view that the key to establishing predictive content of daily commodity prices for exchange rates, hinges upon exploiting their short-lived content in a MIDAS setup.

References

Andreou, E., E. Ghysels, and A. Kourtellos (2010). Regression models with mixed sampling frequencies. *Journal of Econometrics 158*(2), 246–261.

Bacchetta, P. and E. V. Wincoop (2004). A scapegoat model of exchange-rate fluctuations. *American Economic Review 94*(2), 114–118.

Bacchetta, P. and E. V. Wincoop (2013). On the unstable relationship between exchange rates and macroeconomic fundamentals. *Journal of International Economics 91*(1), 18–26.

Berge, T. J. (2013). Forecasting disconnected exchange rates. *Journal of Applied Econometrics 29*(5), 713–735.

Chen, Y.-C., K. S. Rogoff, and B. Rossi (2010). Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics 125*(3), 1145–1194.

Clark, T. E. and K. D. West (2006). Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. *Journal of Econometrics 135*(1), 155–186.

Clark, T. E. and K. D. West (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics 138*(1), 291–311.

Engel, C. and K. D. West (2005). Exchange rates and fundamentals. *Journal of Political Economy 113*(3), 485–517.

Ferraro, D., K. Rogoff, and B. Rossi (2015). Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. *Journal of International Money and Finance 54*(0), 116 – 141.

Foroni, C., M. Marcellino, and C. Schumacher (2013). Unrestricted mixed data sampling (MIDAS): MIDAS regressions with unrestricted lag polynomials. *Journal of the Royal Statistical Society: Series A (Statistics in Society) 178*(1), 57–82.

Fratzscher, M., D. Rime, L. Sarno, and G. Zinna (2015). The scapegoat theory of exchange rates: the first tests. *Journal of Monetary Economics 70*(2015), 1 – 21.

Gelfand, A. E. and D. K. Dey (1994). Bayesian model choice: asymptotics and exact calculations. *Journal of the Royal Statistical Society. Series B (Methodological) 56*(3), 501–514.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. *Bayesian Statistics 4*, 169–194.

Geweke, J. and G. Amisano (2011). Optimal prediction pools. *Journal of Econometrics 164*(1), 130 – 141. Annals Issue on Forecasting.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2005). There is a risk-return trade-off after all. *Journal of Financial Economics 76*(3), 509–548.

Ghysels, E., A. Sinko, and R. Valkanov (2007). MIDAS regressions: further results and new directions. *Econometric Reviews 26*(1), 53–90.

Giacomini, R. and B. Rossi (2010). Forecast comparisons in unstable environments. *Journal of Applied Econometrics 25*(4), 595–620.

Hodrick, R. J. and E. C. Prescott (1997). Postwar US business cycles: an empirical investigation. *Journal of Money, Credit and Banking 29*(1), 1–16.

Koop, G. (2003). *Bayesian econometrics.* London: John Wiley & Sons, Ltd.

Marcellino, M., J. Stock, and M. Watson (2006). A comparison of direct and iterated multistep ar methods for forecasting macroeconomic time series. *Journal of Econometrics 135*, 499–526.

Mark, N. C. (1995). Exchange rates and fundamentals: evidence on long-horizon predictability. *The American Economic Review 85*(1), 201–218.

Meese, R. A. and K. Rogoff (1983). Empirical exchange rate models of the seventies: do they fit out of sample? *Journal of International Economics 14*(1), 3–24.

Mitchell, J. and S. G. Hall (2005). Evaluating, comparing and combining density forecasts using the KLIC with an application to the Bank of England and NIESER fan charts of inflation. *Oxford Bulletin of Economics and Statistics 67*, 995–1033.

Molodtsova, T. and D. H. Papell (2009). Out-of-sample exchange rate predictability with Taylor rule fundamentals. *Journal of International Economics 77*(2), 167–180.

Pettenuzzo, D., A. G. Timmermann, and R. I. Valkanov (2015). A Bayesian MIDAS approach to modeling first and second moment dynamics. CEPR Discussion Papers 10160, C.E.P.R. Discussion Papers.

Rogoff, K. S. and V. Stavrakeva (2008). The continuing puzzle of short horizon exchange rate forecasting. NBER Working Paper 14071, National Bureau of Economic Research.

Rossi, B. (2013). Exchange rate predictability. *Journal of Economic Literature 51*(4), 1063–1119.

Sarno, L. and G. Valente (2009). Exchange rates and fundamentals: footloose or evolving relationship? *Journal of the European Economic Association 7*(4), 786–830.

Watson, M. W. (2007). How accurate are real-time estimates of output trends and gaps? *Economic Quarterly 93*(2), 143–161.

Wright, J. H. (2008). Bayesian model averaging and exchange rate forecasts. *Journal of Econometrics 146*(2), 329–341.

Table 1: Relative RMSFE and Log-score Differentials for Models with Single Predictor, $h = 1$

	Relative RMSFE				Log-score differentials			
	AUD	CAD	NOK	YEN	AUD	CAD	NOK	YEN
Daily regressors (MIDAS model)								
ΔOil_Dp	-	1.006	1.021	**0.989****	**-**	**2.11*****	**2.66*****	**2.23*****
Δgold_Dp	1.026	-	-	-	**2.93*****	**-**	**-**	**-**
Δcopper_Dp	**0.989***	**0.993**	-	-	**2.67*****	**2.85*****	**-**	**-**
Δgas_Dp	-	-	1.003	-	**-**	**-**	**1.73*****	**-**
ΔDP_index	-	-	-	1.000	**-**	**-**	**-**	**1.51*****
Monthly regressors								
Δoil_Mp	-	1.004	1.008	1.011	**-**	**2.10*****	**1.72*****	**2.79*****
Δgold_Mp	1.005	-	-	-	**2.20*****	**-**	**-**	**-**
Δcopper_Mp	1.001	1.000	-	-	**2.27*****	**2.33*****	**-**	**-**
Δgas_Mp	-	-	1.003	-	**-**	**-**	**1.61*****	**-**
ΔMP_index	-	-	-	1.013	**-**	**-**	**-**	**1.90*****
Monthly regressors								
TRsy	1.000	**0.987****	1.009	1.016	**1.92*****	**2.50*****	**1.87*****	**1.58*****
TRasy	1.002	**0.988****	1.000	1.003	**2.72*****	**2.76*****	**1.74*****	**2.27*****
MM	1.015	1.008	1.018	1.008	**2.40*****	**2.84*****	**2.27*****	**1.96*****
PPP	1.007	1.001	1.005	1.008	**2.05*****	**1.49*****	**2.38*****	**2.70*****
UIP	1.005	1.003	1.022	1.004	**2.06*****	**1.83*****	**1.70*****	**3.07*****

Notes: The Table reports forecasting performance of single preditor models. The left panel shows the Root Mean Squared Forecast Error (RMSFE) of the commodity or fundamental-based forecasting model relative to the RMSFE of the driftless Random Walk (RW). Values less than 1 (one) indicate that the commodity or fundamental-based model generates a lower RMSFE than the RW, hence, it forecasts better than the RW. The righ panel presents the average log-score differentials between the same models relative to the RW. Positive values indicate that the commodity or fundamental-based model improves upon the RW in terms of density forecasts. The Table also reports the CW-test with asterisks (10%, **5%, ***1%) denoting the level of significance at which the null hypothesis of equal RMSFE (LS) is rejected, favouring the alternative that the commodity or fundamental-based model provides more accurate point (density) forecasts. The commodity or fundamentals-based forecasting model uses the relevant country-commodity or fundamental listed in the first column and grouped in terms of daily and monthly regressors. In all models, the forecasts are generated recursively for h-month(s)-ahead change in the exchange rate. When only daily regressors are used, the forecasts are from the MIDAS model. The list of daily regressors include, change in daily prices (Dp) of oil, gold, copper, gas, and a daily commodity price index (ΔMP_index). In the monthly regressors group we have a similar set of commodities, but also fundamentals from the symmetric Taylor rule - TRsy, the asymmetric Taylor rule - TRasy, the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. The currency codes in the first row denote the Australian dollar (AUD), the Canadian dollar (CAD), the Norwegian Kroner (NOK), and the Japanese YEN. The forecast evaluation period is 1998M11+h to 2014M3 for all currencies, except the NOK (2005M7 +h to 2014M3).

