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Essays on International Finance and Macroeconomics

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Economics

by

Young Ju Kim

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ABSTRACT OF THE DISSERTATION

Essays on International Finance
and Macroeconomics

by

Young Ju Kim
Doctor of Philosophy in Economics
University of California, Los Angeles, 2014
Professor Jinyong Hahn, Co-chair
Professor Aaron Tornell, Co-chair

This dissertation consists of two studies on international finance and macroeconomics. Each study addresses different topics. The first study, written jointly with Aaron Tornell and Zhipeng Liao, exploits Speculators' positions in futures markets to forecast exchange rates. The forecasting model we propose combines Engel and Hamilton's (1990) point that exchange rates follow long swings with Evans and Lyons' (2004) finding that privately available information about market participants' order flow can predict exchange rates over the short-run. We extract speculators' private information by fitting a microfounded autoregressive Markov regime switching model to the speculators'net positions data in the Commitment-of-Traders report and forecasting the speculators' mode of accumulation. We then use this predicted mode to form both directional and point exchange rate forecasts for the six most traded

currency pairs. Over forecasting horizons ranging from 6 to 12 months, our *directional forecasts* have a 60% average success ratio and most of our *point forecasts* have smaller mean-squared-prediction-errors than those implied by the driftless random walk. To evaluate the performance of our directional forecasts vis-a-vis the random walk we propose a novel test that weights each directional forecast by the realized exchange rate change. For the point forecasts we conduct the Clark-West and the Diebold-Mariano-West tests. The test results indicate that, over 6-to-12 months horizons, our forecasts are significantly better than those from random walk models for most currencies, except the Swiss Franc.

The second study investigates on the sources of macroeconomic fluctuations in emerging economies. Business cycles in emerging countries exhibit notable differences from those in developed economies: the volatility of consumption relative to output is on average greater than one and trade balance is strongly counter-cyclical. Current theoretical explanations of these divergences of business cycle features between emerging economies and developed economies fall into two leading approaches. The First approach, represented by Aguiar and Gopinath (2007), argues that a frictionless standard real business cycle model driven mainly by shocks to trend growth (permanent shocks to TFP) can explain all defining features of emerging economies business cycles. The second approach, exemplified by Neumeyer and Perri (2005) and Uribe and Yue (2006), argues that in order to explain economic fluctuations in emerging economies, one should take into account the roles of financial imperfections and external shocks which asymmetrically affect these countries. To test the hypotheses implied by these two approaches, I compare the performance of the Aguiar and Gopinath (AG) model with that of the encompassing model which combines shocks to trend growth with interest rate shocks and financial frictions. Exploiting the recent developments in the theory and implementation of Bayesian methods, I estimated two models using Korea's data over the same sample period as in Aguiar and Gopinath (2007), and Chang and Fernandez (2010). My findings are contrary to those from previous studies. First, the magnitude of permanent shocks is much larger than that of transitory shocks. Second, the comparison of theoretical second moments of the two models with the moments of Korean data also shows that the frictionless stochastic trend model delivers closer a match to the moments calculated from the data. Lastly, I find that the permanent productivity shocks are responsible for the bulk of the macroeconomic fluctuations as a result of the variance decomposition. However, these results should be interpreted with caution, because the downward trend of the growth rate during the transition path to the steady state in Korea might be captured as permanent shocks. This raises an issue in the empirical study of emerging market business cycles. No existing studies examine explicitly whether the samples they use for the estimation are generated from the transition or balanced growth path. In this regard, extending the time series of data back in time as in Garcia-Cicco, Pancrazi and Uribe (2009) without considering this issue might not be useful since it might be only in the recent decades that emerging countries economies have been in the steady state.

The dissertation of Young Ju Kim is approved.

Nico Voigtlaender

Zhipeng Liao

Aaron Tornell, Committee Co-chair

Jinyong Hahn, Committee Co-chair

University of California, Los Angeles

2014

To my parents, my wife and two loving daughters, and my brother and his family.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I am greatly indebted to my advisors Aaron Tornell and Jinyong Hahn for their excellent guidance and great inspiration. I would like to thank the other members of the committee, Zhipeng Liao and Nico Voigtlaender. I have also benefited from conversations with participants at the international economics and macroeconomics proseminars. All remaining errors are my own.

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1 Speculators' Positions and Exchange Rate Forecasts: Beating the Random Walk Models

1.1 Introduction

Speculators' positions in futures markets contain useful information to forecast exchange rates. We extract such information by fitting a microfounded autoregresive Markov regime switching model to the speculators' net positions data and forecasting the speculators' mode of accumulation. When our model detects that speculators in a currency–say the Yen–shift to an accumulation mode, they tend to remain in such a mode for several months, and during this period the Yen tends to appreciate. Analogously, when speculators in the Yen shift to a decumulation mode, the Yen tends to exhibit a persistent depreciation. Over horizons ranging from 6 to 12 months, our out-of-sample *directional forecasts* have a 60% average success ratio across the six most traded currency pairs vis-a-vis the US Dollar. For the Australian Dollar the average success ratio is 74% and for the Euro 68%, as shown in Table 2. Furthermore, our *point forecasts* have smaller mean-squared-prediction-errors (MSPEs) than those implied by the driftless random walk, across all currency-horizon pairs we consider, except for the Swiss Franc.

To test the statistical significance of the success of our directional forecasts in capturing the big moves in exchange rates, we propose a test that weights each directional forecast by the realized exchange rate change. To our knowledge, this test is new. It captures the profitability of real world trading strategies better than typical binomial tests that compare directional forecasts with the *signs* of realized exchange rate changes, not their magnitudes. To evaluate our point forecasts we carry out the Diebold-Mariano-West and the Clark-West tests.

In our theoretical model, the exchange rate is driven by both a transitory and a persistent component. The latter follows a three-state Markov switching process, as proposed by Engel and Hamilton (1990). Speculators observe a noisy signal of the latent persistent component, which is unobservable to the econometrician. They then form their expectations using Bayesian updating, and take–long or short–positions in the futures market. The model imposes a one-to-one relation between the speculators' positions and their beliefs about the exchange rate's persistent component. By inverting the speculator's demand function for foreign currency, our model implies that the observed speculators' net position follows an autoregressive three-regime Markov switching model (MSM). To estimate this model we exploit the fact that the Commitment of Traders (COT) report of the CFTC breaks down the positions in futures markets into those held by *hedgers*, by *large speculators* and a residual.[1]

We estimate the MSM model sequentially, using a rolling sample of speculators' positions on each of the six most traded currency pairs: Euro, Japanese Yen, British Pound, Australian Dollar, Canadian Dollar and Swiss Franc. Every week we generate, for each currency, h-month ahead forecasts *(h=1,3,6,9,12)* of the latent state variable which governs the speculators' accumulation mode. We then use this predicted mode to construct both directional and point–out of sample–forecasts of the six exchange rates. We use a hybrid forecasting rule: we forecast appreciation between t_0 and $t_0 + h$ if accumulation is the most likely speculators' mode over this period. We forecast depreciation if decumulation is the most likely speculators' mode. In the other cases, we stick to the random walk forecasts and predict zero exchange rate change over an h-horizon.

Our forecasts start in 1994 and end in February 2013, except for the Euro.[2] Our

[1] The COT report is published weekly by the CFTC.

[2] The starting dates of our forecasts are: 01/20/1995 for the Australian Dollar and British Pound; 09/01/1994 for the Canadian Dollar; 04/15/1994 for the Swiss Franc and Japanese Yen;

out-of-sample appreciation/depreciation *directional forecasts* have a 58% average success ratio over 1-to-12 months forecasting horizons, as can be seen in Table 2. They are particularly accurate at the *6m*, *9m* and *12m* horizons: 64% average success ratio excluding the Swiss Franc.

To test whether these high forecast success ratios are not simply the result of luck, we evaluate their statistical significance by conducting two directional tests of the null hypothesis that the extracted information from speculators' positions cannot outperform the forecasts based on the driftless random walk. One test weights each directional forecasts by the realized exchange rate change and controls for auto-correlation in the test statistic. The other test is similar to the typical binomial test that compares directional forecasts with the signs of actual exchange rate changes, but corrects for auto-correlation. At the *6m*, *9m* and *12m* horizons, controlling for auto-correlation using the Newey-West long-run variance (LRV) estimator, the weighted directional test rejects the null in favour of our model across all currencies, except the Swiss Franc. At the *1m* and *3m* horizons, the random walk null is rejected in only 5 out of 12 currency-horizon pairs.[3]

To compare our *point-forecasts* with random-walk forecasts, we carry out the Diebold-Mariano-West test of equal MSPEs of our point forecasts and those of the driftless random walk, as well as the Clark-West test of equal predictive ability of our model and the driftless random walk. Controlling for auto-correlation using the Newey-West LRV estimator, the DMW-test rejects the null–at the 10% significance level–over the *6m*, *9m* and *12m* forecasting horizons across all currencies, except for the British Pound at the *12m* horizon and the Swiss Franc at all horizons. The

and 05/04/2001 for the Euro.

[3]Throughout this paper, when citing the Newey-West LRV estimator, we refer to the kernel smoothed LRV estimator proposed in Newey and West (1987) and bandwidth selection rule suggested in Newey and West (1994).

CW-test is even more favorable to our model: over the *6m*, *9m* and *12m* forecasting horizons, it rejects the null across all currencies, except for the Swiss Franc. The tests results using the Andrews LRV estimator are very similar to those based on the Newey-West LRV estimator.[4]

Choosing an appropriate Long-run variance (LRV) estimator is key in carrying out prediction accuracy tests. The Newey-West and Andrews LRV estimators are consistent. However, they may lead to over-sized inference in finite samples. Thus, one may argue that the rejections of the null are due to the over-sized property of the tests based on these LRV estimators. To alleviate the size distortion caused by consistent LRV estimators, we also conduct the above four tests using a novel orthonormal-series LRV (OS-LRV) estimator and a fixed-bandwidth inference theory. These alternative tests are more accurate in size, but their power may be weakened. We show that even when the power is sacrificed, the OS-LRV tests reject the null in favour of our model at the *6m*, *9m* and *12m* horizons, in a majority of currency-horizon pairs, except for the Swiss Franc.

The rest of the paper is organized as follows. Section 1.2 presents a birds-eye view of our forecasting method. Section 1.3 presents a literature review. Section 1.4 derives the estimation equation from a theoretical model that links the speculators' net positions with the dynamics of the exchange rate. The model implies that net speculators' positions follow an autoregressive model with a Markov switching component. Section 1.5 estimates this model using COT data on six currencies. Section 1.6 generates the directional forecasts and tests two hypotheses to evaluate their performance. Section 1.8 generates the point forecasts and conducts the DMW-test and the CW-test for comparing the pointwise prediction accuracy between our model and the random walk

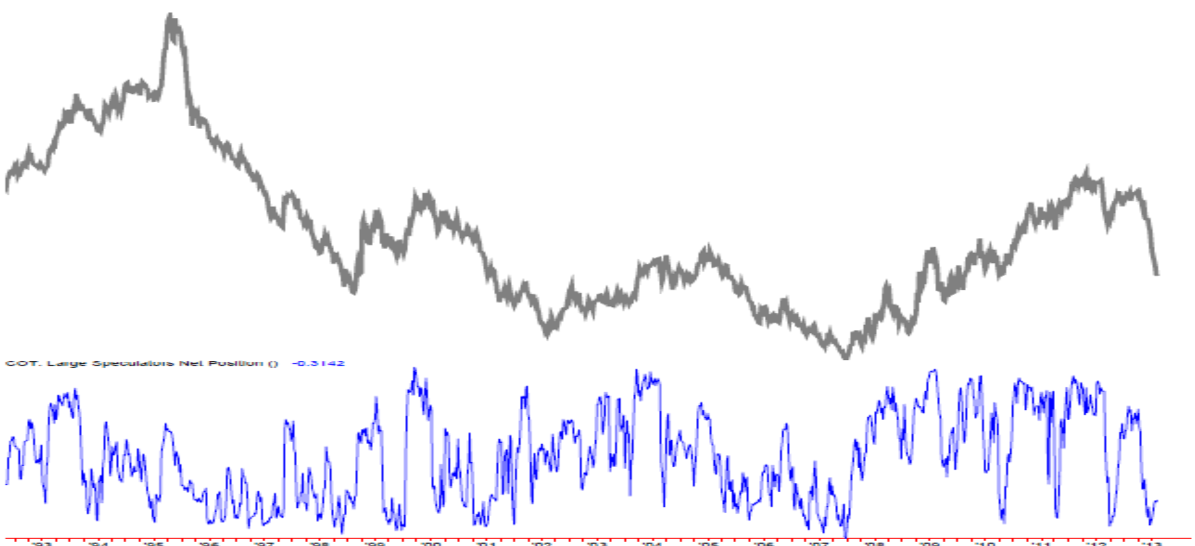
[4]Throughout this paper, when citing the Andrews LRV estimator, we refer to the kernel smoothed LRV estimator using Bartlett kernel and bandwidth selection rule suggested in Andrews (1991).

model. Section 1.9 tests the null hypotheses using the orthonormal-series long-run variance estimator and statistical inference theory which is asymptotically valid and has good size property in finite samples. Section 1.10 tests the forecasting accuracy of our model against the random walk model with drift. Lastly, Section 1.11 concludes.

1.2 Outline

Here, we illustrate the **gist** of our methodology through a series of figures that depict the Yen-Dollar exchange rate together with the forecasting variables we use and with our forecasts. Figure 1 plots the Yen and the large speculators' net positions in Yen futures at a weekly frequency. As we can see, the speculators' net positions tend to increase when the Yen is on an appreciation path, and they tend to decrease when the Yen is on an depreciation path. These patterns tend to be persistent: they may last for several months and sometimes several years.

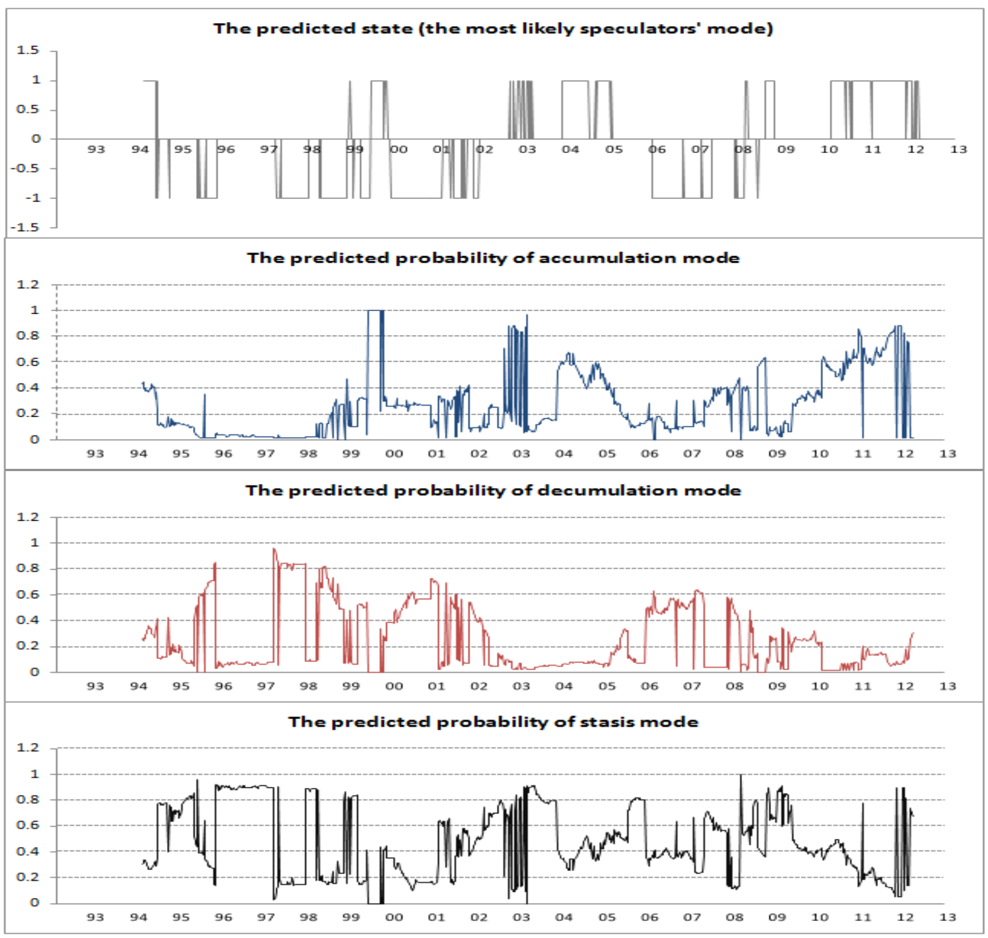
Figure 1: Japanese Yen exchange rate and speculators' net positions



Notes: The grey line depicts the Japanese Yen exchange rate against the US Dollar and blue one the speculators' net positions.

Every week, we fit a three-state Markov switching model to the speculators' net positions. The three states (i.e., speculators' modes) we consider are: accumulation, decumulation, or stasis. Based on our MSM estimates, every week we form forecasts of the state h-months ahead. Figure 2 shows the evolution of the 9-months ahead predicted state for the Yen ($\hat{S}^{Y}_{t+h}$). As we can see, this predicted state is quite persistent.

Figure 2: The evolution of the 9-months ahead predicted state for the Yen and predicted probabilities of each state



Notes: The 9-month ahead predicted state take values -1, 0 or 1. 1 (-1) on the given weeks indicates that 9 months later the most likely speculators' model is accumulation (decumulation). 0 means that the most likely mode is stasis.

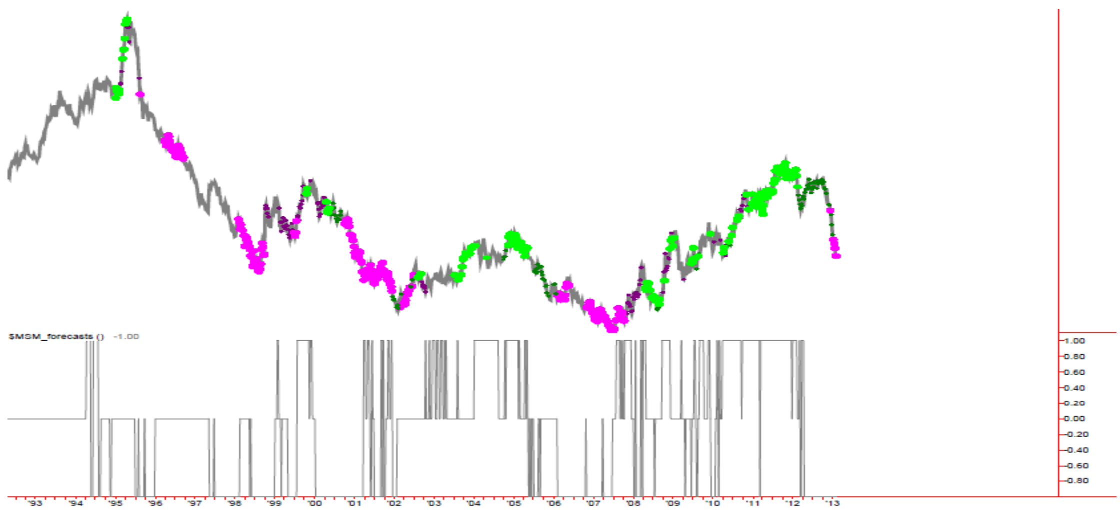
Our directional forecasting rule for the exchange rate predicts, at time t, a Yen appreciation between t and $t+h$ if speculators' accumulation is the predicted state in a majority of periods between t and $t+h$. Meanwhile, it predicts depreciation if speculators' decumulation is the predicted state most of the time between t and $t+h$. In other cases, our rule predicts zero change in the Yen.

Figure 3 plots the Yen-Dollar exchange rate and marks the performance of our *9* months ahead directional forecasts with circles of different sizes and colors. If an appreciation forecast was made *9* months ago (i.e., *38* weeks ago) and it turned out to correctly predict the direction of the Yen between week t-*38* and week t, then we place a big bright-green circle on week t's exchange rate. In contrast, if the appreciation forecast was wrong, the week t's circle is small and dark-green. Similarly, if the depreciation forecast made *38* weeks ago turned out to correctly predict the subsequent Yen depreciation, then in week t there is a large bright-pink circle. Meanwhile, wrong depreciation forecasts are represented with a small dark-red circle.[5]

As we can see, 360 out of 571 circles are either bright-green or bright-pink. This generates the 63% success ratio shown in Table 2. Interestingly, the successful directional forecasts in Figure 3 tend to predict bigger moves in the Yen than the moves following a wrong forecast. The battery of tests we consider below, evaluate formally whether such patterns could be generated by a random walk.

[5]Readers looking at a black and white version of this paper can only see successful forecasts (represented with large circles) and failed forecasts (represented with small circles).

Figure 3: The performance of our 9 months ahead directional forecasts



Notes: The grey line depicts our 9 month ahead directional forecasts, which can take values -1, 0 or 1. 1 (-1) on the given weeks predicts appreciation (depreciation) of the Yen against the US dollar over 9-month forecasting horizon. 0 means that our directional forecasts predict no change over the same forecasting horizon.

1.3 Literature Review

Our paper is linked to several branches of the exchange rate forecasting literature. First, our method of extracting information from the speculators' position data relies on the autoregressive Markov switching model proposed in Hamilton (1989, 1990). Engel and Hamilton (1990) apply this model to exchange rate data to explain the long swings exhibited by exchange rates from the mid 1970s to the end of the 1980s. Engel (1994), however, finds that this model does not clearly outperform the random walk in out-of-sample exchange rate forecasts. In this paper, the Markov switching model is applied to the speculators' positions, instead of the exchange rate itself. Furthermore, rather than a two-state MSM, we consider three regimes: uptrend, downtrend, and range.

By investigating the information content of market participants' trading positions, our paper is linked to the pioneering paper of Evans and Lyons (2002), who show that the order flow of a group of dealers in the interbank foreign exchange market, can forecast exchange rates over a short horizon. While the order flow data they consider is private information, the COT data we use is public information.

According to recent survey papers by Cheung et. al. (2005), Rogoff and Stavrakeva (2008) and Rossi (2013), the Meese and Rogoff (1983) puzzle is still alive: at horizons of less than one year, the driftless random walk beats fundamentals-based exchange rate out-of-sample forecasts, with few exceptions. Using a panel specification, Engel, Mark and West (2007) test whether fundamentals-based models beat the random-walk. Using the CW-test, they find the predictability, over a 4-year horizon, for the monetary model and the PPP model in 11 and 13 out of 18 currencies, respectively. However, over 1 quarter they don't find predictability.[6] Molodtsova and Papell (2009) consider the one-month ahead predictability of Taylor rule based models for individual currencies. In the most successful specification–heterogenous coefficients, smoothing, and a constant–the CW-test rejects the null (at the 10% significance level) in favor of a symmetric Taylor rule model for 10 out of 12 currencies. Gourinchas and Rey (2007) use net foreign assets as a predictor of future exchange rate changes and forecast the trade-weighted US dollar rather than individual exchange rates. Using the CW-test they find that net foreign assets can predict the exchange rate better than the driftless random walk at both long and short horizons.[7] Although, none of these papers carry out the DMW-test, Rossi (2013) reports that both at the 1-quarter and the 4-year forecasting horizons, the DMW-test finds no evidence of forecastability for the monetary model, the PPP model, and the Taylor rule based model across all

[6] Similar results are reported by Mark and Sul (2001).

[7] Net foreign assets is the deviation from trend of a weighted combination of gross assets, gross liabilities, gross exports and gross imports.

currencies she considers.[8] In this paper, we carry out both the CW and DMW tests. As we described in the Introduction, at the 6-to-12 months horizons, both tests reject the respective nulls in favour of our model in basically all currency-horizon pairs, except the Swiss Franc. However, at the 1 and 3 months forecasting horizons there is weak evidence of forecastability of our model.

There are many other papers that test the evidences of traditional predictors of exchange rate changes: interest rate differentials (UIRP) are considered by Meese and Rogoff (1988), Cheung, Chinn and Pascual (2005), Alquist and Chinn (2008) among others; price and inflation differentials (PPP) is considered in Rogoff (1996), Cheung, Chinn and Pascual (2005); Meese and Rogoff (1983), Chinn and Meese (1995), Mark(1995), Kilian (1999), Groen (1999), Berkowitz and Giorgianni (2001), Faust et al (2003) and Rossi (2005) explore exchange rate forecastability using the monetary model. More recently, new predictors have been used: Molodtsova et al (2010), Giacomini and Rossi (2010), Inoue and Rossi (2012) and Molodtsova and Papell (2012) study exchange rate forecasting using Taylor rule fundamentals. Alquist and Chinn (2008), and Della Corte, Sarno and Sestieri (2010) use the net foreign asset model. Chen and Rogoff (2003), Chen, Rogoff and Rossi (2010), and Ferraro, Rogoff and Rossi (2011) exploit commodity price indices. Bacchetta, van Wincoop and Beutler (2010), and Rossi and Sekhposyan (2011) use oil prices.

Finally, like this paper, there are several papers that use commitment-of-traders data. Moskowitz, et. al. (2012) document momentum over the time dimension across different asset classes and find that speculators profit from this time series momentum. Hong and Yogo (2012) find that open-interest in futures markets has predictive power over the excess returns of several assets classes over an one-month horizon. Brunnermeier and Petersen (2008) find that, in-sample, forex crash risk

[8] She does not carry out the DMW test for the net foreign assets model.

increases with speculators' positions in currency futures markets. Tornell and Yuan (2012) find that the peaks and troughs of speculators net positions are generally useful predictors of future exchange rates. Unlike our paper, out-of-sample forecasting is not the focus of these papers.

1.4 The Economic Model and Its Empirical Implications

Our empirical strategy consists of extracting the implicit exchange rate change forecasts from the speculators' net positions data in the COT report. The COT report provides weekly positions for three groups of traders in futures markets: hedgers, large speculators and the residual. Hedgers use the futures markets to insure against exchange rate changes, while large speculators participate in the futures markets to make capital gains. Here, we consider the portfolio problem of a representative investor and derive the estimation equation, which we will bring to the data in the next Section.[9]

1.4.1 The Economic Model

Let e_t be the time-t price of a foreign currency futures contract, in terms of US Dollars. To simplify the exposition, we will refer to any non-US dollar currency as a Euro. Thus, we will refer to e_t simply as the exchange rate and to an increase(decrease) in e_t as an appreciation(depreciation) of the Euro.

As in Engel and Hamilton (1990), the exchange rate is assumed to be driven by

[9]Even though the futures market is tiny compared with the spot foreign exchange market, speculators' positions contain valuable information about exchange rates. According to the 2013 BIS Triennial Central Bank Survey of turnover in foreign exchange markets, the daily average trading volume of spot markets worldwide is 2 trillion dollars in April 2013. Meanwhile, the value of foreign currency futures and options is around 160 billion dollars during the same period.

an unobservable stochastic trend x_t and a transitory component ε_t:

$$\Delta e_{t+1} = e_{t+1} - e_t = x_t + \varepsilon_{t+1},\ \varepsilon_{t+1} \sim WN(0, \sigma_\varepsilon^2) \tag{1}$$

where $WN(0, \sigma_\varepsilon^2)$ denotes white noise with mean zero and variance σ_ε^2. The unobservable trend x_t is the sum of a state-dependent mean $\mu_{(S_t)}$ and a white noise $u_t \sim WN(0, \sigma_u^2)$, i.e.

$$x_t = \mu_{(S_t)} + u_t. \tag{2}$$

Depending on the state S_t, the mean $\mu_{(S_t)}$ of the stochastic trend x_t may take a positive, negative or zero value. The state S_t is a discrete first-order Markov-switching random variable with transition probability matrix $\Pi = [p_{i,j}]_{1 \leq i,j \leq 3}$, i.e.

$$\mu_{(S_t)} = \begin{cases} \mu_{(1)} > 0, & \text{if } S_t = 1 \text{ (up-trend)} \\ \mu_{(2)} = 0, & \text{if } S_t = 2 \text{ (range)} \\ \mu_{(3)} < 0, & \text{if } S_t = 3 \text{ (down-trend)} \end{cases}, \tag{3}$$

where $p_{i,j} = \Pr(S_t = j | S_{t-1} = i)$ is the conditional probability that the state is j at time t, given that it was i at time $t-1$. We take the unobservable trend x_t as a primitive. It might depend on expectations of fundamentals, sentiment or other unobservable factors.

There are overlapping generations of two-period lived risk-averse speculators. A young t-date speculator observes a noisy signal (y_t) of the unobservable exchange rate trend x_t:

$$y_t = x_t + v_t,\ v_t \sim WN(0, \sigma_v^2). \tag{4}$$

This signal allows the speculator to form better forecasts of future exchange rate changes than those based on the historical exchange rate data she observes. Because the unobservable trend x_t affects Δe_{t+1} directly and the information of x_t is directly contained in y_t. Meanwhile, with available exchange rate data, i.e. $\{\Delta e_s\}_{s=1}^{t}$, the speculator can only estimate x_{t-1}.

During the first period of her life, the young representative speculator takes a position b_t in the Euro futures market. During the second period of her life, the now old speculator closes her position. The representative young speculator is risk averse and solves the following problem

$$\max_{b_t \in \mathbb{R}} E\left[-\exp\left(-\gamma W_{t+1}\right)|I_t\right], \text{ with } W_{t+1} = b_t\left(e_{t+1} - e_t\right) \tag{5}$$

where $I_t = \{y_1, \ldots, y_t\}$ denotes the information at time t and γ is the risk-aversion coefficient and W_{t+1} is her wealth next period.[10] The speculator may take either a long position ($b_t > 0$), a short position ($b_t < 0$) or stay out of the market ($b_t = 0$). Notice that the speculator faces no position limits (there are no bounds on b_t) and she needs not post margin.[11] Furthermore, we did not include the interest rate differential in the payoff because it is included in the futures' price spread Δe_{t+1}.

The representative date-t young speculator's prior distribution on the stochastic exchange rate trend x_t is given by the posterior distribution of her predecessor. To close the model, we assume that the prior of the first cohort (date-*1*) of young speculators is $x_0 \sim N(0, \sigma_u^2)$.