Table 2: Relative RMSFE and CW-test for Forecast Combinations, $h = 1$

	Daily regressors - Commodity Prices (CmdtyP)		Monthly regressors (CmdtyP and macro fundamentals)		Daily and monthly regressors (CmdtyP and macro fundamentals)	
	BMA	BMS	BMA	BMS	BMA	BMS
AUD	**0.992**	**0.987***	1.002	1.000	**0.993**	**0.987***
CAD	1.000	**0.999**	**0.991****	**0.995***	**0.996**	**0.998**
NOK	1.014	1.016	1.009	1.005	1.019	1.017
YEN	**0.989****	**0.989****	1.004	1.003	**0.998**	**0.999**
	OptPool	EqWeights	OptPool	EqWeights	OptPool	EqWeights
AUD	**0.990***	1.000	1.013	1.002	**0.990***	1.000
CAD	1.002	1.002	**0.990****	**0.997**	**0.996**	**0.997**
NOK	1.019	1.007	1.029	1.008	1.036	1.007
YEN	**0.990****	**0.995***	1.011	1.003	1.009	1.001

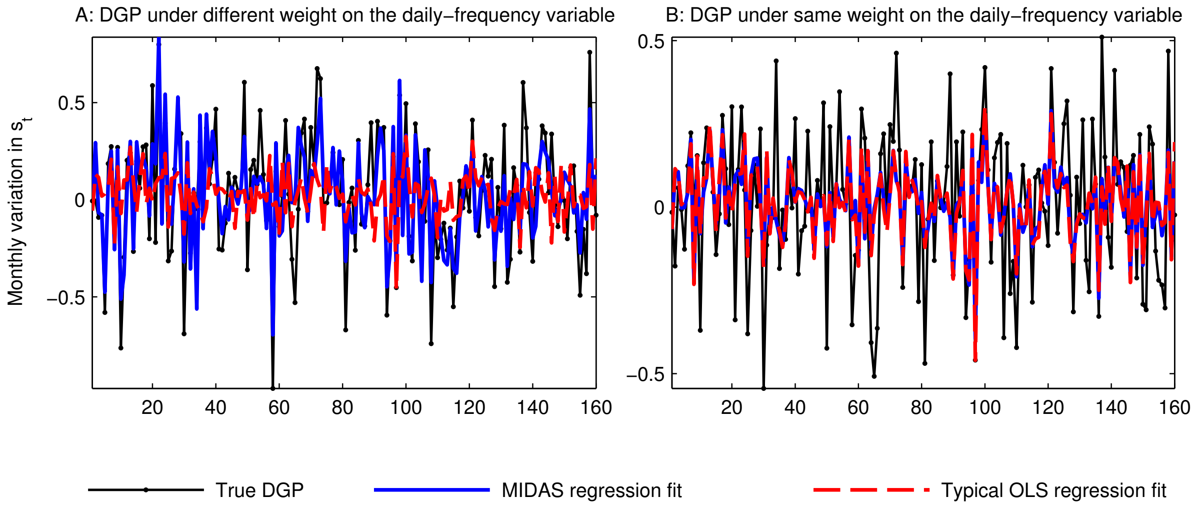
Notes: The table reports the Root Mean Squared Forecast Error (RMSFE) for forecast combination methods relative to the RMSFE of the driftless Random Walk (RW). The methods include, Bayesian Model Averaging (BMA), Bayesian Model Selection, (BMS), the Optimal Predictive Pool (OptPool) of Geweke and Amisano (2011), and a simple equal-weighting scheme (EqWeights). Values less than 1 (one) indicate that the combination method generates a lower RMSFE than the RW, hence, it forecasts better than the RW. The table also reports the CW-test with asterisks (10%, **5%, ***1%) denoting the level of significance at which the null hypothesis of equal RMSFE is rejected, favouring the alternative that the combination method has a lower RMSFE. The forecast combinations are based on the relevant commodity-currency and standard macroeconomic fundamentals. For the Australian dollar (AUD) the relevant commodities are gold and copper; for the Canadian dollar (CAD) - oil and copper; and for the Norwegian Kroner (NOK) these include oil and gas. When only daily regressors are used the combination is based on forecasts from the MIDAS models - reported in columns [2-3]. In columns [4-5] the combination is based on forecasts from monthly regressors, while the last two columns report results from combining daily and monthly regressors. In all cases, the forecasts are generated recursively for h-month(s)-ahead change in the exchange rate. In the group of monthly regressors we have a set of commodity pairs similar to the daily group, but also fundamentals from the symmetric Taylor rule - TRsy, the asymmetric Taylor rule - TRasy, the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. The forecast evaluation period is 1998M11+h to 2014M3 for all currencies, except the NOK (2005M7 +h to 2014M3).

Table 3: Forecast Evaluation Sensitivity Analysis, $h = 1$

	Relative RMSFE and CW-test							
	Sensitivity to change in priors				Sensitivity to the choice of the polynomial			
	AUD	CAD	NOK	YEN	AUD	CAD	NOK	YEN
Daily regressors (MIDAS model)								
ΔOil_Dp	-	1.011	1.026	**0.983****	-	1.005	1.012	**0.991***
ΔGold_Dp	1.007	-	-	-	1.022	-	-	-
ΔCopper_Dp	**0.987***	**0.988***	-	-	**0.994**	**0.993**	-	-
ΔGas_Dp	-	-	1.002	-	-	-	**0.995**	-
ΔDP_index	-	-	-	1.003	-	-	-	**0.994***
Monthly regressors								
ΔOil_Mp	-	1.001	1.002	1.002	-	1.001	1.004	1.002
Δgold_Mp	1.003	-	-	-	1.004	-	-	-
ΔCopper_Mp	1.001	**0.999**	-	-	1.000	**0.999**	-	-
ΔGas_Mp	-	-	1.003	-	-	-	1.001	-
ΔMP_index	-	-	-	1.002	-	-	-	1.001
Monthly regressors								
TRsy	1.000	**0.993****	1.007	1.006	**0.998**	**0.991****	1.005	1.007
TRasy	**0.999**	**0.993****	1.000	1.001	**0.999**	**0.992****	1.001	**0.997**
MM	1.005	1.003	1.006	1.003	1.007	1.003	1.009	1.000
PPP	1.004	1.001	1.001	1.000	1.003	1.001	1.002	1.001
UIP	1.001	1.003	1.012	**0.998**	1.003	1.002	1.011	1.002
Forecast combination (daily and monthly regressors)								
BMA	**0.991**	**0.993**	1.015	**0.991****	**0.992**	**0.996**	1.019	**0.994**
BMS	**0.989***	**0.994**	1.013	**0.991****	**0.990**	**0.996**	1.017	**0.994**
OptPool	**0.986***	**0.990***	1.030	**0.992****	**0.994**	**0.993**	1.012	**0.992**
EqWeights	**0.998**	**0.998**	1.005	1.000	1.000	**0.998**	1.003	1.000