In order to solve the t-date young representative speculator's problem, note that she enters period t with a prior $\hat{x}_{t|t-1} \sim N(\hat{x}_{t-1}, \sigma_{t-1}^2)$, where $\hat{x}_{t-1}$ and σ_{t-1}^2 are the mean and variance of her predecessor's posterior distribution. Bayesian updating

[10] We treat b_t as a real number, while the futures contract in the Chicago Mercantile Exchange is for 125,000 Euros.

[11] To a first-order this is a realistic assumption as the margin requirements are quite small. For instance, on February 7, 2013 the initial margin required on a Euro futures contract at the CME was around \$2500, while the dollar value of the Euro futures contract was \$167,000.

implies that after observing the signal y_t, the t-date speculator's posterior on x_t is normal with mean $\hat{x}_t$ and variance σ_t^2, which are given by the following filter

$$\hat{x}_t = (1 - k_t)\hat{x}_{t-1} + k_t y_t \tag{6}$$

$$\sigma_t^2 = k_{t-1}\sigma_v^2 \text{ and } k_{t-1} = \frac{\sigma_{t-1}^2 + \sigma_u^2}{\sigma_{t-1}^2 + \sigma_u^2 + \sigma_v^2}. \tag{7}$$

Since the prior of the first cohort (date-*1*) of speculators is $x_0 \sim N(0, \sigma_u^2)$, this recursion is initialized at $\hat{x}_0 = 0$ and $\sigma_0^2 = \sigma_u^2$.

It follows from (52) and (6) that the speculator's posterior belief is that exchange rate changes are normal with mean $E_t[\Delta e_{t+1}] = \hat{x}_t$ and variance $\mathrm{Var}_t(\Delta e_{t+1}) = \sigma_t^2 + \sigma_\varepsilon^2$. Thus, the speculator's problem (5) can be rewritten as

$$\max_{b_t \in \mathbb{R}} \left[-\exp\left(-\gamma \hat{x}_t b_t + \frac{\gamma^2}{2}(\sigma_t^2 + \sigma_\varepsilon^2) b_t^2 \right) \right].$$

By taking the derivative with respect to b_t, we have that the representative speculator's demand for Euro futures is

$$b_t^* = \frac{E\left(\Delta e_{t+1} \,|I_t\right)}{\gamma \cdot \mathrm{Var}(\Delta e_{t+1} \,|I_t)} = \frac{\hat{x}_t}{\gamma(\sigma_t^2 + \sigma_\varepsilon^2)}. \tag{8}$$

Equation (8) says that the representative speculator's Euro position is positive(negative) if she expects an appreciation(depreciation) of the Euro, i.e., $\hat{x}_t > 0 (< 0)$. The position size is decreasing in the degree of risk-aversion and the variance of expected returns.

1.4.2 The Empirical Model

The empirical counterpart of the model's demand for Euro futures b_t^* is the speculators' net position data in the COT report, which we denote by Z_t. That is, $Z_t = b_t^*$.

Here, we use the solution to the speculator's problem (equations (6)-(8)) to recover the information about y_t–the noisy signal observed by speculators–from the observed data on the speculators' net positions Z_t. These equations show that if speculators observe a long enough sequence of positive(negative) y_t-signals, they gradually increase their belief that the Euro will appreciate(depreciate). Based on these posterior beliefs speculators gradually increase their long(short) Euro position b_t^*.

Note from the first equation in the speculators' filter (6) that we can express the y_t-signal as follows

$$y_t = \frac{1}{k_t}\hat{x}_t - \frac{1-k_t}{k_t}\hat{x}_{t-1} = g_t\hat{x}_t + (1-g_t)\hat{x}_{t-1}, \text{ where } g_t \equiv k_t^{-1}. \tag{9}$$

Using the representative speculator's demand for Euro futures (8) we have that $\hat{x}_t = \gamma(\sigma_t^2 + \sigma_\varepsilon^2)g_t b_t^*$. Replacing this expression in (9), we see that the unobserved signal can be expressed in terms of speculators' net positions as follows

$$y_t = \gamma(\sigma_t^2 + \sigma_\varepsilon^2)b_t^* + \gamma(\sigma_{t-1}^2 + \sigma_\varepsilon^2)(1-g_t)b_{t-1}^*. \tag{10}$$

Since $Z_t = b_t^*$, equation (10) implies that the speculators' net positions follow an AR(1) process

$$Z_t = \theta_t Z_{t-1} + \sigma_{x,t} y_t, \tag{11}$$

where

$$\sigma_{x,t} = \frac{1}{\gamma(\sigma_t^2 + \sigma_\varepsilon^2)g_t} \text{ and } \theta_t = \frac{\sigma_{t-1}^2 + \sigma_\varepsilon^2}{\sigma_t^2 + \sigma_\varepsilon^2}(1-k_t). \tag{12}$$

In Appendix A.1, we show that there σ_t^2 is convergent such that the limit of θ_t is in $(0, 1)$.

1.5 Estimation of the Empirical Model

In this section, we describe the method used to estimate the empirical model (11). We allow for heterogeneous DGPs for the speculators' positions $Z_{i,t}$ in different currencies, indexed by i. For ease of notation, however, we ignore the subscript 'i' in $Z_{i,t}$, unless necessary.

To recover the signal observed by speculators, we estimate the following AR(1) Markov switching model using rolling samples:

$$Z_t = \theta Z_{t-1} + \mu^*_{(S_t)} + v^*_t, \text{ with } \mu^*_{(S_t)} = \sigma_x \mu_{(S_t)} \text{ and } v^*_t = \sigma_x(v_t + u_t), \tag{13}$$

where the Markov switching component $\mu_{(S_t)}$ is defined in (3) and v^*_t is i.i.d. normal with mean zero and variance $\sigma^2_{v^*}$.[12] Given the unknown parameters $\alpha = (\theta, \mu^*_{(1)}, \mu^*_{(2)}, \mu^*_{(3)}, \sigma^2_{v^*}, \Pi)$ and observations on the speculators' net positions up to time t: $\mathbf{Z}^t = (Z_t, Z_{t-1}, ..., Z_0)$, the density of Z_t conditional on the state S_t taking the value j is given by

$$f(Z_t|\mathbf{Z}^{t-1}, S_t = j; \alpha) = \frac{1}{\sqrt{2\pi\sigma_{v^*}}} \exp\left[-\frac{(Z_t - \theta Z_{t-1} - \mu^*_{(j)})^2}{2\sigma^2_{v^*}}\right], \ j = 1, 2, 3. \tag{14}$$

Given the prediction probabilities

$$\xi_{j,t-1} = \Pr(S_t = j|\mathbf{Z}^{t-1}; \alpha), \ j = 1, 2, 3 \tag{15}$$

[12]The theoretical model (11)-(12) indicates that Z_t follows an auto-regressive process with time varying coefficients $(\theta_t, \sigma_{x,t})$. The rolling sample estimation of model (13) can be viewed as a local constant approximation of the theoretical model (11)-(12). In Appendix A.1, we show that $(\theta_t, \sigma_{x,t})$ has a convergent fixed point (θ^*, σ^*_x) with $|\theta^*| < 1$.

we can calculate the conditional density of Z_t given $\mathbf{Z}^{(t-1)}$ as

$$f(Z_t|\mathbf{Z}^{(t-1)};\alpha) = \sum_{j=1}^{3} f(Z_t|S_t = j, \mathbf{Z}^{t-1};\alpha)\xi_{j,t-1}. \tag{16}$$

Using the above conditional density we can compute filtered probabilities

$$\Pr(S_t = j|\mathbf{Z}^t;\alpha) = \frac{f(Z_t|\mathbf{Z}^{t-1}, S_t = j;\alpha)\xi_{j,t-1}}{f(Z_t|\mathbf{Z}^{t-1};\alpha)} \text{ for } j = 1, 2, 3, \tag{17}$$

which together with the transition probabilities implies that the filtered probabilities are

$$\xi_{j,t} = \sum_{k=1}^{3} p_{k,j} \Pr(S_t = k|\mathbf{Z}^t, \alpha) \text{ for } j = 1, 2, 3. \tag{18}$$

The log-likelihood function is therefore

$$Q_n(\alpha) = \sum_{t=1}^{n} \log\left[f\left(Z_t|\mathbf{Z}^{t-1}, \alpha\right)\right],$$

where, given α, $f(Z_t|\mathbf{Z}^{t-1}, \alpha)$ is calculated using (14)-(18) with the initial values $\Pr(S_1 = k|\mathbf{Z}^0, \alpha)$ for $t = 1, ..., n$.

The log-likelihood function $Q_n(\alpha)$ is a highly nonlinear and complicated function of α. Thus, we use the EM algorithm proposed by Hamilton (1990) to obtain the maximum likelihood (ML) estimator $\widehat{\alpha}_n$ of α.[13] To ensure that a global maximum is attained, we consider 150 different initial values for maximum likelihood estimation. Given the ML estimator $\widehat{\alpha}_n$, we estimate the filtered probabilities by $\Pr(S_t = j|\mathbf{Z}^t, \widehat{\alpha}_n)$ and the prediction probabilities by $\Pr(S_{t+1} = j|\mathbf{Z}^t, \widehat{\alpha}_n)$ for $t = 1, ..., n$.

[13] The main advantage of the EM algorithm over direct numerical optimization methods is its robustness with respect to the multiple local maxima problem.

1.5.1 Data

We obtain data on the large speculators' positions and open interest from the Commitments-of-Traders (COT) Report published by the Commodities and Futures Trade Commission (CFTC). Typically, every week the CFTC gathers positions data as of Tuesday and publishes the COT report three days later, on Friday after markets close. Thus, for each of the six currencies we consider, every Friday we fit Markov switching model (13) to the speculators' net positions normalized by open interest. Based on these estimates we generate our new forecasts every Friday. We evaluate our forecasts using weekly spot exchange rates at the end of trading on Friday, released by the FRB.

Our sample begins in September 1992, which is when the CFTC started to release the COT report on a weekly basis, except for the Euro, for which the data begins in January 1999. There are a few missing values in net positions and open interest data over the sample period.[14] We replace the missing values using a linear interpolation, using the last available value before the missing value and the first available value after the missing value.

For each of the six currencies ($i = 1, ..., 6$), we estimate the Markov switching model (13) using an initial sample with $n_0^{(i)}$ observations, i.e. $\{Z_{i,t}\}_{t=1}^{n_0^{(i)}}$. We then re-estimate the Markov switching model using a rolling sample: Every week we add a new observation and drop the first observation in the previous sample. Thus, if for currency i we have $n^{(i)}$ observations, the model is estimated $n^{(i)} - n_0^{(i)}$ many times. We consider three rolling window sizes {80,100,120} weeks. For each currency, we choose the rolling window size that generates the highest average forecast success ratio across the five forecasting horizons we consider: *1m, 3m, 6m, 9m,* and *12m.*[15]

[14] There are 27 missing values for the Australian Dollar and 2 for the Swiss Franc.
[15] The forecast success ratios are considered in the next subsection.

We thus set the rolling window size and the initial sample to 80 for the Japanese Yen and Swiss Franc; 100 for the Canadian Dollar; and 120 for the Euro, British Pound and Australian Dollar.

Figure 4 depicts the series of the three estimated means $\left\{\mu^*_{(1)}, \mu^*_{(2)}, \mu^*_{(3)}\right\}$ of each state in our AR(1) Markov switching model (13). As we can see, for all currencies the means of the up-trend states $\mu^*_{(1)}$ are strictly positive; the means of the down-trend states $\mu^*_{(3)}$ are negative; while the means of the range states $\mu^*_{(2)}$ fluctuate around zero. Figure 5 depicts the series of the estimated autoregresive coefficient θ for each currency. Its value ranges between 0 and 1, which is consistent with our theoretical model (see equation (11)).

1.6 Directional Forecasts of the Exchange Rate

We construct our exchange rate forecasts in two steps. In the first step, we use the estimates of our model (13) to compute the most likely accumulation mode of the speculators in each period between t_0 and $t_0 + h$. In the second step, we use this sequence of "predicted states" to obtain our exchange rate forecasts. Specifically, we forecast appreciation between t_0 and $t_0 + h$ if in a majority of periods, accumulation is the most likely speculators' mode. Conversely, we forecast depreciation if decumulation is the most likely speculators' mode. In the other cases, we stick to the random walk forecasts and predict no exchange rate change over an h-horizon.

In the first step, we compute the h-week ahead prediction probabilities of each state for each currency i, based on t_0 information, as follows

$$\left(\widehat{\xi}^{(i)}_{1,t_0+h}, \widehat{\xi}^{(i)}_{2,t_0+h}, \widehat{\xi}^{(i)}_{3,t_0+h}\right) = \left(\widehat{\xi}^{(i)}_{1,t_0}, \widehat{\xi}^{(i)}_{2,t_0}, \widehat{\xi}^{(i)}_{3,t_0}\right)(\widehat{\Pi}^{(i)}_{t_0})^h, \tag{19}$$

where $\widehat{\Pi}^{(i)}_{t_0}$ is the estimated transition matrix based on the rolling sample of speculators' net positions $\mathbf{Z}_i^{(t_0)} = (Z_{i,t_0-n_0+1}, ..., Z_{i,t_0})$, and $\widehat{\xi}_{j,t_0}^{(i)}$ is the estimated filtered probabilities state j. It is given by

$$\widehat{\xi}_{j,t_0}^{(i)} = P(S_{t_0}^{(i)} = j | \mathbf{Z}_i^{(t_0)}, \widehat{\alpha}_{n_0}^{(i)}(t_0)) \text{ for } j = 1, 2, 3, \tag{20}$$

where $\widehat{\alpha}_{n_0}^{(i)}(t_0)$ is the estimator of the unknown parameters based on the rolling sample $\mathbf{Z}_i^{(t_0)}$.

Based on the prediction probabilities (19), our time-t_0 prediction of the most likely speculators' mode in period $t_0 + h$, which we will refer to as the "predicted state" is given by

$$\widehat{S}_{t_0+h}^{(i)} = \begin{cases} 1, & \text{if } \widehat{\xi}_{1,t_0+h}^{(i)} > \max\left\{\widehat{\xi}_{2,t_0+h}^{(i)}, \widehat{\xi}_{3,t_0+h}^{(i)}\right\} \\ 2, & \text{if } \widehat{\xi}_{2,t_0+h}^{(i)} > \max\left\{\widehat{\xi}_{1,t_0+h}^{(i)}, \widehat{\xi}_{3,t_0+h}^{(i)}\right\} \\ 3, & \text{if } \widehat{\xi}_{3,t_0+h}^{(i)} > \max\left\{\widehat{\xi}_{1,t_0+h}^{(i)}, \widehat{\xi}_{2,t_0+h}^{(i)}\right\} \end{cases} . \tag{21}$$

$\widehat{S}_{t_0+h}^{(i)} = 1$(resp. 3) means that the time-t_0 forecast of the most likely speculators' mode on currency i at time $t_0 + h$ is accumulation(resp. decumulation).

In the second step, we use the sequence of most likely speculators' modes $\left\{\widehat{S}_{t_0+1}^{(i)}, \widehat{S}_{t_0+2}^{(i)}, ..., \widehat{S}_{t_0+h}^{(i)}\right\}$ to construct our exchange rate directional forecasts. Specifically, at t_0 we forecast an exchange rate appreciation(depreciation) over the following h periods, if between t_0 and $t_0 + h$ the majority of the predicted states indicate speculators' accumulation(decumulation). In other cases, we forecast zero exchange rate change. That is, for any t_0 with $n_0^i \leq t_0 \leq n - h$, our directional exchange rate forecasts are:

$$D_{t_0,h}^{(i)} = \begin{cases} 1, & \text{if } X_{t_0,h}^{(i)} > 0 \\ 0, & \text{if } X_{t_0,h}^{(i)} = 0 \\ -1, & \text{if } X_{t_0,h}^{(i)} < 0 \end{cases}, \quad X_{t_0,h}^{(i)} \equiv \sum_{s=1}^{h} \left(2 - \widehat{S}_{t_0+s}^{(i)}\right) \tag{22}$$

Notice that $D^{(i)}_{t_0,h} = 1$ (resp. -1) means that our directional forecast over an h-period horizon is appreciation (resp. depreciation). Meanwhile, if $D^{(i)}_{t_0,h} = 0$, we predict no change. The variable $X^{(i)}_{t,h}$ can take values ranging from -h to +h. It indicates the net number of periods with predicted speculators' accumulation between t_0 and $t_0 + h$ (if $X^{(i)}_{t,h} > 0$) or the net number of periods with predicted decumulation (if $X^{(i)}_{t,h} < 0$). For example, $X^{(i)}_{t,h} = -h$ when speculators' decumulation is the predicted state in every period on *(t,t+h)*; while $X^{(i)}_{t,h} = +h$ when speculators' accumulation is the predicted state in every period on *(t,t+h)*.

Intuitively, one can think of the transition probabilities as capturing the low frequency component of the speculators' accumulation mode, whereas the filtered probabilities capture the high frequency component of the speculators mode. Equation (19) implies that for a short forecasting horizon *h,* the predicted probabilities of the state $\hat{\xi}^{(i)}_{j,t_0+h}$ are determined mainly by the time-t filtered probabilities $\hat{\xi}^{(i)}_{j,t_0}$. In contrast, for long enough h the predictions are determined by the ergodic distribution implied by the transition matrix $\hat{\Pi}^{(i)}_{t_0}$, by the well known convergence property of Markov chains. Our directional exchange rate forecasts in (22) have the same properties: at short horizons they are determined the estimated filtered probabilities, whereas at long horizons the are determined mainly by the estimated transition matrix.

During every week, we generate out-of-sample exchange rate directional forecasts for five horizons: *1m, 3m, 6m, 9m,* and *12m.* For each currency i, our directional forecasts start the week after the first estimation of the MSM, and end h weeks prior to the end of the COT sample (week n). That is, they start in week $n^{(i)}_0$ and end in week $n^{(i)} - h$. Our sample starts on 10/2/1992 (In terms of the date of publication of COT report) for all currencies except the Euro, which starts on 01/08/1999. Our sample ends on 02/08/2013 for all currencies. Thus, our directional forecasts start on 01/20/1995 for the Australian Dollar and British Pound; 09/01/1994 for the Canadian

Dollar; 04/15/1994 for the Swiss Franc and Japanese Yen; and 05/04/2001 for the Euro.[16]

Table 2 exhibits the forecast success ratio of our out-of-sample directional forecasts at the *1m, 3m, 6m, 9m,* and *12m* horizons.[17] The forecast success ratio is the number of *successful* depreciation or appreciation forecasts divided by the ***total*** number of depreciation and appreciation forecasts. As we can see, the aggregate forecast success ratio is 58% over the period October 1992-February 2013. Interestingly, our forecast accuracy is greater at the *6m* to *12m* horizons than at the *1m* to *3m* months horizons. If we confine our attention to *6m*, *9m* and *12m* forecasting horizons, the aggregate success ratio is 60.2% (63.8% excluding the Swiss Franc). When taken individually, we can see that the *6m* to *12m* success ratios are greater than 56% in all cases–except for the Swiss Franc–and that in several cases the success ratio is larger than 66%.

The high average success ratios observed in Table 2 are not dominated by specific periods of successful forecasts. In most country-horizon pairs, the performance of the directional forecast is stable over the sample period. Figures 6, 7, 8, 9 and 10 show this stability by plotting the evolution of the cumulative forecast success ratios for each forecasting horizon. As we can see, approximately after 400 weeks, these ratios converge to a stable level, above 50% in most country-horizon pairs. Initially, however, these ratios fluctuate quite a bit because the sample size is small. For example, the *9m* ahead forecasts for the yen initially fluctuate between 60% and 90% before converging to the mid-60%s in Figure 9.

Like Table 2, Table 3 exhibits the forecast success ratios of our directional forecasts, but partitions the sample period into two sub-periods: 04/15/1994-11/29/2002

[16] The dates of the last forecasts are 2013-01-18 for $h = 1$ month, 2012-11-16 for $h = 3m$, 2012-08-24 for $h = 6m$, 2012-05-25 for $h = 9m$, and 2012-03-01 for $h = 12m$.

[17] Throughout the paper 1, 3, 6, 9 and 12 months correspond to 4, 13, 25, 38 and 50 weeks, respectively.

and 12/06/2002-02/08/2013. As we can see, the forecast success ratios are very similar across the two sub-periods for the Yen, the British Pound, Australian Dollar and the Swiss Franc. For the Canadian Dollar, however, the ratios are around 20% higher in the second period.

1.7 Evaluating the Statistical Significance of Directional Forecasts

The high forecasting success ratios in Table 2 illustrate the usefulness of the COT data in generating directional exchange rate forecasts. The issue remains, however, whether this success isn't simply the result of luck. Wouldn't flipping a coin result in similar success ratios? Here, we investigate the statistical significance of the success of our directional forecasts by conducting two formal tests of the null hypothesis that our MSM-based forecasts cannot improve the directional forecasts relative to a driftless random walk model:

$$e_{t+1}^{(i)} = e_t^{(i)} + \varepsilon_{t+1}^{(i)}, \tag{23}$$

where $\{\varepsilon_t^{(i)}\}$ is a white noise process with mean zero and variance $\sigma_{i,\varepsilon}^2$.

We carry out two tests and both of them control for auto-correlation of the data. The first test gives more weight to the directional forecasts associated bigger exchange rate moves, while the second test gives the same weight to all forecasts. The first test is more closely linked to the profitability of trading strategies, and captures the spirit of George Soros's observation: It's not whether you're right or wrong, but how much money you make when you're right and how much you loose when you're wrong.

The weighted directional test is, to our knowledge, new. The second test has the same spirit as the traditional binomial tests of directional forecast performance.[18] However, our test controls for auto-correlation, while traditional tests do not.

Figures 11 through 15 depict the evolution of our directional forecasts $D_{t,h}^{(i)}$ in (22) together with the actual exchange rate movement for all currencies.

1.7.1 Directional Test Weighted by the Magnitude of Exchange Rate Changes

Here, we test the null hypothesis that our weighted directional forecasts are unable to improve upon random walk forecasts. We maintain the assumption that, under the null, $\{\varepsilon_t\}$ is a martingale difference sequence. Given the observations $\{e_{t+h}^{(i)} - e_t^{(i)}\}_{t=n_0^{(i)}}^{n^{(i)}-h}$ and our directional forecasts $\{D_{t,h}^{(i)}\}_{t=n_0^{(i)}}^{n^{(i)}-h}$ on each currency i, we consider the following test statistic

$$T_{a,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n^{(i)}-h} D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)}), \text{ where } n_1^{(i)} \equiv n^{(i)} - n_0^{(i)} - h + 1. \tag{24}$$

Under the driftless random walk specification, the optimal forecast is a zero exchange rate change. If we replace $D_{t,h}^{(i)}$ in $T_{a,n}^{(i)}$ by the optimal forecasts generated under the driftless random walk hypothesis, $T_{a,n}^{(i)}$ becomes zero for all n. Thus, the null hypothesis underlying the test statistic $T_{a,n}^{(i)}$ can be specified as

$$H_0 : \qquad E\left[D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)})\right] = 0 \text{ for any } i \text{ and } t. \tag{25}$$

That is, under the null our directional forecasts are uncorrelated with future realized exchange rate changes.

Notice that the above zero expectation holds as $\{\varepsilon_t^{(i)}\}$ is a martingale difference

[18] For instance, the binomial test in Pesaran and Timmerman (1992), Gordon Leitch and J. Ernest Tanner (1991), Engel (1994) and Cheung, et.al. (2005).

sequence with respect to the natural sigma field generated by the COT process $\{Z_{i,t}\}_t$ and the variables $D^{(i)}_{t,h}$ only depend on the COT data up to time t. On the other hand, if the COT data was useful in forecasting $e^{(i)}_{t+h} - e^{(i)}_t$, then one would expect that $T^{(i)}_{a,n}$ converge to some strictly positive number.

In order to test null hypothesis (25), let $V_{T^{(i)}_a,n}$ denote the consistent estimator of the asymptotic variance of $T^{(i)}_{a,n}$.[19] Then by Slutsky's theorem and the martingale central limit theorem, we deduce that

$$\sqrt{n^{(i)}_1} V^{-1/2}_{T^{(i)}_{a,n}} T^{(i)}_{a,n} \to_d N(0,1). \tag{26}$$

For the empirical implementation, we consider several different LRV estimators. Table C.2 does not control for auto-correlation in $\left\{D^{(i)}_{t,h}(e^{(i)}_{t+h} - e^{(i)}_t)\right\}_{t=n_0}^{n-h}$. Meanwhile, Table C.3 controls for auto-correlation by using the Newey-West LRV estimator or the Andrews LRV estimator to construct $V_{T^{(i)}_a,n}$. Below, in Section 1.9, we consider orthonormal series LRV (OS-LRV) estimators.

Two overall results are worth mentioning. First, the high forecast success ratios in Table 2 translate into strong predictability of our directional forecasts for future exchange rate changes (except for the Swiss Franc). Second, these results are robust to the correction for auto-correlation in $\{D^i_{t,h}(e^i_{t+h} - e^i_t)\}_{t=n^{(i)}_0}^{n^{(i)}-h}$ over the *6m* to *12m* forecasting horizons.

Tables 4 and 5 present the values of the $T^{(i)}_{a,n}$ statistic, and its t-values (test statistics), for the 6 currencies (Euro, Japanese Yen, British Pound, Australian Dollar, Canadian Dollar and Swiss Franc) and the 5 horizons (*1m*, *3m*, *6m*, *9m* and *12m*) we consider. Tables 4 and 5 test the same null (25) that our directional forecasts are uncorrelated with future realized exchange rate changes. They just differ in the

[19] See Appendix 1.12.B for the construction of various LRV estimators.

construction of the LRV estimators of $T_{a,n}^{(i)}$. In both tables, the null is rejected if the test statistic $T_{a,n}^{(i)}$ is significantly larger than zero. For the one-sided test, a t-value greater than 1.282 implies a *10%* significance level.

As we can see in Table 4–which does not control for autocorrelation–the null is rejected in all the *3m* to *12m* forecasting horizons in 5 out of the 6 currencies, except for the Swiss Franc. At the *1m* forecasting horizon the null is rejected in 4 currencies.

Table 5 shows that even after controlling for autocorrelation, over the *6m* to *12m* horizons, there is very strong evidence of exchange rate predictability in all currencies except for the Swiss Franc. As we can see in panel A, using the Newey-West LRV estimator, the null is rejected in all the 15 country-horizon pairs at the *6m*, *9m* and *12m* horizons. Panel B shows that using the Andrews LRV estimator to control for autocorrelation, the null is rejected in 12 out of those 15 country-horizon pairs. At the *1m* and *3m* horizons there is weak evidence of predictability: the random walk null is rejected in only 5 out of 12 currency-horizon pairs.

1.7.2 Binomial Directional Test

Here, we test the significance of our model in forecasting the sign of $e_{t+h}^{(i)} - e_t^{(i)}$. When the exchange rate is a driftless random walk, we define a new dummy variable $R_{t,h}^{(i)}$ that captures the direction of the realized exchange rate change of currency i over horizon h:

$$R_{t,h}^{(i)} = \begin{cases} 1, & \text{if } e_{t+h}^{(i)} - e_t^{(i)} \geq 0 \\ -1, & \text{if } e_{t+h}^{(i)} - e_t^{(i)} < 0 \end{cases} . \tag{27}$$

The null hypothesis we test is that our directional forecasts $D_{t,h}^{(i)}$ are uncorrelated with the future direction of the exchange rate $R_{t,h}^{(i)}$

$$H_0\colon\ Cov\left(D_{t,h}^{(i)}, R_{t,h}^{(i)}\right) = 0, \tag{28}$$

while the alternative hypothesis could be one sided or two sided:

$$H_1^{\text{one-sided}}\colon\ Cov\left(D_{t,h}^{(i)}, R_{t,h}^{(i)}\right) > 0 \text{ or } H_1^{\text{two-sided}}\colon\ Cov\left(D_{t,h}^{(i)}, R_{t,h}^{(i)}\right) \neq 0.$$

Consider then the following test statistic

$$T_{b,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} R_{t,h}^{(i)} - \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h} \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} R_{t,h}^{(i)},$$

which is the sample covariance of the two random variables: $D_{t,h}^{(i)}$ and $R_{t,h}^{(i)}$. In order to test null hypothesis (28), let $V_{T_{b,n}^{(i)}}$ denote the consistent estimator of the asymptotic variance of $T_{b,n}^{(i)}$.[20] Then we have

$$\sqrt{n_1^{(i)}} V_{T_{b,n}^{(i)}}^{-\frac{1}{2}} T_{b,n}^{(i)} \to_d N(0,1).$$

Overall the test results are very similar to those of the weighted directional test. Over *6m*, *9m* and *12m* forecasting horizons, the binomial test suggests that our directional forecasts have strong predictability for the directional changes in future exchange rate in 5 currencies, except the Swiss Franc.

Tables 6 and 7 present the values of the $T_{b,n}^{(i)}$ statistic, and its t-values, for the 6 currencies and the 5 horizons we consider. They test the same null, but differ in the construction of the long-run variance estimators of $T_{b,n}^{(i)}$. Table 6 does not control for auto-correlation, while Table 7 controls for it. The null is rejected if the t-value of the $T_{b,n}^{(i)}$ statistic is positive and statistically significant. For the one-sided test, a t-value greater than 1.282 implies a *10%* significance level.

As we can see in Table 6–that does not control for autocorrelation–excluding the

[20]See Appendix 1.12.B for the construction of various LRV estimators.

Swiss Franc, evidence of predictability for directional change is found in 21 out of the 25 currency-horizon pairs. Table 7 reports the test results using Newey-West LRV estimator (Panel A) and Andrews LRV estimator (Panel B) to control for autocorrelation. Excluding the Swiss Franc, the null is rejected in 17 (Panel A) and 16 (Panel B) out of the 25 currency-horizon pairs. Especially over *6m*, *9m* and *12m* horizons, strong evidence of directional predictability is found in 14 (Panel A) and 13 (Panel B) out of 15 cases, excluding the Swiss Franc.

1.8 Evaluating the Accuracy of Point Forecasts

The standard practice in the exchange rate forecasting literature has been to test the accuracy of out-of-sample point-forecasts of various models vis-a-vis random-walk forecasts. The most widely used tests are those proposed by Diebold and Mariano (1995) and West (1996)–the DMW test–and by Clark and West (2006)–the CW test. In this section, we use our MSM model to generate h-period-ahead point forecasts and carry out the standard DMW and CW tests against the driftless random walk, which has proven to be a tougher benchmark to beat than the random walk with drift. In Section 1.9 we carry out these tests using OS-LRV estimators. In Section 1.10 we consider the random walk with drift.