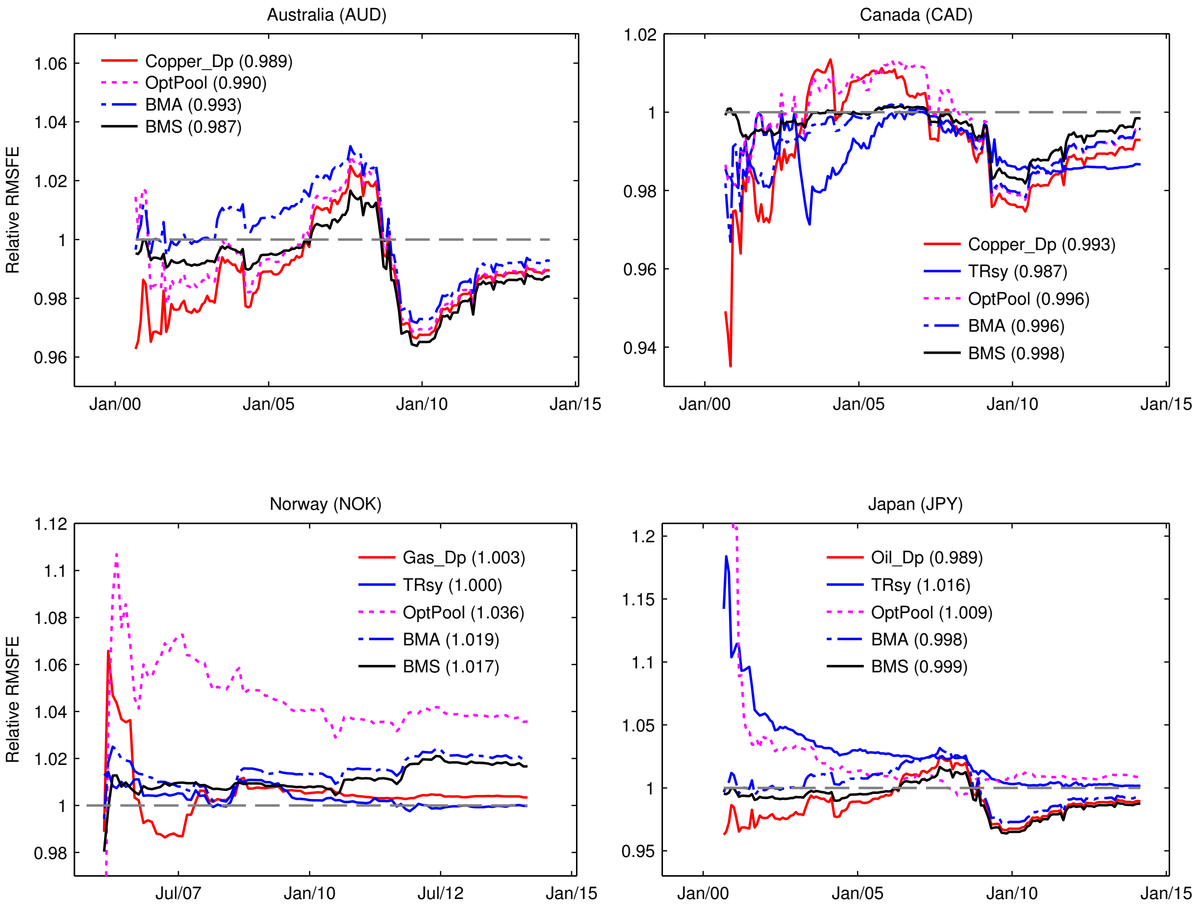
Notes: The table presents results for forecasting performance based on the relative RMSFE for two robustness checks. In the left panel we use a g-type prior for the coefficients vector in our Bayesian estimation method. In the right panel, models with daily commodity prices (MIDAS models) are estimated with the Almon lag polynomial. The last four rows show results for forecast combination methods. In all cases, values less than 1 (one) indicate that the commodity or fundamental-based model generates a lower RMSFE than the RW, hence, it forecasts better than the RW. The table also reports the CW-test with asterisks (10%, **5%, ***1%) denoting the level of significance at which the null hypothesis of equal RMSFE is rejected, favouring the alternative that the commodity or fundamental-based model has a lower RMSFE. In all models, the forecasts are generated recursively for h-month(s)-ahead change in the exchange rate. The list of daily regressors include, change in daily prices (Dp) of oil, gold, copper, gas, and a daily commodity price index (ΔMP_index). In the monthly regressors group we have a similar set of commodities, but also fundamentals from the symmetric Taylor rule - TRsy, the asymmetric Taylor rule - TRasy, the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. The currency codes in the first row denote the Australian dollar (AUD), the Canadian dollar (CAD), the Norwegian Kroner (NOK), and the Japanese YEN. The forecast evaluation period is 1998M11+h to 2014M3 for all currencies, except the NOK (2005M7 +h to 2014M3).

Figure 1: Fitting a MIDAS and a Typical OLS Regression to Daily-frequency Variables



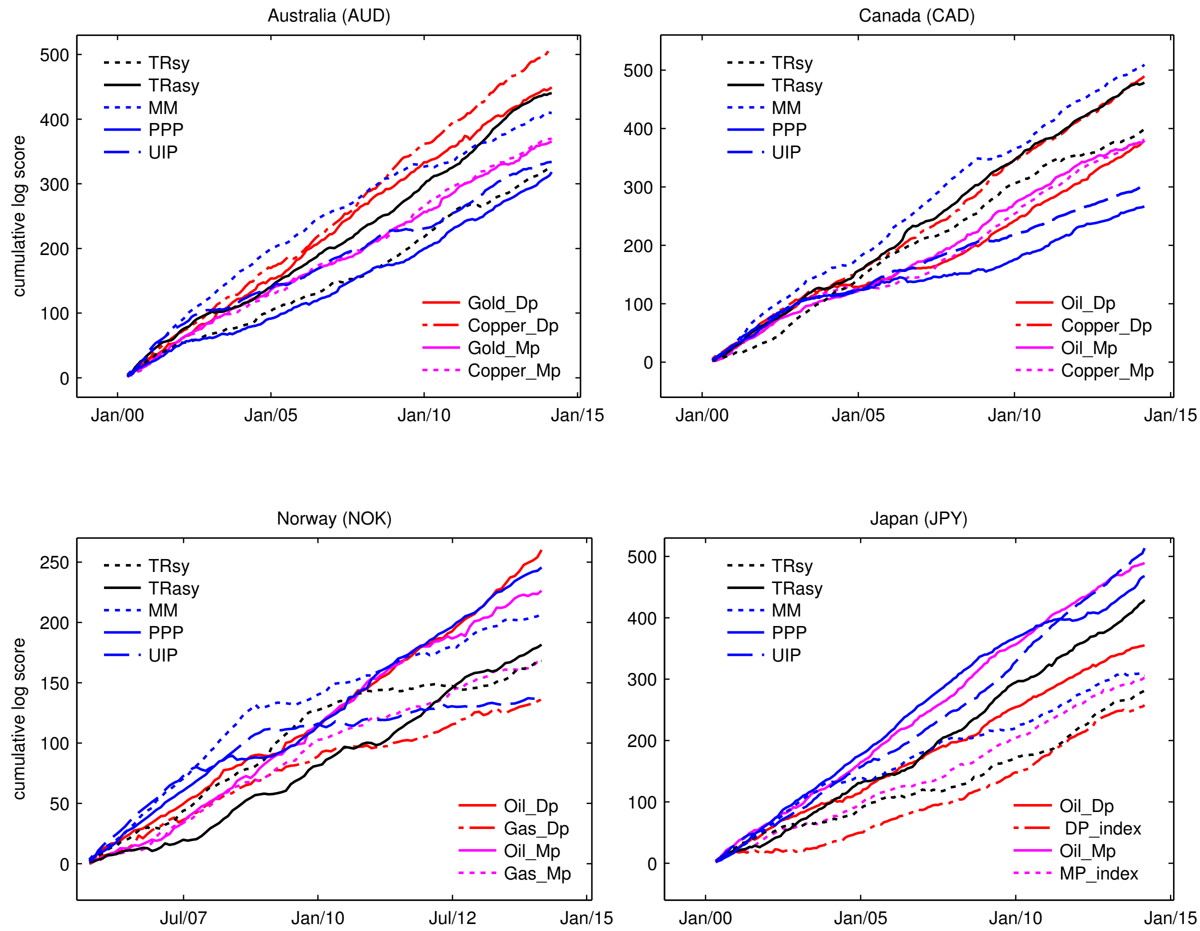
Notes: The figure shows to what extent we can recover a simulated Data Generating Process (DGP) using a MIDAS model as opposed to a typical Linear regression. In Panel A data are generated attributing different weights to each daily observation. In Panel B data are generated with equal weights to each daily observation. Further details on the DGPs are in the text.