Our h-period ahead point forecast for currency i is that between t and $t+h$, the magnitude of the appreciation(depreciation) will be proportional to the net number of periods with predicted speculators' accumulation(decumulation) over the following h-weeks, given by $X_{t,h}^{(i)}$ in (22). That is, the h-period ahead point forecasts for currency i, made at time t, is

$$\widehat{e}_{t+h}^{(i)} \;=\; e_t^{(i)} + \widehat{\beta}_{h,m_0} X_{t,h}^{(i)}, \text{ for } m_0 + 1 \le t \le n^{(i)} - h, \tag{29}$$

where m_0 is the first week that the out-of-sample point forecasts begin, $n^{(i)}$ is the last week of the speculator's net position data sample, and $\widehat{\beta}_{h,m_0}$ denotes the estimated effect of $X_{t,h}^{(i)}$ on the exchange rate change over horizon h. It is given by

$$\widehat{\beta}_{h,m_0} = \frac{\sum_{i=1}^{5} \sum_{t=n_0^{(i)}+1}^{m_0-h} X_{t,h}^{(i)} \left(e_{t+h}^{(i)} - e_t^{(i)} \right)}{\sum_{i=1}^{5} \sum_{t=n_0^{(i)}+1}^{m_0-h} [X_{t,h}^{(i)}]^2}. \tag{30}$$

Three comments are in order. First, the summation in (30) starts in $n_0^{(i)} + 1$ because we use the initial $n_0^{(i)}$ COT weekly observations to estimate the MSM for currency i. Second, while for five currencies our sample period starts on October 2, 1992, for the Euro it starts on January 8, 1999. Thus, to maximize the number of out-of-sample forecasts, we exclude the Euro from the estimation of $\widehat{\beta}_{h,m_0}$. Third, we estimate $\widehat{\beta}_{h,m_0}$ using OLS, setting $m_0 = 360$. In this way, we synchronize to the 360^{th} week in which the first point forecast is generated across all currencies, except the Euro. It follows that our first out-of-sample point forecasts start on 04/09/1999 for the five currencies excluding the Euro. For the latter it starts on 05/04/2001. Our last point forecasts are generated on February 8, 2013. Figure 16 through 20 depict the evolution of the net number of periods with predicted speculators' accumulation (decumulation) over the following h-weeks $X_{t,h}^{(i)}$ in (22) together with actual exchange rate movement for all currencies.

1.8.1 The Diebold-Mariano-West Test

The test proposed by Diebold and Mariano (1995) tests the null that the mean squared prediction error (MSPE) of a random walk is equal to the MSPE generated by the point forecasts of a given model. Under the assumption that the exchange rate follows a driftless random walk, the h-period-ahead point forecast for currency i is

$\overline{e}_{t+h}^{(i)} = e_t^{(i)}$ $(i = 1, ..., 6)$. Thus, we can evaluate the accuracy of our point forecast using the $DMW_{h,n}^{(i)}$ test statistic

$$DMW_{h,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=m_0+1}^{n^{(i)}-h} \left[\left(e_t^{(i)} - e_{t+h}^{(i)} \right)^2 - \left(\widehat{\beta}_{h,m_0} X_{t,h}^{(i)} + e_t^{(i)} - e_{t+h}^{(i)} \right)^2 \right], \tag{31}$$

where $n_1^{(i)} = n^{(i)} - m_0 - h$. That is, our point forecasts are more (less) accurate than those produced by the driftless random walk model if $DMW_{h,n}^{(i)} > 0$ ($DMW_{h,n}^{(i)} < 0$).

The null hypothesis of equal MSPEs of our model and the driftless random walk can be expressed as follows.

$$H_0^{(i)}: \quad \text{plim}_n DMW_{h,n}^{(i)} = 0 \text{ for any } i. \tag{32}$$

Diebold and Mariano (1995) suggest testing this null using the following asymptotic distribution

$$V_{DMW^{(i)},h}^{-\frac{1}{2}} \sqrt{n_1^{(i)}} DMW_{h,n}^{(i)} \to_d N(0,1) \tag{33}$$

for $i = 1, ..., 6$, where $V_{DMW^{(i)},h}$ denotes the LRV estimator of $\sqrt{n_1^{(i)}} DMW_{h,n}^{(i)}$.[21]

Overall, the test results show that, over *6m*, *9m* and *12m* forecasting horizons, our point forecasts significantly outperform the driftless random walk in the Australian dollar, Canadian dollar, Euro, Yen and the British Pound.

Tables 8 and 9 contain the $DMW_{h,n}^{(i)}$ test statistics and their p-values for the 6 currencies and the 5 forecasting horizons we consider. Both tables test the same null, but differ in the construction of the LRV estimators of $\sqrt{n_1^{(i)}} DMW_{h,n}^{(i)}$. Table 8 does not control for autocorrelation, while Table 9 controls for it by using Newey-West LRV estimator and Andrews LRV estimator. Below, in Section 1.9, we test the null using a OS-LRV estimator of $\sqrt{n_1^{(i)}} DMW_{h,n}^{(i)}$ to control for auto-correlation.

[21] See Appendix 1.12.B for the construction of various LRV estimators.

The null is rejected if the $DMW_{h,n}^{(i)}$ test statistic is statistically significant and positive. For the one-sided test we consider, a t-value greater than 1.282 implies a 10% significance level. As we can see in Table 8, if we do not control for autocorrelation, the null is rejected at the *3m* to *12m* horizons in all currencies except for the Swiss Franc. At the *1m* horizon, the null is rejected only for the Australian Dollar. These result are in line with those for the directional forecast in Tables 4 through 7.

Panel A in Table 9 reports the test results using Newey-West LRV estimator when we compute $V_{DMW^{(i)},h}$. Excluding the Swiss Franc, over the *6m*, *9m* and *12m* horizons our point forecasts statistically significantly outperform the driftless random walk in all currencies, except for the British Pound at the *12m* horizon. At the *3m* horizon the null is rejected for 3 currencies, while at the *1m* horizon it is rejected only for the Australian Dollar. Panel B shows that when using the Andrews LRV estimator, the test results are a bit weaker: The *12m* Yen and the *3m* British Pound cease to be significant. Still, over *6m*, *9m* and *12m* forecasting horizons, the null is rejected in 13 out of 15 currency-horizon pairs.

1.8.2 The Clark-West Test

The test proposed by Clark and West (2006) uses out-of-sample forecasts to test the null that a forecasting model is equivalent to the random walk model. In the case of our model (29), the null is

$$H_0^{cw} : \; E\left[X_{t,h}^{(i)}\left(e_{t+h}^{(i)} - e_t^{(i)}\right)\right] = 0 \tag{34}$$

That is, the null is that the h-period ahead predicted directional intensity of appreciation(depreciation) is uncorrelated with realized exchange rate changes. Clark and West (2006) note that this null is different from the null tested by the DMW test–

that the MSPE of the random walk is equal to the MSPE generated by the point forecasts of our model. They show that if the two models are nested, the DMW-test under-rejects the null (34). Clark and West (2006) propose a revised statistic–the CW test–that eliminates the bias in favour of the random walk from the DMW-statistic.

We carry out the standard CW test, in which it is assumed that under the null the exchange rate follows a driftless random walk. Decomposing the statistic $DMW_{h,n}^{(i)}$, we get

$$DMW_{h,n}^{(i)} = -\frac{\widehat{\beta}_{h,n_0}^2}{n_1^{(i)}} \sum_{t=m_0+1}^{n^{(i)}-h} [X_{t,h}^{(i)}]^2 + \frac{2\widehat{\beta}_{h,n_0}}{n_1^{(i)}} \sum_{t=m_0+1}^{n^{(i)}-h} X_{t,h}^{(i)} \left(e_{t+h}^{(i)} - e_t^{(i)} \right)$$

where the first term on the right hand side of the above equation represents the bias in the DMW test statistic. The CW test statistic is defined as

$$CW_{h,n}^{(i)} = DMW_{h,n}^{(i)} + \frac{\widehat{\beta}_{h,n_0}^2}{n_1^{(i)}} \sum_{t=m_0+1}^{n^{(i)}-h} [X_{t,h}^{(i)}]^2 = \frac{2\widehat{\beta}_{h,n_0}}{n_1^{(i)}} \sum_{t=m_0+1}^{n^{(i)}-h} X_{t,h}^{(i)} \left(e_{t+h}^{(i)} - e_t^{(i)} \right).$$

Let $V_{CW^{(i)},h}$ denote the consistent LRV estimator of the CW test statistic.[22] Then using the central limit theorem and the continuous mapping theorem, we have

$$V_{CW,h}^{-\frac{1}{2}} \sqrt{n_1^{(i)}} CW_{h,n}^{(i)} \to_d N(0,1). \tag{35}$$

As in the recent literature (e.g., Rossi (2013)) the CW test is implemented using Newey-West LRV estimator $V_{CW^{(i)},h}$. In addition, we also present test results using Andrews LRV estimator.

Tables 10 and 11 contain the $CW_{h,n}^{(i)}$ test statistics, and their p-values for the 6 currencies and the 5 horizons. These tables test the same null, but differ in the

[22]See Appendix 1.12.B for the construction of various LRV estimators.

construction of the long-run variance estimators. While Table 10 does not control for auto-correlation, Table 11 controls for it. The null is rejected if the $CW^{(i)}_{h,n}$ test statistic is significantly greater than zero. For the one-sided test we consider, a t-value greater than 1.282 implies a *10%* significance level.

This standard CW test is easier to pass than the previous DMW test. Thus, we expect that the CW test results will turn out to be more in favor of our point forecasts than those reported in Tables 8 and 9. Indeed, as we can see in Table 10, the null is rejected in all currencies except for the Swiss Franc over all of the *3m* to *12m* months horizons, and the p-values are lower than in the DMW test presented in Table 8. Moreover, at the *1m* horizon, the null is rejected in 3 currencies rather than only in 2 currencies as in Table 8.

When we control for auto-correlation using the Newey-West LRV estimator, we can see in Table 11 that the null is rejected in all currencies, except for the Swiss Franc, over the *6m*, *9m* and *12m* forecasting horizons. The number of rejections is larger and p-values are lower than the DMW-test results shown in Table 9. At the *3m*(*1m*) horizon the null is rejected in the same three(one) currencies as with the DMW-test. Tests results using Andrews LRV estimator are similar as those using Newey-West LRV estimator, except for the *12m* horizon, in which the null is not rejected in two currencies.

1.9 Tests Based on Orthonormal Series LRV Estimators

In this section, we implement alternative tests about the null hypotheses in Sections 1.6 and 1.8. Our main motivation here is to check whether the test results of the previous sections change when different statistics and inference theories are applied to test the null hypotheses (25), (28), (32) and (34).

The asymptotic theory underlying the inference based on consistent LRV estimators typically requires that the bandwidth goes to zero when the sample size diverges to infinity. In reality, however, the smoothing parameter is always finite, which may bias the resulting inference and cause size-distortion in finite samples. Here, we consider an orthonormal series LRV estimator and test the null hypotheses using a fixed bandwidth asymptotic theory. The OS-LRV estimator is very easy to compute in practice and is automatically positive definite in finite samples. The fixed bandwidth asymptotic theory does not require the bandwidth to be zero or converge to zero. As a result, these tests enjoy high order accuracy and hence good size properties in finite samples, as illustrated in Jansson (2004), Sun et al. (2008), Sun (2013) and Zhang and Shao (2013). The cost of the better size properties of these alternative tests is that their power may be weakened. Appendix A.2 includes detailed description of the OS-LRV estimators of test statistics investigated in this section.

1.9.1 Directional Tests

Let $\Sigma_{T^{(i)}_{a,n}}(M)$ and $\Sigma_{T^{(i)}_{b,n}}(M)$ denote the OS-LRV estimators for $T^{(i)}_{a,n}$ and $T^{(i)}_{b,n}$ using M many orthonormal basis functions in $L^2[0,1]$.[23] By the martingale central limit theorem and continuous mapping theorem, we have that

$$\Sigma^{-\frac{1}{2}}_{T^{(i)}_{a,n}}(M)\sqrt{n^{(i)}_1}T^{(i)}_{a,n} \to_d t(M) \text{ and } \Sigma^{-\frac{1}{2}}_{T^{(i)}_{b,n}}(M)\sqrt{n^{(i)}_1}T^{(i)}_{b,n} \to_d t(M), \tag{36}$$

where $t(M)$ denotes the student-t random variable with M degrees of freedom. The asymptotic theory in (36) is used to test the null hypothesis (25) and (28).

Table 12 presents the weighted directional test results using the OS-LRV estimators.[24] Even in this case, the null is rejected in 15 (Panel A) and 18 (Panel B)

[23]See Appendix 1.12.B for the construction of OS-LRV estimators.

[24]In Table 12, the test statistic follows t-distribution with M degrees of freedom. M equal to 4 (6)

out of 25 currency-horizon pairs excluding the Swiss franc. Over *6m*, *9m* and *12m* horizons, the null is rejected in 11 (Panel A) and 13 (Panel B) out of 15 cases. Table 13 presents the binomial directional test results using the OS-LRV estimators. The null is rejected in 11 (Panel A) and 10 (Panel B) out of 15 cases in the same currency-horizon combinations.

1.9.2 DMW and CW Tests

Let $\Sigma_{DMW^{(i)}}(M)$ and $\Sigma_{CW^{(i)}}(M)$ denote the OS-LRV estimators of the DMW-test statistic and CW-test statistic respectively. Using the OS-LRV estimator $\Sigma_{DMW^{(i)}}(M)$, we can also test the null hypothesis (32) using the following asymptotic theory

$$\Sigma_{DMW^{(i)}}^{-\frac{1}{2}}(M)\sqrt{n_1^{(i)}}DMW_{h,n}^{(i)} \rightarrow_d t(M). \tag{37}$$

Meanwhile, using the OS-LRV estimator $\Sigma_{CW^{(i)}}(M)$, we can test the null hypothesis (34) using the following asymptotic theory

$$\Sigma_{CW^{(i)}}^{-\frac{1}{2}}(M)\sqrt{n_1^{(i)}}CW_{h,n}^{(i)} \rightarrow_d t(M). \tag{38}$$

The test results are presented in Tables 14 and 15. When the size of the test is emphasized, we see that the predictability of exchange rate becomes less evident. However, our point forecasts perform better than the driftless random walk in 4 currencies (Australian dollar, Canadian dollar, Euro, Japanese Yen) over *6m*, *9m* and *12m* forecasting horizons.

and thus a t-value of 1.533 (1.440) corresponds to a 10% significance level.

1.10 Comparison with the Random Walk with Drift

The forecasting accuracy evaluation tests conducted in the previous sections are against the driftless random walk model. In this section, we compare our directional and point forecasts with these constructed from the random walk model with drift:

$$e_{t+1}^{(i)} = e_t^{(i)} + c^{(i)} + \varepsilon_{t+1}^{(i)}, \tag{39}$$

where $\{\varepsilon_t^{(i)}\}$ is a white noise process with mean zero and variance $\sigma_{i,\varepsilon}^2$, and $c^{(i)}$ is some finite constant. The motivation is that we want to evaluate the robustness of our empirical findings by considering different random walk models.

1.10.1 Directional Tests

When the null hypothesis is a random walk with drift, the optimal h-period ahead forecast of $e_{t+h}^{(i)}$ is $hc^{(i)} + e_t^{(i)}$ given the martingale assumption on $\{\varepsilon_t^{(i)}\}$. Because the term $hc^{(i)}$ is unknown and can be estimated by $\bar{e}_{n,h}^{(i)} = n_1^{-1} \sum_{t=m_0}^{n-h} (e_{t+h}^{(i)} - e_t^{(i)})$, the feasible point forecast from random walk with drift is $e_t^{(i)} + \bar{e}_{n,h}^{(i)}$. Our weighted directional forecast evaluation test is defined as

$$T_{c,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} (e_{t+h}^{(i)} - e_t^{(i)} - \bar{e}_{n,h}^{(i)}), \tag{40}$$

where $D_{t,h}^{(i)}$ is defined in (22).

The null hypothesis is that

$$E\left[D_{t,h}^{(i)} (e_{t+h}^{(i)} - e_t^{(i)} - hc^{(i)})\right] = 0 \tag{41}$$

for any pre-specified h and any t, which means that after the adjustment of deterministic trend, our directional forecasts are uncorrelated with future realized exchange rate changes. Let $V_{T_{c,n}^{(i)}}$ and $\Sigma_{T_{c,n}^{(i)}}(M)$ denote the consistent and OS-LRV estimators for $T_{c,n}^{(i)}$ respectively.[25] The inference of the null in (41) is based on the following asymptotic theory

$$V_{T_{c,n}^{(i)}}^{-\frac{1}{2}}\sqrt{n_1^{(i)}}T_{c,n}^{(i)} \rightarrow_d N(0,1) \text{ and } \Sigma_{T_{c,n}^{(i)}}^{-\frac{1}{2}}(M)\sqrt{n_1^{(i)}}T_{c,n}^{(i)} \rightarrow_d t(M). \tag{42}$$

Tables 16, 17 and 18 present the values of the $T_{c,n}^{(i)}$ statistic, and its t-values, for the 6 currencies and the 5 horizons we consider. Tables 16, 17 and 18 are the counterparts of Tables 4, 5 and 12, respectively, in the sense that they use the same variance estimators. The only difference is that they test the null that our directional forecast is uncorrelated with future realized exchange rate changes adjusted by the deterministic trend (i.e., $E[D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)} - hc^{(i)})] = 0$). The overall results confirm that our directional forecasts provide strong evidence of exchange rate predictability over the same forecasting horizons (i.e., *6m*, *9m* and *12m*) and they are robust to controlling for the deterministic trend.

Table 16 uses the naive variance estimator which does not control for the autocorrelation in $\{D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)} - hc^{(i)})\}_{t=m_0}^{n^{(i)}-h}$. As we can see, the results are very similar to those in Table C.3. Excluding the Swiss Franc, the null is rejected in 5 out of 6 currencies for most forecasting horizons. Table 17 provides the tests results with autocorrelation robust variance estimators. Similarly, strong evidence of exchange rate predictability can be found in 5 currencies over *6m*, *9m* and *12m* horizons. When we use Newey-West and Andrews LRV estimators in Table 17, the null is rejected in 14 (Panel A) and 12 (Panel B) out of 15 currency-horizon pairs over *6m*, *9m* and *12m* horizons excluding the Swiss Franc. Table 18 shows the results of using OS-LRV

[25]See Appendix 1.12.B for the construction of various LRV estimators.

estimators. Even in this case, the null is rejected in 11 (Panel A) and 10 (Panel B) out of the same pairs over the same forecasting horizons.

For the Binomial directional test, the test statistic becomes

$$T_{d,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} \widehat{R}_{t,h}^{(i)} - \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} \widehat{R}_{t,h}^{(i)}$$

where $\widehat{R}_{t,h}^{(i)} = 1$ if $e_{t+h}^{(i)} - e_t^{(i)} - h\overline{e}_n^{(i)} \geq 0$, and $\widehat{R}_{t,h}^{(i)} = -1$ otherwise, $\overline{e}_n^{(i)} = \frac{1}{n^{(i)}} \sum_{t=1}^{n^{(i)}} e_t^{(i)}$. Let $V_{T_{d,n}^{(i)}}$ and $\Sigma_{T_{d,n}^{(i)}}(M)$ denote the consistent LRV estimator and OS-LRV estimator for $T_{d,n}^{(i)}$ respectively.[26] Then we have

$$V_{T_{d,n}^{(i)}}^{-\frac{1}{2}} \sqrt{n_1^{(i)}} T_{d,n}^{(i)} \to_d N(0,1) \text{ and } \Sigma_{T_{d,n}^{(i)}}^{-\frac{1}{2}}(M) \sqrt{n_1^{(i)}} T_{d,n}^{(i)} \to_d t(M)$$

which is used in testing the null hypothesis

$$H_0\colon \; Cov(D_{t,h}^{(i)}, \overline{R}_{t,h}^{(i)}) = 0, \tag{43}$$

where $\overline{R}_{t,h}^{(i)} = 1$ if $e_{t+h}^{(i)} - e_t^{(i)} - hc^{(i)} \geq 0$, and $\overline{R}_{t,h} = -1$ otherwise.

Tables 19, 20 and 21 present the values of the $T_{d,n}^{*}$ statistic, and its t-values, for the 6 currencies and the 5 horizons we consider. They are analogous to Table 6, 7 and 13 respectively, in the sense that they use the same variance estimators. The only difference is that they test the null that our directional forecast is uncorrelated with the directional sign of future realized exchange rate changes adjusted by the deterministic trend (i.e., $Cov(D_{t,h}^{(i)}, \overline{R}_{t,h}^{(i)}) = 0$). The overall results confirm that the previous results remain valid even if the realized exchange rate trend is controlled in the determination of the sign of change. Furthermore, some evidence of predictability

[26] See Appendix 1.12.B for the construction of various LRV estimators.

is found for the Swiss Franc at *9m* and *12m* horizons. Table 19 uses the naive variance estimator which does not control for the autocorrelation. Including the Swiss Franc, the null is rejected in 24 out of 30 currency-horizon pairs. Table 20 and 21 provide the tests results with autocorrelation robust variance estimators. When we use Newey-West LRV estimator and Andrews LRV estimator in Table 20, the null is rejected in 16 (Panel A) and 14 (Panel B) out of 18 currency-horizon pairs over *6m*, *9m* and *12m* horizons including the Swiss Franc. In Table 21 where OS-LRV estimators are used, the null is rejected 10 (Panel A) and 12 (Panel B) out of 18 cases in the same currency-horizon combinations.

1.10.2 DMW test

In this subsection, we compare the point prediction accuracy of our model with the random walk with a drift term, i.e.

$$e_{t+h}^{(i)} = \gamma_h + e_t^{(i)} + \varepsilon_{t+h}^{(i)} \tag{44}$$

where $\gamma_h = ch$ is a finite constant. The h-period ahead prediction based on the random walk model is

$$\overline{e}_{t+h}^{(i)} = \widehat{\gamma}_{h,m_0} + e_t^{(i)} \text{ for } m_0 + 1 \leq t \leq n$$

where

$$\widehat{\gamma}_{h,m_0} = \frac{\sum_{i=1}^{6} \sum_{t=1}^{m_0-h} \left(e_{t+h}^{(i)} - e_t^{(i)} \right)}{6(m_0 - h)}.$$

Using the quadratic loss function, we can evaluate the accuracy of our point forecast by the statistic $DMW_{h,n}^{(i)}$, i.e.

$$DMW_{h,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=m_0+1}^{n^{(i)}-h} \left[\left(\widehat{\gamma}_{h,m_0} + e_t^{(i)} - e_{t+h}^{(i)} \right)^2 - \left(\widehat{\beta}_{h,m_0} X_{t,h}^{(i)} + e_t^{(i)} - e_{t+h}^{(i)} \right)^2 \right] \quad (45)$$

where $\widehat{\beta}_{h,m_0}$ is defined in (30).

From the definition of the $DMW_{h,n}^{(i)}$ statistic in (45), we can construct consistent LRV estimators and OS-LRV estimator.[27] Hence asymptotic theory similar to these stated in (33) and (37) can be used to test the null hypothesis (32).

Tables 22 and 23 contain the test statistics of $DMW_{h,n}^{(i)}$, and their p-values for different currencies i and different forecasting horizons h, for the 6 currencies and the 5 horizons. Table C.21 and C.22 test the same null that the MSPE of a random walk with a drift is equal to that of our point forecasts. Table 22 uses Newey-West LRV estimator and Andrews LRV estimator to construct the test statistics, while Table 23 uses OS-LRV estimators. The null is rejected if the test statistics of $DMW_{h,n}^{(i)}$ is significantly greater than zero. For the one-sided test we consider, a t-value greater than 1.282 implies a *10%* significance level in Table 22. The overall results show that our point forecasts significantly outperform the random walk with a drift in 5 currencies in most forecasting horizons. Interestingly, evidence of forecastability against random walk with a drift can be found for the Swiss Franc while the null is not rejected for the British pound.

Table 22 reports the test results using Newey-West LRV estimator (Panel A) and Andrews LRV estimator (Panel B) methods to control for auto-correlation. Our point forecasts significantly outperform the random walk with a drift in 25 (Panel A) and 22 (Panel B) out of 30 currency-horizon pairs. When we uses more robust OS-LRV

[27]See Appendix 1.12.B for the construction of various LRV estimators.

estimators to control for autocorrelation in Table 23, our point forecasts perform better than the random walk with a drift in 16 (Panel A) and 16 (Panel B) out of 30 currency-horizon pairs.

1.11 Conclusion

Exchange rates tend to exhibit swings of appreciation and depreciation. Although these swings can be identified in-sample, they have proven difficult to predict out-of-sample. In this paper, we forecast exchange rates by fitting an autoregressive Markov regime switching model to the speculators' position data in futures markets. The forecasting method we propose combines Engel and Hamilton's (1990) point that exchanges rate follow *long swings* with Evans and Lyons' (2004) finding that privately available information about market participants' order flow can predict exchange rates over the short-run.

While Evans and Lyons focus on weekly forecasting horizons and use private information, we concentrate on the *1*-to-*12* months horizons and use public information from the Commitment-of-Traders report. Interestingly, we find that over forecasting horizons ranging from 6 to 12 months, our forecasts outperform those from random walk models for most currencies, except the Swiss Franc. Our *directional forecasts* have a 60% average success ratio and most of our *point forecasts* have smaller mean-squared-prediction-errors than those implied by the driftless random walk. A battery of econometric tests indicate that, over 6-to-12 months horizons, the outperformance of these two types of forecasts is statistically significant at the 10% level for five out of the six most traded currency pairs vis-a-vis the US Dollar: Euro, Japanese Yen, British Pound, Australian Dollar, Canadian Dollar.

1.12 Appendix

1.12.A Equilibrium of the Dynamic Model (11)-(12)

In this appendix, we show that the dynamic model (11)-(12) has a convergent fixed point. From the equations in (7), we can write

$$\sigma_t^2 = \frac{\sigma_{t-1}^2 + \sigma_u^2}{\sigma_{t-1}^2 + \sigma_u^2 + \sigma_v^2}\sigma_v^2$$

which implies that

$$\begin{aligned}
\sigma_{t+1}^2 - \sigma_t^2 &= \left[\frac{\sigma_t^2 + \sigma_u^2}{\sigma_t^2 + \sigma_u^2 + \sigma_v^2} - \frac{\sigma_{t-1}^2 + \sigma_u^2}{\sigma_{t-1}^2 + \sigma_u^2 + \sigma_v^2}\right]\sigma_v^2 \\
&= \frac{(\sigma_t^2 - \sigma_{t-1}^2)\sigma_v^2}{(\sigma_t^2 + \sigma_u^2 + \sigma_v^2)(\sigma_{t-1}^2 + \sigma_u^2 + \sigma_v^2)}\sigma_v^2.
\end{aligned}$$

This means that if we have $\sigma_t^2 = \sigma_{t-1}^2$ for some $t = t^*$, then $\sigma_{t+1}^2 = \sigma_t^2$ for any $t \geq t^*$. Otherwise, we have

$$\frac{\sigma_{t+1}^2 - \sigma_t^2}{\sigma_t^2 - \sigma_{t-1}^2} = \frac{\sigma_v^4}{(\sigma_t^2 + \sigma_u^2 + \sigma_v^2)(\sigma_{t-1}^2 + \sigma_u^2 + \sigma_v^2)}$$

which together with

$$(\sigma_t^2 + \sigma_u^2 + \sigma_v^2)(\sigma_{t-1}^2 + \sigma_u^2 + \sigma_v^2) > \sigma_v^4$$

implies that

$$\frac{\sigma_{t+1}^2 - \sigma_t^2}{\sigma_t^2 - \sigma_{t-1}^2} < 1.$$

Hence, by the contraction mapping theorem we know that σ_t^2 converges to a unique equilibrium (fixed point). Moreover, by definition,

$$\theta_t = \frac{\sigma_{t-1}^2 + \sigma_\varepsilon^2}{\sigma_t^2 + \sigma_\varepsilon^2}(1 - k_t) = \frac{\sigma_{t-1}^2 + \sigma_\varepsilon^2}{\sigma_t^2 + \sigma_\varepsilon^2} \frac{\sigma_v^2}{\sigma_t^2 + \sigma_u^2 + \sigma_v^2}$$

which together with the convergence of σ_t^2 implies that the limit of θ_t is between 0 and $\sigma_v^2(\sigma_u^2 + \sigma_v^2)^{-1}$.

1.12.B Constructing the LRV Estimators

For any weakly dependent process $\{W_{t,n}\}_{t=1}^n$ with

$$E\left[W_{t,n}\right] = 0 \text{ for all } t \text{ and } n, \tag{46}$$

and finite positive LRV V_W, its sample autocovariance can be defined as

$$\Gamma_{W,n}(j) = \frac{1}{n-j} \sum_{t=1}^{n-j} \left(W_{t,n} - \overline{W}_n\right)\left(W_{t+j,n} - \overline{W}_n\right) \tag{47}$$

for $j = 0, \ldots, n-1$. It is clear that the sample autocovariance satisfies $\Gamma_{W,n}(-j) = \Gamma_{W,n}(j)$ for $j = 0, \ldots, n-1$. Note that the sample autocovariance is sample mean centered, which improves the power of the test of the hypothesis in (46).

The kernel based LRV estimator for $\{W_{t,n}\}_{t=1}^n$ is then defined as

$$V_{W,n} = \sum_{j=-n+1}^{n+1} K(j/M)\Gamma_{W,n}(j) \tag{48}$$

where $K(\cdot)$ is some kernel smoothing function with bandwidth M. Under some regularity conditions (see, e.g., Newey and West (1987), Andrews (1991) and Hansen

(1992)), there is

$$V_{W,n} \to_p V_W. \tag{49}$$

One key condition for the above consistency result is that M goes to infinity at certain rate. In finite samples, there are two different rules of selecting M: One is the rule proposed in Newey and West (1994) and the other is the parametric (AR(1)) approximation rule in Andrews (1991).