Figure 2: Recursive relative RMSFE for Selected Predictors and Forecast Combination Methods



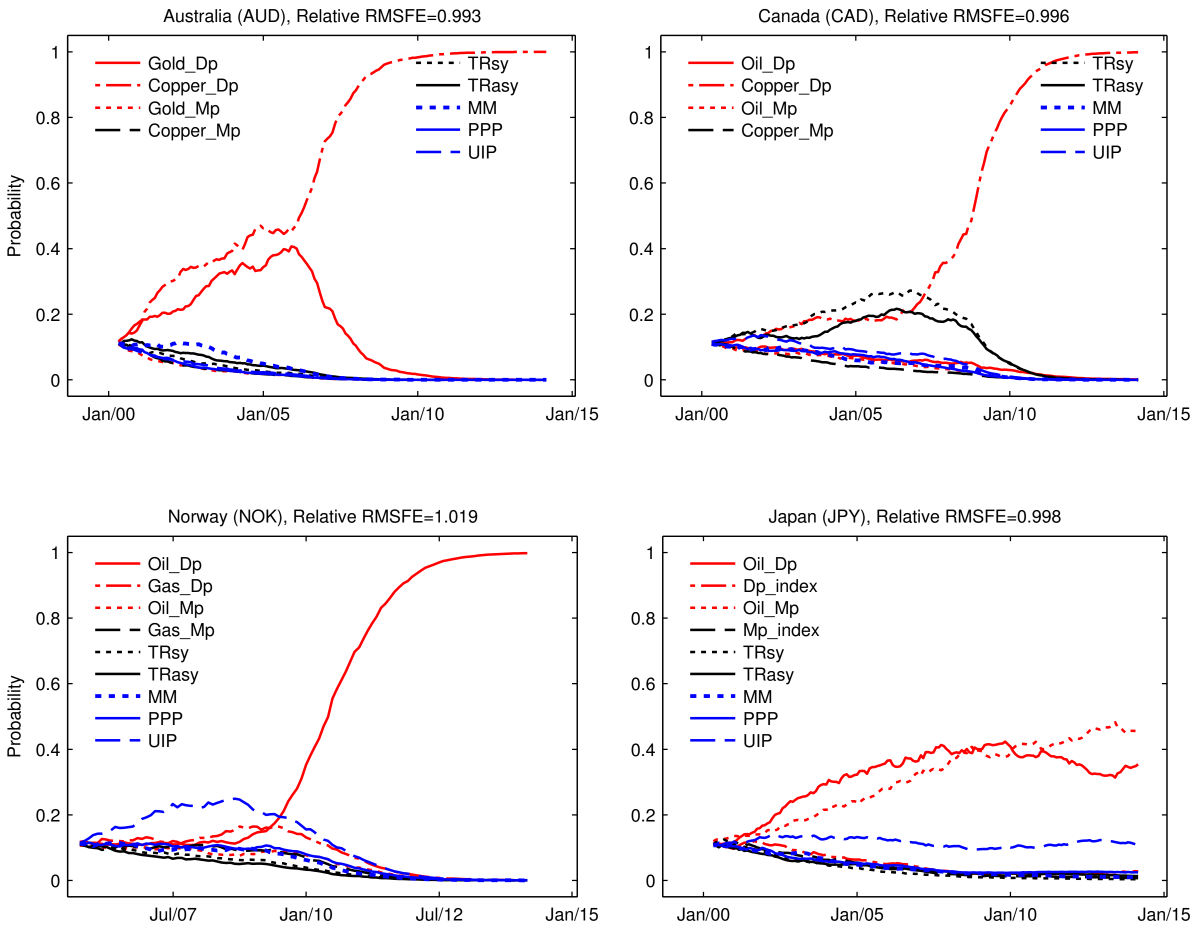
Notes: The figure shows the recursive relative Root Mean Squared Forecast Error (RMSFE) for selected commodity or fundamental-based models and forecast combinations methods. In all cases the benchmark is the driftless Random Walk (RW), so that values less than 1 (one) mean that the commodity/fundamental-based model or the combination method improves upon the RW at that point in time. The numbers in each plot's legend (in brackets) are the relative RMSFE at the last recursion, which coincide with the relative RMSFE reported in Tables 1 and 2 for the respective regressor-currency pair and method. In the legend, the suffix Dp attached to the commodity prices denote daily and monthly prices respectively. The other monthly regressors include fundamentals from the symmetric (TRsy) and asymmetric Taylor rules (TRasy). When the regressor is sampled daily, the recursive relative RMSFE is generated from the MIDAS model. The forecast combinations methods, namely the Optimal Predictive Pool (OptPool), Bayesian Model Averaging (BMA) or Selection (BMS), are based on regressors sampled daily and monthly.

Figure 3: Statistical Evaluation based on Cumulative Log-Scores for Models with Single Predictor



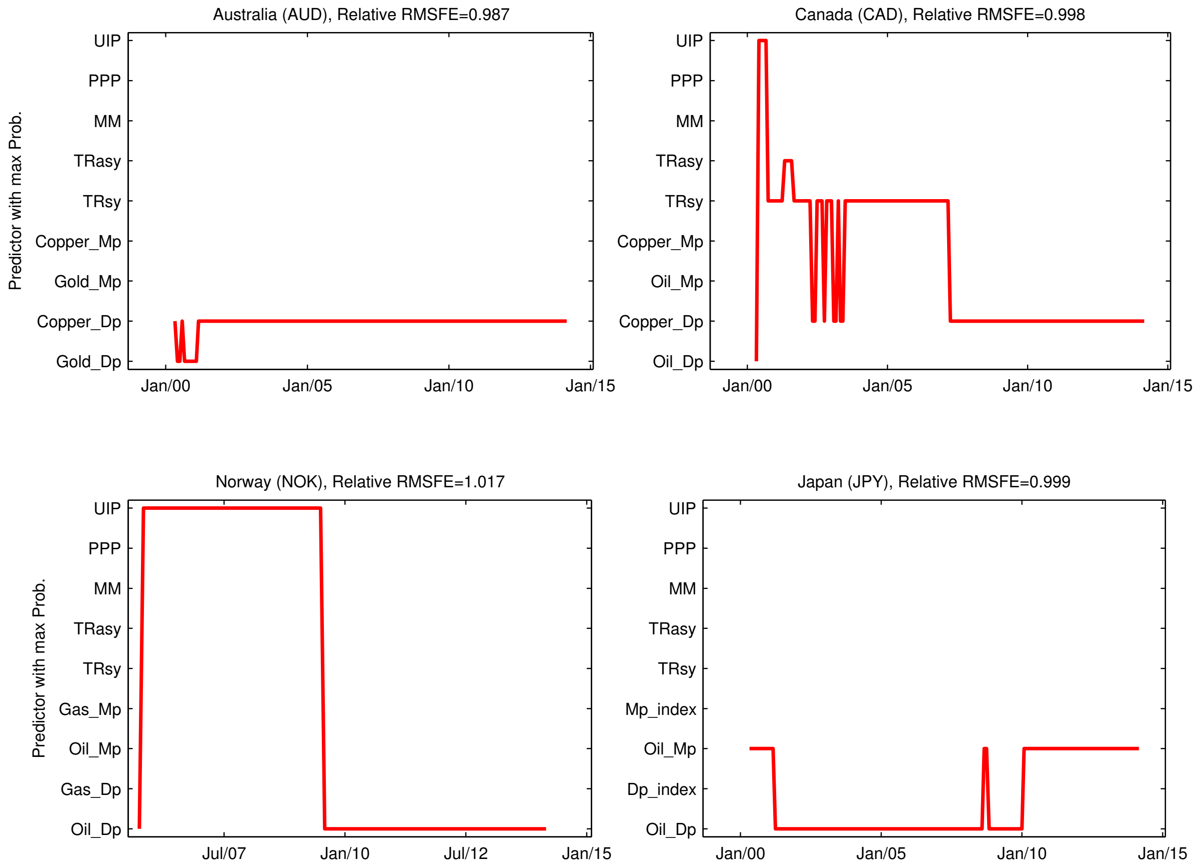
Notes: The figure presents the cumulative sum of log predictive scores of the commodity or fundamental-based forecasting model, computed relative to cumulative sum of log predictive scores of the Random Walk. Positive values indicate that the commodity/fundamental-based model outperforms the RW at that point in time, while negative values suggest the opposite. In the plot's legend, the suffixes Dp and Mp attached to the commodity prices denote daily and monthly prices respectively. The other monthly regressors include fundamentals from the symmetric (TRsy) and asymmetric Taylor rules (TRasy), the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. When the regressor corresponds to a daily commodity price, the recursive cumulative log-scores differentials are generated from MIDAS models.