Let M to be any fixed even integer. For the weakly dependent process $\{W_{t,n}\}_{t=1}^{n}$, we define

$$\Lambda_{W,2m-1} = n_1^{-1/2} \sum_{t=1}^{n} \varphi_{2m-1}(\frac{t}{n}) W_{t,n} \text{ and } \Lambda_{W,2m} = n_1^{-1/2} \sum_{t=n_0}^{n-h} \varphi_{2m}(\frac{t}{n}) W_{t,n},$$

for $m = 1, ..., M/2$, where

$$\varphi_{2m-1}(x) = \sqrt{2}\cos(2m\pi x) \text{ and } \varphi_{2m}(x) = \sqrt{2}\sin(2m\pi x).$$

Then the OS-LRV estimator can be defined as

$$\Sigma_{W,n}(M) = \frac{1}{M} \sum_{m=1}^{M/2} \left(\Lambda_{W,2m-1}^2 + \Lambda_{W,2m}^2\right). \tag{50}$$

The functional central limit theorem and the continuous mapping theorem imply that

$$\Lambda_{W,k} = n_1^{-1/2} \sum_{t=1}^{n} \varphi_k(\frac{t}{n}) W_{t,n} \to_d V_W^{\frac{1}{2}} \int_0^1 \varphi_k(u) dB(u) \text{ for } k = 1, ..., M \tag{51}$$

where $B(\cdot)$ denotes the standard Brownian motion. By the orthogonality between

$\varphi_i(u)$ and $\varphi_j(u)$ with $i \neq j$ and the fact that

$$\int_0^1 \varphi_k(u) = 0 \text{ and } \int_0^1 \varphi_k^2(u) = 1 \text{ for } k = 1, ..., M,$$

we know that $B(u)$ and $\int_0^1 \varphi_k(u) dB(u)$ $(k = 1, ..., M)$ are independent standard normal random variables. This implies that

$$\Sigma_{W,n}^{-1/2}(M) n_1^{-1/2} \sum_{t=1}^{n} W_{t,n} \to_d \frac{B(1)}{\sqrt{\frac{1}{M} \sum_{k=1}^{M} \left[\int_0^1 \varphi_k(u) dB(u) \right]^2}} \sim t(M).$$

For more details on the theoretical properties of the OS-LRV estimators and the related auto-correlation robust inference, we refer to Phillips (2005) and Sun (2013).

The weak convergence $n_1^{-1/2} \sum_{t=1}^{n} W_{t,n} \to_d B(1)$ is derived under the assumption in (46). When this assumption does not hold, we will have $n_1^{-1/2} \sum_{t=1}^{n} W_{t,n} \to_p \infty$. The LRV estimator $V_{W,n}$ defined in (48) converges to the LRV of the process $\{W_{t,n} - E[W_{t,n}]\}_{t=1}^{n}$, regardless assumption in (46) holds or not. This implies that the test of the assumption in (46) based on the statistic

$$T_{V_W,n} = V_{W,n}^{-\frac{1}{2}} n_1^{-1/2} \sum_{t=1}^{n} W_{t,n}$$

has good power property because $V_{W,n}$ converges to a finite real constant V_W under both the null and alternative hypotheses. On the other hand, even when the assumption in (46) is invalid, we still have the weak convergence in (51), because

$$\begin{aligned}\Lambda_{W,k} &= n_1^{-1/2}\sum_{t=1}^{n}\varphi_k(\frac{t}{n})W_{t,n}\\ &= n_1^{-1/2}\sum_{t=1}^{n}\varphi_k(\frac{t}{n})\left(W_{t,n}-E\left[W_{t,n}\right]\right)+E\left[W_{t,n}\right]n_1^{-1/2}\sum_{t=1}^{n}\varphi_k(\frac{t}{n})\\ &= V_W^{\frac{1}{2}}\int_0^1\varphi_k(u)dB(u)+o_p(1)\end{aligned}$$

where the last equality is by the functional central limit theorem and the fact that $\int_0^1\varphi_k(u)=0$. This indicates that the power of the test statistic

$$T_{\Sigma_W,n}=\Sigma_{W,n}^{-\frac{1}{2}}n_1^{-1/2}\sum_{t=1}^{n}W_{t,n}$$

may not be as good as that of $T_{V_W,n}$, because the numerator $\Sigma_{W,n}^{\frac{1}{2}}$ in $T_{\Sigma_W,n}$ converges in distribution to a scaled Chi-square random variable

$$\frac{1}{M}\sum_{k=1}^{M}\left[\int_0^1\varphi_k(u)dB(u)\right]^2\sim\frac{\chi^2(M)}{M}$$

which is larger than any finite constant with non-zero probability.

In the rest of this appendix, we briefly describe how to construct the LRV estimators for the test statistics presented in the main text. The Newey-West and Andrews LRV estimators can be constructed using the formula in (47), and the OS-LRV estimator can be calculated using the expression in (50). Hence for each test statistic, we only need to define its corresponding "$W_{t,n}$" for the construction of LRV estimators, which are summarized in Table 1. For the ease of notation, we ignore the index "i" in each test statistic.

1.12.C Tables and Figures

Table 1: Construction of LRV Estimators

Test Statistic	$W_{t,n}$
$T_{a,n}$	$D_{t,h}(e_{t+h} - e_t)$
$T_{b,n}$	$(D_{t,h} - \overline{D}_{n,h})(R_{t,h} - \overline{R}_{n,h})$
$T_{c,n}$	$D_{t,h}(e_{t+h} - e_t - \overline{e}_{n,h})$
$T_{d,n}$	$(D_{t,h} - \overline{D}_{n,h})(\widehat{R}_{t,h} - \overline{\widehat{R}}_{n,h})$
$CM_{h,n}$	$2\widehat{\beta}_{h,n_0}X_{t,h}\,(e_{t+h} - e_t)$
$DMW_{h,n}^{dl}$	$(e_{t+h} - e_t)^2 - (e_{t+h} - e_t - X_{t,h}\widehat{\beta}_{h,m_0})^2$
$DMW_{h,n}^{d}$	$(e_{t+h} - e_t - \widehat{\gamma}_{h,m_0})^2 - (e_{t+h} - e_t - X_{t,h}\widehat{\beta}_{h,m_0})^2$

Notes: $DMW_{h,n}^{dl}$ and $DMW_{h,n}^{d}$ refer to the DMW test statistics against the random walk with and without the drift term respectively. Similarly, $CW_{h,n}^{dl}$ denotes the CW test statistic

Table 2: Forecast Success Ratio

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
EUR	46.4%	50.8%	69.0%	66.7%	67.0%
	(125)	(124)	(113)	(99)	(88)
JPY	56.3%	56.1%	60.9%	63.0%	58.6%
	(547)	(574)	(573)	(571)	(560)
GBP	50.6%	55.2%	58.4%	60.3%	60.1%
	(324)	(364)	(365)	(363)	(363)
AUD	58.0%	67.4%	72.4%	72.7%	77.7%
	(269)	(282)	(283)	(275)	(265)
CAD	54.9%	55.3%	56.0%	68.0%	66.8%
	(381)	(398)	(398)	(391)	(391)
CHF	52.1%	49.1%	51.4%	50.2%	50.1%
	(576)	(621)	(623)	(614)	(603)

Notes:

1. This table reports the forecast success ratio of our model. The forecast success ratio is defined as the number of successful depreciation or appreciation forecasts divided by the total number of depreciation and appreciation forecasts. The total number of appreciation and depreciation forecasts is in parentheses. When we predict no change ($D_{t,h} = 0$), we do not count it in the calculation of forecast success ratio.

2. Our sample starts on 10/02/1992 for all currencies except the Euro, which starts on 01/08/1999. Our sample ends on 02/08/2013 for all currencies.

3. For each currency, our directional forecasts start the week after the first estimation of the MSM, and end h weeks prior to the end of the COT sample. Thus, our directional forecasts start on 01/20/1995 for AUD and GBP; 09/01/1994 for CAD; 04/15/1994 for CHF and JPY; and 05/04/2001 for the Euro.

4. The dates of the last forecasts are 01/18/2013 for $h = 1m$, 11/16/2012 for $h = 3m$, 08/24/2012 for $h = 6m$, 05/25/2012 for $h = 9m$, and 03/01/2012 for $h = 12m$.

Table 3: Forecast Success Ratio: Two subperiods

Currency	Forecasting Horizon (h) 1m	3m	6m	9m	12m
	First half period: 04/15/1994 - 11/29/2002				
EUR	28.6%	57.1%	71.4%	28.6%	57.1%
	(7)	(7)	(7)	(7)	(7)
JPY	59.5%	57.4%	64.4%	66.0%	60.4%
	(232)	(242)	(247)	(247)	(240)
GBP	51.8%	54.5%	58.3%	63.1%	63.5%
	(218)	(244)	(242)	(241)	(241)
AUD	60.0%	80.0%	90.0%	87.5%	75.0%
	(10)	(10)	(10)	(8)	(4)
CAD	47.2%	45.2%	30.8%	33.8%	28.8%
	(89)	(84)	(78)	(77)	(66)
CHF	54.4%	50.2%	48.8%	47.7%	52.7%
	(307)	(307)	(297)	(283)	(273)
	Second half period: 12/06/2002 - 02/08/2013				
EUR	47.5%	50.4%	68.9%	69.6%	67.9%
	(118)	(117)	(106)	(92)	(81)
JPY	54.0%	55.1%	58.3%	60.8%	57.2%
	(315)	(332)	(326)	(324)	(320)
GBP	48.1%	56.7%	58.5%	54.9%	53.3%
	(106)	(120)	(123)	(122)	(122)
AUD	57.9%	66.9%	71.8%	72.3%	77.8%
	(259)	(272)	(273)	(267)	(261)
CAD	57.2%	58.0%	62.2%	76.4%	74.5%
	(292)	(314)	(320)	(314)	(325)
CHF	49.4%	48.1%	53.7%	52.3%	47.9%
	(269)	(314)	(326)	(331)	(330)

Notes:

1. The information on our directional forecasts is described in the notes to Table 2.

Table 4: Directional test weighted by the magnitude of exchange rate changes: No control for autocorrelation

This table tests the null that our directional forecasts are uncorrelated with future exchange rate changes:

$$E[D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)})] = 0$$

For each forecasting horizon, the following statistics is reported: $T_{a,n}^{(i)} = \frac{\sum_{t=n_0^{(i)}}^{n^{(i)}-h} D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)})}{n_1^{(i)}}$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
EUR	−0.0003	0.0012*	0.0034***	0.0051***	0.0044***
	(−0.6219)	(1.3942)	(3.0859)	(3.5578)	(2.9045)
JPY	0.0020***	0.0024**	0.0071***	0.0115***	0.0097***
	(2.5682)	(1.7542)	(3.9060)	(5.4813)	(3.7022)
GBP	0.0002	0.0023***	0.0040***	0.0057***	0.0061***
	(0.3838)	(3.3596)	(4.6674)	(5.5837)	(4.4786)
AUD	0.0018***	0.0038***	0.0105***	0.0163***	0.0187***
	(2.5797)	(3.1934)	(6.0708)	(8.2381)	(7.9564)
CAD	0.0008**	0.0030***	0.0037***	0.0109***	0.0156***
	(1.9240)	(3.8377)	(3.2232)	(8.1831)	(10.1058)
CHF	0.0014**	−0.0012	−0.0023	0.0016	−0.0034
	(1.9902)	(−0.8921)	(−1.3107)	(0.7725)	(−1.3669)

Notes:

1. This table presents the test results without controlling for autocorrelation induced by overlapping observations in the forecasts.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 5: Directional test weighted by the magnitude of exchange rate changes: Control for autocorrelation

This table tests the null that our directional forecasts are uncorrelated with future exchange rate changes:

$$E[D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)})] = 0$$

For each forecasting horizon, the following statistics is reported: $T_{a,n}^{(i)} = \frac{\sum_{t=n_0^{(i)}}^{n^{(i)}-h} D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)})}{n_1^{(i)}}$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
			Panel A: Newey-West		
EUR	−0.0003	0.0012	0.0034**	0.0051***	0.0044**
	(−0.4164)	(0.7794)	(1.8532)	(2.5681)	(2.3198)
JPY	0.0020**	0.0024	0.0071**	0.0115***	0.0097*
	(1.7643)	(0.7881)	(1.6739)	(2.3762)	(1.5367)
GBP	0.0002	0.0023**	0.0040**	0.0057***	0.0061**
	(0.2469)	(1.6863)	(2.1486)	(2.5339)	(2.0537)
AUD	0.0018**	0.0038*	0.0105***	0.0163***	0.0187***
	(1.7390)	(1.5055)	(2.7428)	(3.5925)	(3.3212)
CAD	0.0008	0.0030**	0.0037*	0.0109***	0.0156***
	(1.2193)	(1.8026)	(1.4773)	(4.0637)	(4.4803)
CHF	0.0014	−0.0012	−0.0023	0.0016	−0.0034
	(1.1540)	(−0.4040)	(−0.5656)	(0.3277)	(−0.5672)
			Panel B: Andrews		
EUR	−0.0003	0.0012	0.0034**	0.0051***	0.0044***
	(−0.4169)	(0.6852)	(1.6869)	(2.5681)	(2.3343)
JPY	0.0020**	0.0024	0.0071	0.0115*	0.0097
	(1.6543)	(0.6078)	(1.1873)	(1.6196)	(0.9933)
GBP	0.0002	0.0023*	0.0040*	0.0057**	0.0061*
	(0.2412)	(1.4758)	(1.6431)	(1.8056)	(1.5694)
AUD	0.0018**	0.0038	0.0105**	0.0163***	0.0187**
	(1.7054)	(1.2678)	(1.9416)	(2.4115)	(2.1030)
CAD	0.0008	0.0030***	0.0037	0.0109***	0.0156***
	(1.1910)	(1.5088)	(1.1638)	(3.1393)	(3.0347)
CHF	0.0014*	−0.0012	−0.0023	0.0016	−0.0034
	(1.3752)	(−0.3916)	(−0.4262)	(0.2421)	(−0.4002)

Notes:

1. Panel A and B report the test results using Newey-West and Andrews LRV estimators to control for auto-correlation, respectively.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 6: Binomial directional test: No control for autocorrelation

This table tests the null that our directional forecasts are uncorrelated with the future direction of the exchange rate:

$$Cov(D_{t,h}^{(i)}, R_{t,h}^{(i)}) = 0$$

For each forecasting horizon, the following statistics is reported:

$$T_{b,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} R_{t,h}^{(i)} - [\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)}][\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} R_{t,h}^{(i)}]$$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
EUR	-0.0033	0.0284*	0.0963***	0.0775***	0.0658***
	(-0.1780)	(1.5357)	(5.4232)	(4.5399)	(4.0015)
JPY	0.0684***	0.0722***	0.1310***	0.1606***	0.1082***
	(2.8749)	(2.9366)	(5.3150)	(6.4845)	(4.2999)
GBP	0.0017	0.0405**	0.0597***	0.0763***	0.0774***
	(0.0868)	(1.9751)	(2.8837)	(3.6518)	(3.6553)
AUD	0.0291*	0.0695***	0.0966***	0.0896***	0.1102***
	(1.6727)	(3.9220)	(5.4394)	(5.0463)	(6.3396)
CAD	0.0258	0.0334*	0.0252	0.1061***	0.1028***
	(1.2679)	(1.5940)	(1.1898)	(5.1046)	(4.8624)
CHF	0.0269	-0.0011	0.0319	0.0295	0.0339
	(1.0987)	(-0.0421)	(1.2258)	(1.1249)	(1.2860)