Figure 4: Weights Associated with Each Predictor in the BMA with Daily and Monthly Predictors



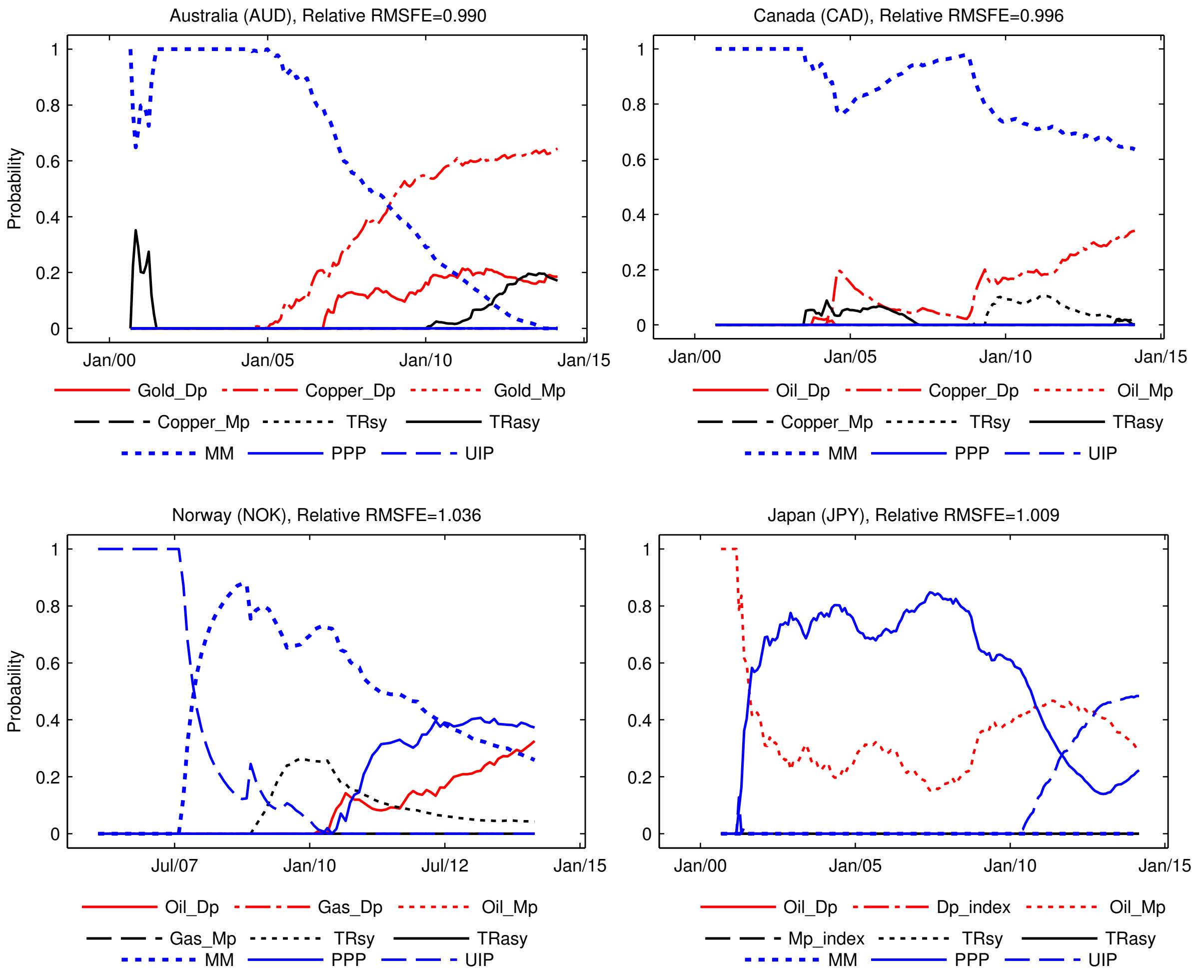
Notes: The figure presents the weights associated with each predictor in the Bayesian Model Averaging (BMA) method with daily and monthly regressors. In the plot's legend, the suffixes Dp and Mp attached to the commodity prices denote daily and monthly prices respectively. The other monthly regressors include fundamentals from the symmetric (TRsy) and asymmetric Taylor rules (TRasy), the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. When the regressor corresponds to a daily commodity price, the posterior probability corresponds to the MIDAS model based on that specific commodity. In each plot's heading, we indicate the relative RMSFE corresponding to the entire-out-of sample period obtained from the BMA with all predictors.

Figure 5: Predictors with the Highest Weight in the BMS method (Among Daily and Monthly)



Notes: The figure shows the models (defined according to the predictor they include) with the largest posterior probability at each point in time in the Bayesian Model Selection (BMS) method. In the graph's vertical axis, the suffixes Dp and Mp attached to the commodity prices denote daily and monthly prices respectively. The other monthly regressors include fundamentals from the symmetric (TRsy) and asymmetric Taylor rules (TRasy), the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. When the regressor corresponds to a daily commodity price, the model with the largest posterior probability corresponds to a MIDAS regression. In each plot's heading, we indicate the relative RMSFE corresponding to the entire-out-of sample period obtained from the BMS among all predictors.

Figure 6: Weights Associated with Each Predictor in the Optimal Predictive Pool



Notes: The figure presents the weights associated with each predictor in the Optimal Predictive Pool. In the plot's legend, the suffixes Dp and Mp attached to the commodity prices denote daily and monthly prices respectively. The other monthly regressors include fundamentals from the symmetric (TRsy) and asymmetric Taylor rules (TRasy), the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. When the regressor corresponds to a daily commodity price, the weights corresponds to the MIDAS model based on that specific commodity. In each plot's heading, we indicate the relative RMSFE corresponding to the entire-out-of sample period obtained from the Optimal Predictive Pool.

A MIDAS Model: Bayesian Estimation and Forecasting

A.1 MIDAS model

In this Appendix we provide further details of the Bayesian approach we pursue to estimate and forecast with our MIDAS models.[12]

We begin by transcribing the MIDAS model we consider in the main text:

$$\Delta s_{t+h} = \beta_0 + \beta_1 B(L^{1/m};\theta_1)x_t^{(m)} + \varepsilon_{t+h}, \qquad \varepsilon_{t+h} \sim N(0,\sigma^2); \tag{29}$$

where we use the exponential Almon polynomial to characterize the weight of each high frequency (daily) observation. This polynomial has the following form:

$$B(k;\theta) = \frac{e^{(\theta_1 k + \theta_2 k^2)}}{\sum_{i=1}^{K} e^{\theta_1 i + \theta_2 i^2}}. \tag{30}$$

If we consider, for example, that only the past 21 trading days affect the value of Δs_{t+h}, then Equation (29) is a compact representation of:

$$\Delta s_{t+h} = \beta_0 + \beta_1 \left(\frac{e^{(\theta_1 \times 1 + \theta_2 \times 1^2)}}{\sum_{i=1}^{K} e^{\theta_1 i + \theta_2 i^2}} x_{td21} + \frac{e^{(\theta_1 \times 2 + \theta_2 \times 2^2)}}{\sum_{i=1}^{K} e^{\theta_1 i + \theta_2 i^2}} x_{td20} + ... + \frac{e^{(\theta_1 \times 21 + \theta_2 \times 21^2)}}{\sum_{i=1}^{K} e^{\theta_1 i + \theta_2 i^2}} x_{td1} \right) + \varepsilon_{t+h}. \tag{31}$$

where β_0 is the coefficient associated with the constant, β_1 captures the overall impact of all past values of daily observations on Δs_{t+h}, and θ_1 and θ_2 are the polynomials' parameters. Equation (31) is a non-linear regression equation in the following unknown parameters to be estimated: $(\beta_0, \beta_1, \theta_1, \theta_2, \sigma^2)$.

A.2 Estimation

To estimate the model we use the random walk chain Metropolis–Hastings within Gibbs algorithm. To simplify notation we express Equation (31) in the following functional form:

$$S = f(X,\gamma) + \varepsilon, \qquad \varepsilon \sim N(0, \frac{1}{\eta}), \text{ and } \qquad \frac{1}{\eta} = \sigma^2. \tag{32}$$

[12] (See also Koop, 2003 Ch. 5 and Ch. 11)

where $f(.)$ indicates that our function of interest depends on the data X (containing x_{td}) and the parameters γ, which include $\beta_0, \beta_1, \theta_1, \theta_2$.

In a Bayesian setup, estimation involves definition of prior distributions, the likelihood function, and the posterior distributions. We use independent Normal-Gamma priors. Thus, the prior for γ is independent of the prior for η and is defined as:

$$\gamma \sim N(\underline{\gamma}, \underline{V}). \tag{33}$$

We set $\underline{\gamma} = (0,0,0,0)'$ and $\underline{V} = 0.35I$. For η the prior is:

$$\eta \sim G(\underline{s}^{-2}, \underline{\nu}), \tag{34}$$

where $\underline{\nu} = 1$ and $\underline{s}^{-2}$ is based on OLS estimate under equal weighting assumption.

Using the definition of the multivariate Normal density, the likelihood function has the following form (see Koop 2003, Ch. 5):

$$p(S|\gamma,\eta) = \frac{\eta^{\frac{T}{2}}}{(2\pi)^{\frac{T}{2}}} \left\{ \exp\left[-\frac{\eta}{2} \{S - f(X,\gamma)\}' \{S - f(X,\gamma)\} \right] \right\}. \tag{35}$$

Combining the prior with this likelihood yields the following conditional posterior for η:

$$p(\eta|S,\gamma) \sim G(\overline{s}^{-2}, \overline{\nu}), \tag{36}$$

$$\overline{s}^2 = \frac{[S - f(X,\gamma)]'[S - f(X,\gamma)] + \underline{\nu}\underline{s}^2}{\overline{\nu}}, \tag{37}$$

$$\overline{\nu} = \underline{\nu} + T; \tag{38}$$

while the conditional posterior distribution of γ is:

$$p(\gamma|S,\eta) \propto \exp\left[-\frac{\eta}{2} \{S - f(X,\gamma)\}' \{S - f(X,\gamma)\} \right] \exp\left[(-\frac{1}{2}(\gamma - \underline{\gamma})' \underline{V}^{-1} (\gamma - \underline{\gamma})) \right]. \tag{39}$$

The form of this conditional density $p(\gamma|S,\eta)$ does not suggest any density from which to draw upon. Therefore, we employ the random walk chain Metropolis–Hastings (RW-MH) within Gibbs algorithm to sequentially draw η conditional on γ. The RW-MH algorithm consists of the following steps:

1. Choose starting values for η and $\gamma^{(0)}$:

   We use data available up to the beginning of our first forecast to fix these values. Precisely, we set $\eta = 1/s^2$, where s^2 is based on OLS estimates assuming that $\theta_1 = \theta_2 = 0$. Using the same data, we maximize the likelihood function in (35) and set $\gamma^{(0)} = \widehat{\gamma}_{ML}$; i.e., to maximum likelihood estimates under $\theta_1 = \theta_2 = 0$;

2. Draw η from its conditional posterior as given by Expression (36);

3. Conditional on η take a candidate draw, $\gamma^{(*)}$, from the candidate candidate generating density:

   $\gamma^{(*)} \sim N(\gamma^{(0)}, \Sigma)$,

   where $\Sigma = var(\widehat{\gamma}_{ML})$ is the covariance matrix of the maximum likelihood estimator obtained in step 1;

4. Calculate acceptance probability:

   $\alpha(\gamma^{(dr-1)}, \gamma^{(*)}) = \min\left[\frac{p(\gamma=\gamma^{(*)}|\mathbf{S})}{p(\gamma=\gamma^{(dr-1)}|\mathbf{S})}, 1\right]$,

   where $p()$ is evaluated at the current, $\gamma^{(*)}$, and previous, $\gamma^{(dr-1)}$, draw using (39);

5. Set $\gamma^{(dr)} = \gamma^{(*)}$ with probability $\alpha(\gamma^{(dr-1)}, \gamma^{(*)})$ else $\gamma^{(dr)} = \gamma^{(dr-1)}$;

6. Repeat above steps many times (e.g. 31000) and after discarding the first draws (e.g. 1000), keep every third draw. Point estimates of the parameters are obtained as average of the retained draws.

A.3 Prediction

Prediction is based on the predictive density (Koop 2003, Ch. 5):

$p(S^*|S, \gamma) = t(S^*|f(X^*, \gamma), \overline{s}^2 I_T, T)$, where $\overline{s}^2 = (S - f)'(S - f)/T$.

Given M^N models defined by the predictors included, we first assign (diffuse) prior probabilities to each: $\Pr(M_i) = 1/M^N$. Based on the model's realized likelihood we obtain posterior probabilities:

$$\Pr(M_i|D^t) = \frac{\Pr(D^t|M_i)\Pr(M_i)}{\sum_{j=1}^{M^N} \Pr(D^t|M_j)\Pr(M_j)}, \tag{40}$$

where $\Pr(D^t|M_i)$ is the marginal likelihood of the i^{th} model. We use the Gelfand and Dey (1994) method for marginal likelihood calculation. The method requires careful selection of the probability density function from which to simulate draws. We follow the usual practice and use a multivariate Normal density truncated to the region $\widehat{\Theta}$:

$$\widehat{\Theta} = \{\gamma : (\widehat{\gamma} - \gamma)' \widehat{var(\gamma)}^{-1} (\widehat{\gamma} - \gamma) \leq \chi^2_{1-p}(dof)\} \tag{41}$$

where $\chi^2_{1-p}(dof)$ is the (1-p) percentile of the Chi-squared distribution with degrees of freedom (dof) determined by the number of parameters in γ. Thus, our truncated multivariate Normal density function is:

$$f(\gamma) = \frac{1}{p(2\pi)^{\frac{1}{2}dof}} \left|\widehat{var(\gamma)}\right|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(\widehat{\gamma} - \gamma)' \widehat{var(\gamma)}^{-1} (\widehat{\gamma} - \gamma)\right] 1(\gamma \in \widehat{\Theta}) \tag{42}$$

with 1() denoting the indicator function.

B Data

This Appendix describes the sources (Table B.1) and descriptive statistics (Tables B.3 and B.2) for the data used in the empirical section. In Table B.1, for each country in the first column we indicate the source of information for each variable in the subsequent columns. The sample period is 1986M9:2014M3 for Australia, Canada, Japan, and the US. Due to unavailability of data on daily gas prices fluctuations, the sample period for Norway comprises 1997M1:2014M3.

Data on commodity prices is from Datastream. The oil price is the Crude Oil-WTI Spot Cushing, USD/BBL (Mnemoic: S71926). Gold price corresponds to the Gold Bullion London Bullion Market price, USD/Troy Ounce (S20665). Copper price is the London Metal Exchange Copper Grade A Cash price, USD/Metric Tonne (S76871). Gas price corresponds to the Henry Hub Natural Gas Spot Price USD/MMBTU (S214W9). The commodity price index is as compiled by the Commodity Research Bureau under BLS Spot Index. The Index measures price movements of 22 commodities (see the Commodity Research Bureau webpage for more details).

Table B.1: Data Sources for Exchange Rates and Macroeconomic Fundamentals

Country	**Nominal exchange rate (national currency/USD)**	**Short-term nominal interest rate (%)**	**Consumer price index SA (2010=100)**	**Industrial production index (SA)**	**Money supply, SA, (national currency, 10^6)**
Australia	IFS,193..AE-ZF	IFS,60...ZF	OECD MEI[a]	IFS66..CZF[a]	OECD MEI, M1
Canada	IFS,156..AE-ZF	IFS,60B..ZF	OECD MEI	IFS66..CZF	OECD MEI, M1
Norway	IFS,142..AE-ZF	IFS,60...ZF	OECD MEI	IFS66..CZF	Norges Bank, M2
Japan	IFS,158..AE-ZF	IFS,60B..ZF	OECD MEI	IFS66..CZF	OECD MEI, M1
US	IFS,111..AE-ZF	FRED	OECD MEI	IFS66..CZF	OECD MEI, M1

Notes: The exchange rate is the end-of-month value of the national currency per U.S. dollar. IFS denotes International Financial Statistics as published by the IMF. OECD MEI denotes the OECD's Main Economic Indicators database. FRED indicates Federal Reserve Economic Data database. SA stands for seasonally adjusted and the superscript (^{a}) denotes monthly data obtained via quadratic-match-average interpolation method from quartely data.

Table B.2: Commodity Prices Data - Descriptive Statistics and Pairwise Correlations

	Daily data					Monthly data				
	Δoil_Dp	Δgold_Dp	Δcopper_Dp	Δgas_Dp	ΔDP_index	Δoil_Mp	Δgold_Mp	Δcopper_Mp	Δgas_Mp	ΔMP_index
Mean	0.0003	0.0002	0.0002	0.0002	0.0001	0.0059	0.0034	0.0049	0.0045	0.0025
Std	0.0239	0.0098	0.0175	0.0360	0.0040	0.0906	0.0442	0.0812	0.1753	0.0274
Skew	-0.8619	-0.4049	0.4683	0.6452	-0.5036	-0.1251	-0.0625	-0.4110	-0.0812	-1.8304
Kurt	20.5525	11.0925	17.5955	17.6805	9.5617	4.8736	4.2976	7.6427	5.6248	18.0528
					Pairwise Correlation					
Δoil_Dp	1.000									
Δgold_Dp	0.155	1.000								
Δcopper_Dp	0.160	0.209	1.000							
Δgas_Dp	0.053	0.044	0.024	1.000						
ΔDP_index	0.176	0.177	0.318	0.053	1.000					
Δoil_Mp						1.000				
Δgold_Mp						0.236	1.000			
Δcopper_Mp						0.265	0.301	1.000		
Δgas_Mp						0.230	0.079	0.009	1.000	
ΔMP_index						0.337	0.282	0.494	0.015	1.000
Δs (AUD), h=1						-0.327	-0.380	-0.469	-0.131	-0.496
Δs (CAD), h=1						-0.329	-0.326	-0.375	-0.099	-0.420
Δs (NOK), h=1						-0.332	-0.335	-0.322	-0.130	-0.401
Δs (YEN), h=1						-0.220	-0.314	-0.267	-0.128	-0.289
Δs (AUD), h=3						-0.317	-0.171	-0.337	-0.068	-0.453
Δs (CAD), h=3						-0.268	-0.162	-0.289	-0.075	-0.337
Δs (NOK), h=3						-0.262	-0.163	-0.269	-0.068	-0.328
Δs (YEN), h=3						-0.150	-0.181	-0.213	-0.037	-0.215

The table shows the mean, standard deviation, skewness and kurtosis for commodity prices data (at daily and monthly frequency). It also shows the pairwise correlations among commodity prices, as well as between exchange rates variations (Δs) at h-month(s)-horizon and monthly commodity price changes. The suffixes Dp and Mp attached to the commodity prices denote daily and monthly prices respectively. The currency codes are AUD - for the Australian dollar, CAD - Canadian dollar, NOK - Norwegian Kroner, and YEN for the Japanese currency.

Table B.3: Exchange Rates and Economic Fundamentals Data - Descriptive Statistics

		Δs	TRsy	TRasy	MM	PPP	UIP
AUD	Mean	-0,001	0,001	0,033	-2,629	-0,319	0,031
	Std	0,032	0,035	0,037	0,498	0,192	0,025
	Skew	0,766	-1,373	-0,485	-0,197	0,036	0,917
	Kurt	5,718	7,092	4,385	1,974	2,731	3,983
CAD	Mean	-0,001	-0,001	0,015	-1,713	-0,165	0,008
	Std	0,022	0,037	0,039	0,335	0,133	0,015
	Skew	0,688	4,002	3,364	0,297	-0,350	0,568
	Kurt	9,359	20,236	16,326	1,761	1,919	3,638
NOK	Mean	-0,001	-0,005	0,185	-2,549	-1,870	0,029
	Std	0,031	0,031	0,031	0,447	0,119	0,024
	Skew	0,471	1,467	0,999	0,504	-0,872	0,848
	Kurt	4,277	6,579	4,583	1,780	3,447	3,431
YEN	Mean	-0,001	-0,007	0,442	0,586	-4,478	-0,023
	Std	0,031	0,153	0,155	0,548	0,137	0,023
	Skew	-0,231	5,075	5,032	-0,340	0,390	0,012
	Kurt	4,556	27,197	26,950	1,513	3,010	1,704

Notes: Descriptive statistics for monthly economic fundamentals and monthly changes in the log exchange rate (Δs). Monthly fundamentals include those from the symmetric Taylor rule - TRsy, the asymmetric Taylor rule - TRasy, the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. The currency codes in the first column denote the Australian dollar (AUD), the Canadian dollar (CAD), the Norwegian Kroner (NOK), and the Japanese YEN.

Table B.4: Commodity Average Exports as a Percentage of Total Merchandise Exports

Australia (1988-2014)		Canada (1997-2014)		Norway (1997-2014)	
Gold	Copper	Oil	Copper	Oil	Gas
6	17	6	1	39	16

Notes: Commodity Export Share in the Country's Total Merchandise Export. Compiled by the authors based on countries' official statistics as publised by (i) the Australian Bureau of Statistics (Table on International Trade in Goods and Services, Australia, May 2015); (ii) Statistics Canada (Table on Merchandise imports and exports between Canada and World, by Harmonized System section, customs basis, May 2015); and (iii) Statistics Norway (STATBANK, Table on External Trade in Goods).

C Convergence Assessment

Our forecasting models are estimated using algorithms pertaining to Markov Chain Monte Carlo Methods (MCMC), which rely on drawing samples from candidate generating densities. We recall that we generated 31000 draws from which we discarded the first 1000 and used every third draw in the estimates. In this Appendix we evaluate the convergence of our algorithms.

In Table C.1 we report the average acceptance probability in the random walk Metropolis-Hastings (RW-MH) component of the algorithm. Values in the region 0.2 to 0.5 are regarded as satisfactory. The averages are computed over estimates across all data points in the recursive estimations.

In Table C.2 we look at the convergence of the overall RW-MH within Gibbs algorithm. In particular, we focus on Geweke's (1992) measure of numerical standard error (NSE). Smaller values of NSE relative to the posterior standard deviations convey an acceptable degree of approximation error. The NSE is based on 4% tapered window in the estimate of the spectral density at zero frequency. To manage space, we also average the estimates obtained over all data points in our recursive estimations. Overall, results indicate an acceptable degree of efficiency of our algorithms.

Table C.1: Mean Acceptance Rates in the RW-MH Algorithm

	AUD	CAD	NOK	YEN	AUD	CAD	NOK	YEN
	h=1				h=3			
ΔOil_Dp	-	0.2	0.3	0.3	-	0.3	0.2	0.3
ΔGold_Dp	0.3	-	-	-	0.2	-	-	-
ΔCopper_Dp	0.3	0.3	-	-	0.3	0.3	-	-
ΔGas_Dp	-	-	0.3	-	-	-	0.2	-
ΔDP_index	-	-	-	0.1	-	-	-	0.1

Notes: The table reports the average acceptance probability in the random walk Metropolis-Hastings algorithm. The averages are computed over estimates across all data points in the recursive estimations. Values in the region 0.2 to 0.5 are regarded as satisfactory.

Table C.2: Convergence Diagnostics for the RW-MH within Gibbs Algorithm

	h=1			h=3		
	postMean	postStdv	NSE	postMean	postStdv	NSE
Australia (AUD)			MIDAS with ΔGold_Dp			
β_0	0.000	0.002	0.000	0.001	0.003	0.000
β_1	-0.907	0.348	0.016	-0.621	0.357	0.009
θ_1	0.210	0.474	0.036	0.016	0.500	0.027
θ_2	0.034	0.033	0.005	0.360	0.048	0.008
η	0.001	0.000	0.000	0.003	0.000	0.000
			MIDAS with ΔCopper _Dp			
β_0	0.000	0.002	0.000	0.001	0.003	0.000
β_1	-1.430	0.339	0.019	-0.593	0.286	0.012
θ_1	0.168	0.400	0.024	0.037	0.489	0.034
θ_2	0.039	0.019	0.002	-0.048	0.041	0.007
η	0.001	0.000	0.000	0.003	0.000	0.000
Canada (CAD)			MIDAS with ΔOil_Dp			
β_0	0.000	0.001	0.000	0.000	0.002	0.000
β_1	-0.368	0.162	0.012	-0.319	0.226	0.019
θ_1	0.207	0.409	0.012	0.092	0.491	0.018
θ_2	0.060	0.061	0.011	-0.153	0.115	0.022
η	0.000	0.000	0.000	0.001	0.000	0.000
			MIDAS with ΔCopper _Dp			
β_0	0.000	0.001	0.000	0.000	0.002	0.000
β_1	-0.745	0.250	0.017	-0.320	0.175	0.007
θ_1	0.150	0.381	0.012	-0.046	0.485	0.017
θ_2	0.022	0.039	0.006	-0.300	0.078	0.015
η	0.000	0.000	0.000	0.001	0.000	0.000
Norway (NOK)			MIDAS with ΔOil_Dp			
β_0	-0.001	0.003	0.000	-0.004	0.005	0.000
β_1	-0.802	0.293	0.012	-0.405	0.288	0.014
θ_1	0.261	0.388	0.013	-0.020	0.485	0.013
θ_2	0.015	0.059	0.010	-0.289	0.249	0.046
η	0.001	0.000	0.000	0.003	0.000	0.000
			MIDAS with ΔGas_Dp			
β_0	-0.001	0.003	0.000	-0.004	0.005	0.000
β_1	-0.071	0.128	0.011	0.053	0.181	0.010
θ_1	0.072	0.495	0.018	0.051	0.503	0.013
θ_2	-0.202	0.108	0.020	0.048	0.304	0.057
η	0.001	0.000	0.000	0.003	0.000	0.000
Japan (YEN)			MIDAS with ΔOil_Dp			
β_0	-0.001	0.002	0.000	-0.002	0.004	0.000
β_1	-0.267	0.191	0.011	-0.340	0.258	0.010
θ_1	0.105	0.472	0.036	-0.048	0.489	0.027
θ_2	-0.269	0.086	0.016	-0.293	0.077	0.014
η	0.001	0.000	0.000	0.004	0.000	0.000
			MIDAS with ΔDP_index			
β_0	-0.001	0.002	0.000	-0.003	0.004	0.000
β_1	0.056	0.472	0.028	0.095	0.528	0.015
θ_1	0.006	0.500	0.013	-0.002	0.498	0.014
θ_2	-0.021	0.436	0.078	-0.025	0.240	0.046
η	0.001	0.000	0.000	0.004	0.000	0.000

Notes: The table presents convergence diagnostics for the RW-MH within Gibbs algorithm, namely the average numerical standard error (NSE). These are averages from the estimates obtained over all data points in the recursive estimations of the forecasting procedure. Smaller values of NSE relative to the posterior standard deviations (postStdv) convey an acceptable degree of approximation error. The NSE are based on 4% tapered window in the estimate of the spectral density at zero frequency.

D Further Results Appendix

This Appendix reports further empirical results, including:

- Forecast assessment for single predictor models at 3-months horizon, in Table D.3;
- Forecast assessment for combination methods at 3-months horizon, in Table D.4.

The key findings are as follows. First, point forecasts based on daily commodity price fluctuations are generally less precise than forecasts from the driftless Random Walk (RW) at 3-months forecasting horizon. This result is contrary to our findings at 1-month forecasting horizon in the main text. Second, like our results at 1-month horizon, when we exploit density forecasts we always find improvement over the RW at 3-months horizon. As shown in the right panel of Table D.3, the log-score differentials are significantly positive in all cases. As well, forecast combinations methods lead to more accurate forecasts than our benchmark.

Table D.3: Relative RMSFE and Log-score Differentials for Models with Single Predictor, $h = 3$

	Relative RMSFE				Log-score differentials			
	AUD	CAD	NOK	YEN	AUD	CAD	NOK	YEN
Daily regressors (MIDAS model)								
ΔOil_Dp	-	1.013	1.003	1.003	-	**2.42*****	**2.71*****	**2.45*****
ΔGold_Dp	1.022	-	-	-	**2.44*****	-	-	-
ΔCopper_Dp	**0.995**	1.016	-	-	**2.69*****	**2.78*****	-	-
ΔGas_Dp	-	-	1.020	-	-	-	**2.59*****	-
ΔDP_index	-	-	-	1.008	-	-	-	**1.88*****
Monthly regressors								
ΔOil_Mp	-	1.004	1.009	1.010	-	**2.46*****	**2.64*****	**2.45*****
ΔGold_Mp	1.014	-	-	-	**2.00*****	-	-	-
ΔCopper_Mp	1.004	1.003	-	-	**2.18*****	**2.71*****	-	-
ΔGas_Mp	-	-	1.017	-	-	-	**2.51*****	-
ΔMP_index	-	-	-	1.021	-	-	-	**2.28*****
Monthly regressors								
TRsy	1.001	**0.969****	1.027	1.018	**2.68*****	**2.81*****	**2.60*****	**1.94*****
TRasy	**0.997**	**0.968****	1.003	1.005	**3.22*****	**3.08*****	**2.70*****	**2.78*****
MM	1.042	1.041	1.058	1.029	**2.78*****	**3.61*****	**2.27*****	**2.60*****
PPP	1.017	1.007	1.023	1.022	**2.93*****	**2.44*****	**2.67*****	**3.29*****
UIP	1.015	1.014	1.046	1.014	**2.25*****	**2.65*****	**2.71*****	**3.65*****

Notes: The Table reports forecasting performance of single preditor models. The left panel shows the Root Mean Squared Forecast Error (RMSFE) of the commodity or fundamental-based forecasting model relative to the RMSFE of the driftless Random Walk (RW). Values less than 1 (one) indicate that the commodity or fundamental-based model generates a lower RMSFE than the RW, hence, it forecasts better than the RW. The righ panel presents the average log-score differentials between the same models relative to the RW. Positive values indicate that the commodity or fundamental-based model improves upon the RW in terms of density forecasts. The Table also reports the CW-test with asterisks (10%, **5%, ***1%) denoting the level of significance at which the null hypothesis of equal RMSFE (LS) is rejected, favouring the alternative that the commodity or fundamental-based model provides more accurate point (density) forecasts. The commodity or fundamentals-based forecasting model uses the relevant country-commodity or fundamental listed in the first column and grouped in terms of daily and monthly regressors. In all models, the forecasts are generated recursively for h-month(s)-ahead change in the exchange rate. When only daily regressors are used, the forecasts are from the MIDAS model. The list of daily regressors include, change in daily prices (Dp) of oil, gold, copper, gas, and a daily commodity price index (ΔMP_index). In the monthly regressors group we have a similar set of commodities, but also fundamentals from the symmetric Taylor rule - TRsy, the asymmetric Taylor rule - TRasy, the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. The currency codes denote the Australian dollar (AUD), the Canadian dollar (CAD), the Norwegian Kroner (NOK) and the Japanese YEN. The forecast evaluation period is 1998M11+h to 2014M3 for all currencies, except the NOK (2005M7 +h to 2014M3).

Table D.4: Relative RMSFE and CW-test for Forecast Combinations, $h = 3$

	Daily regressors - Commodity Prices (CmdtyP)		Monthly regressors (CmdtyP and macro fundamentals)		Daily and monthly regressors (CmdtyP and macro fundamentals)	
	BMA	BMS	BMA	BMS	BMA	BMS
AUD	**0.998**	**0.996**	**0.999**	**0.998**	**0.997**	**0.997**
CAD	**0.995**	**0.995**	**0.975****	**0.987****	**0.975****	**0.980****
NOK	1.007	1.001	1.025	1.013	1.021	1.006
YEN	**0.996**	**0.994**	1.014	1.018	1.012	1.016
	OptPool	EqWeights	OptPool	EqWeights	OptPool	EqWeights
AUD	**0.998**	1.004	1.026	1.009	1.024	1.008
CAD	**0.991**	**0.996**	**0.980***	**0.995**	**0.976****	**0.998**
NOK	1.005	1.008	1.042	1.022	1.040	1.019
YEN	**0.999**	1.001	1.041	1.004	1.047	1.003

Notes: The table reports the Root Mean Squared Forecast Error (RMSFE) for forecast combination methods relative to the RMSFE of the driftless Random Walk (RW). The methods include, Bayesian Model Averaging (BMA), Bayesian Model Selection, (BMS), the Optimal Predictive Pool (OptPool) of Geweke and Amisano (2011), and a simple equal-weighting scheme (EqWeights). Values less than 1 (one) indicate that the combination method generates a lower RMSFE than the RW, hence, it forecasts better than the RW. The table also reports the CW-test with asterisks (10%, **5%, ***1%) denoting the level of significance at which the null hypothesis of equal RMSFE is rejected, favouring the alternative that the combination method has a lower RMSFE. The forecast combinations are based on the relevant commodity-currency and standard macroeconomic fundamentals. For the Australian dollar (AUD) the relevant commodities are gold and copper; for the Canadian dollar (CAD) - oil and copper; and for the Norwegian Kroner (NOK) these include oil and gas. When only daily regressors are used the combination is based on forecasts from the MIDAS models - reported in columns [2-3]. In columns [4-5] the combination is based on forecasts from monthly regressors, while the last two columns report results from combining daily and monthly regressors. In all cases, the forecasts are generated recursively for h-month(s)-ahead change in the exchange rate. In the group of monthly regressors we have a set of commodity pairs similar to the daily group, but also fundamentals from the symmetric Taylor rule - TRsy, the asymmetric Taylor rule - TRasy, the Monetary Model - MM, Purchasing Power Parity - PPP, and Uncovered Interest Rate Parity - UIP. The forecast evaluation period is 1998M11+h to 2014M3 for all currencies, except the NOK (2005M7 +h to 2014M3).