Notes:

1. This table presents the test results without controlling for autocorrelation induced by overlapping observations in the forecasts.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 7: Binomial directional test: Control for autocorrelation

This table tests the null that our directional forecasts are uncorrelated with the future direction of the exchange rate:

$$Cov(D_{t,h}^{(i)}, R_{t,h}^{(i)}) = 0$$

For each forecasting horizon, the following statistics is reported:

$$T_{b,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} R_{t,h}^{(i)} - [\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)}][\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} R_{t,h}^{(i)}]$$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
	Panel A: Newey-West				
EUR	-0.0033	0.0284	0.0963***	0.0775***	0.0658***
	(-0.1290)	(0.8961)	(2.9207)	(2.9415)	(2.7704)
JPY	0.0684**	0.0722*	0.1310***	0.1606***	0.1082**
	(2.0627)	(1.5776)	(2.5936)	(2.9155)	(1.8589)
GBP	0.0017	0.0405	0.0597*	0.0763**	0.0774**
	(0.0647)	(1.0472)	(1.5385)	(1.7746)	(1.7234)
AUD	0.0291	0.0695**	0.0966***	0.0896***	0.1102***
	(1.0783)	(2.0978)	(2.6608)	(2.4684)	(2.9635)
CAD	0.0258	0.0334	0.0252	0.1061**	0.1028**
	(0.8769)	(0.8232)	(0.5558)	(2.3356)	(2.2760)
CHF	0.0269	-0.0011	0.0319	0.0295	0.0339
	(0.7460)	(-0.0221)	(0.5656)	(0.5017)	(0.5646)
	Panel B: Andrews				
EUR	-0.0033	0.0284	0.0963***	0.0775***	0.0658***
	(-0.1268)	(0.8006)	(2.4029)	(2.8796)	(2.7278)
JPY	0.0684**	0.0722*	0.1310**	0.1606**	0.1082
	(2.0450)	(1.3684)	(1.9976)	(2.0856)	(1.2871)
GBP	0.0017	0.0405	0.0597*	0.0763*	0.0774*
	(0.0638)	(0.9460)	(1.3360)	(1.4015)	(1.3526)
AUD	0.0291	0.0695**	0.0966**	0.0896**	0.1102**
	(1.0907)	(1.8671)	(2.0918)	(1.9158)	(2.0373)
CAD	0.0258	0.0334	0.0252	0.1061**	0.1028**
	(0.8663)	(0.7230)	(0.4473)	(1.7898)	(1.6907)
CHF	0.0269	-0.0011	0.0319	0.0295	0.0339
	(0.7808)	(-0.0219)	(0.4419)	(0.3735)	(0.4039)

Notes:

1. Panel A and B report the test results using Newey-West and Andrews LRV estimators to control for autocorrelation, respectively.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 8: DMW test: No control for autocorrelation

This table presents the results of DMW test of the null of equal MSPEs between random walk without a drift and our forecasts.
For each forecasting horizon, the following statistics is reported:

$$\frac{\sqrt{n_1^{(i)}}DMW_{h,n}^{(i)}}{\sqrt{V_{DMW_{h,n}^{(i)}}}}$$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
EUR	−0.444	2.110**	2.940***	3.918***	3.239***
	(0.671)	(0.017)	(0.002)	(0.000)	(0.001)
JPY	1.225	2.268**	4.811***	5.284***	3.443***
	(0.110)	(0.012)	(0.000)	(0.000)	(0.000)
GBP	0.004	2.979***	4.864***	4.667***	2.413***
	(0.498)	(0.001)	(0.000)	(0.000)	(0.008)
AUD	2.388***	4.079***	6.206***	8.863***	8.090***
	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)
CAD	1.055	3.642***	3.994***	7.854***	10.683***
	(0.146)	(0.000)	(0.000)	(0.000)	(0.000)
CHF	−0.171	−1.473	−2.905	−1.923	−2.535
	(0.568)	(0.930)	(0.998)	(0.973)	(0.994)

Notes:

1. This table presents the test results without controlling for auto-correlation induced by overlapping observations.

2. p-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively. Positive and statistically significant test statistics indicate that our forecasts outperform the driftless random walk in forecasting the future exchange rate.

3. The first point forecast starts on 04/09/1999 for five currencies excluding the Euro. For the Euro it starts on 05/04/2001. The dates of the last point forecasts are 01/18/2013 for $h = 1m$, 11/16/2012 for $h = 3m$, 08/24/2012 for $h = 6m$, 05/25/2012 for $h = 9m$, and 03/01/2012 for $h = 12m$.

Table 9: DMW test: Control for autocorrelation

This table presents the results of DMW test of the null of equal MSPEs between random walk without a drift and our forecasts.
For each forecasting horizon, the following statistics is reported:

$$\frac{\sqrt{n_1^{(i)}}DMW_{h,n}^{(i)}}{\sqrt{V_{DMW_{h,n}^{(i)}}}}$$

Currency	Forecasting Horizon (h) 1m	3m	6m	9m	12m
	Panel A: Newey-West				
EUR	−0.287	1.111	1.614*	2.541***	2.384***
	(0.613)	(0.133)	(0.053)	(0.006)	(0.009)
JPY	0.770	1.057	2.118**	2.261**	1.438*
	(0.221)	(0.145)	(0.017)	(0.012)	(0.075)
GBP	0.003	1.554*	2.251**	2.065**	1.089
	(0.499)	(0.060)	(0.012)	(0.019)	(0.138)
AUD	1.622*	1.964**	2.995***	4.020***	3.509***
	(0.052)	(0.025)	(0.001)	(0.000)	(0.000)
CAD	0.643	1.675**	1.819**	3.630***	4.787***
	(0.260)	(0.047)	(0.034)	(0.000)	(0.000)
CHF	−0.102	−0.678	−1.260	−0.829	−1.060
	(0.541)	(0.751)	(0.896)	(0.797)	(0.856)
	Panel B: Andrews				
EUR	−0.286	0.979	1.356*	2.473***	2.384***
	(0.613)	(0.164)	(0.088)	(0.007)	(0.009)
JPY	0.685	0.793	1.408*	1.337*	0.794
	(0.247)	(0.214)	(0.080)	(0.091)	(0.214)
GBP	0.003	1.249	1.548*	1.286*	0.728
	(0.499)	(0.106)	(0.061)	(0.099)	(0.233)
AUD	1.586*	1.596*	2.038**	2.531***	2.044**
	(0.056)	(0.055)	(0.021)	(0.006)	(0.020)
CAD	0.650	1.366*	1.370*	2.524***	2.917***
	(0.258)	(0.086)	(0.085)	(0.006)	(0.002)
CHF	−0.123	−0.693	−0.845	−0.549	−0.673
	(0.549)	(0.756)	(0.801)	(0.708)	(0.750)

Notes:

1. Panel A and B report the test results using the Newey-West and Andrews LRV estimators to control for autocorrelation, respectively.

2. p-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our point forecasts is described in the notes to Table 8.

Table 10: CW test: No control for autocorrelation

This table presents the results of Clark and West (2006) test of the null of equal predictive power under the martingale assumption.

For each forecasting horizon, the following statistics is reported:

$$\frac{\sqrt{n_1^{(i)}}CW_{h,n}^{(i)}}{\sqrt{V_{CW_{h,n}^{(i)}}}}$$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
EUR	-0.002	2.226**	3.415***	4.333***	3.503***
	(0.501)	(0.013)	(0.000)	(0.000)	(0.000)
JPY	1.949**	2.483***	5.732***	6.336***	4.057***
	(0.026)	(0.007)	(0.000)	(0.000)	(0.000)
GBP	0.580	3.156***	5.534***	5.501***	2.899***
	(0.281)	(0.001)	(0.000)	(0.000)	(0.002)
AUD	2.782***	4.210***	6.715***	9.430***	8.416***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
CAD	1.857**	3.862***	4.835***	8.929***	11.312***
	(0.032)	(0.000)	(0.000)	(0.000)	(0.000)
CHF	0.547	-1.268	-2.043	-0.921	-1.979
	(0.292)	(0.898)	(0.979)	(0.822)	(0.976)

Notes:

1.This table presents the test results without controlling for auto-correlation induced by overlapping observations.

2. p-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively. Positive and statistically significant test statistics indicate that our forecasts have predictive power over the future exchange rate movement.

3.The information on our point forecasts is described in the notes to Table 8.

Table 11: CW test: Control for autocorrelation

This table presents the results of Clark and West (2006) test of the null of equal predictive power under the martingale assumption.

For each forecasting horizon, the following statistics is reported:

$$\frac{\sqrt{n_1^{(i)}}CW_{h,n}^{(i)}}{\sqrt{V_{CW_{h,n}^{(i)}}}}$$

Currency	Forecasting Horizon (h) 1m	3m	6m	9m	12m
	Panel A: Newy-West				
EUR	−0.001	1.173	1.872**	2.767***	2.547***
	(0.500)	(0.120)	(0.031)	(0.003)	(0.005)
JPY	1.221	1.157	2.521***	2.713***	1.696**
	(0.111)	(0.124)	(0.006)	(0.003)	(0.045)
GBP	0.378	1.643**	2.540***	2.420***	1.305*
	(0.353)	(0.050)	(0.006)	(0.008)	(0.096)
AUD	1.884**	2.028**	3.234***	4.267***	3.650***
	(0.030)	(0.021)	(0.001)	(0.000)	(0.000)
CAD	1.126	1.777**	2.200**	4.113***	5.059***
	(0.130)	(0.038)	(0.014)	(0.000)	(0.000)
CHF	0.327	−0.584	−0.886	−0.397	−0.828
	(0.372)	(0.720)	(0.812)	(0.654)	(0.796)
	Panel B: Andrews				
EUR	−0.001	1.033	1.568*	2.647***	2.516***
	(0.500)	(0.151)	(0.058)	(0.004)	(0.006)
JPY	1.084	0.867	1.663**	1.596*	0.935
	(0.139)	(0.193)	(0.048)	(0.055)	(0.175)
GBP	0.380	1.314*	1.711**	1.480*	0.870
	(0.352)	(0.094)	(0.044)	(0.069)	(0.192)
AUD	1.838**	1.644**	2.191**	2.647***	2.114**
	(0.033)	(0.050)	(0.014)	(0.004)	(0.017)
CAD	1.121	1.445*	1.646**	2.821***	3.043***
	(0.131)	(0.074)	(0.050)	(0.002)	(0.001)
CHF	0.390	−0.597	−0.592	−0.261	−0.520
	(0.348)	(0.725)	(0.723)	(0.603)	(0.699)

Notes:

1.Panel A and B report the test results using Newey-West and Andrews LRV estimators to control for auto-correlation.

2.p-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3.The information on our point forecasts is described in the notes to Table 8

Table 12: Directional test weighted by the magnitude of exchange rate changes: OS LRV estimators

This table tests the null that our directional forecasts are uncorrelated with future exchange rate changes:

$$E[D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)})] = 0$$

For each forecasting horizon, the following statistics is reported: $T_{a,n}^{(i)} = \frac{\sum_{t=n_0^{(i)}}^{n^{(i)}-h} D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)})}{n_1^{(i)}}$

Currency	Forecasting Horizon (h) 1m	3m	6m	9m	12m
	Panel A: $M = 4$				
EUR	−0.0003	0.0012	0.0034*	0.0051**	0.0044*
	(−0.9234)	(1.1511)	(1.9584)	(2.6264)	(2.1776)
JPY	0.0020**	0.0024	0.0071**	0.0115**	0.0097
	(2.4021)	(1.3343)	(2.9734)	(2.1805)	(0.9934)
GBP	0.0002	0.0023*	0.0040**	0.0057**	0.0061*
	(0.3178)	(2.0673)	(3.2564)	(2.7072)	(1.6275)
AUD	0.0018*	0.0038*	0.0105*	0.0163*	0.0187*
	(1.6570)	(1.7805)	(1.5664)	(1.5347)	(1.7342)
CAD	0.0008	0.0030	0.0037	0.0109	0.0156
	(0.9414)	(1.2225)	(1.0489)	(1.5176)	(1.4232)
CHF	0.0014*	−0.0012	−0.0023	0.0016	−0.0034
	(1.9156)	(−0.4193)	(−0.3399)	(0.1751)	(−0.3799)
	Panel A: $M = 6$				
EUR	−0.0003	0.0012	0.0034*	0.0051*	0.0044*
	(−1.0177)	(0.9696)	(1.4493)	(1.8687)	(1.8305)
JPY	0.0020*	0.0024	0.0071**	0.0115**	0.0097
	(1.6240)	(0.7347)	(1.9800)	(2.3194)	(1.0844)
GBP	0.0002	0.0023**	0.0040**	0.0057**	0.0061*
	(0.3497)	(2.4807)	(2.6964)	(2.0323)	(1.4958)
AUD	0.0018*	0.0038*	0.0105*	0.0163*	0.0187*
	(1.7253)	(1.5130)	(1.7868)	(1.7633)	(1.7429)
CAD	0.0008	0.0030	0.0037	0.0109*	0.0156*
	(0.9913)	(1.2183)	(1.0057)	(1.8129)	(1.7429)
CHF	0.0014**	−0.0012	−0.0023	0.0016	−0.0034
	(1.9578)	(−0.4732)	(−0.4049)	(0.2081)	(−0.3842)

Notes:

1. Panel A and B report the test results using the orthonormal series long-run variance estimators of $T_{a,n}$. Panel A and B use 4 and 6 for smoothing parameter (M), respectively.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from student t-distributions with degree of freedom 4 and 6 distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 13: Binomial directional test: OS LRV estimators

This table tests the null that our directional forecasts are uncorrelated with the future direction of the exchange rate:

$$Cov(D_{t,h}^{(i)}, R_{t,h}^{(i)}) = 0$$

For each forecasting horizon, the following statistics is reported:

$$T_{b,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} R_{t,h}^{(i)} - [\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)}][\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} R_{t,h}^{(i)}]$$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
			Panel A: $M = 4$		
EUR	-0.0033	0.0284*	0.0963	0.0775*	0.0658*
	(-0.3407)	(1.7169)	(1.4018)	(1.9911)	(1.9806)
JPY	0.0684*	0.0722*	0.1310***	0.1606***	0.1082*
	(2.2768)	(2.0478)	(5.0622)	(6.2087)	(1.7975)
GBP	0.0017	0.0405**	0.0597*	0.0763	0.0774*
	(0.0715)	(2.4183)	(2.0539)	(1.5299)	(1.5617)
AUD	0.0291	0.0695***	0.0966**	0.0896*	0.1102**
	(1.4453)	(4.0074)	(2.1648)	(1.7510)	(2.5816)
CAD	0.0258	0.0334	0.0252	0.1061**	0.1028
	(1.2145)	(1.4375)	(1.4088)	(2.2646)	(1.2906)
CHF	0.0269	-0.0011	0.0319	0.0295	0.0339
	(1.5000)	(-0.0226)	(0.3497)	(0.2727)	(0.3801)
			Panel A: $M = 6$		
EUR	-0.0033	0.0284	0.0963*	0.0775**	0.0658**
	(-0.1686)	(1.2583)	(1.7394)	(2.1653)	(2.0292)
JPY	0.0684**	0.0722*	0.1310***	0.1606***	0.1082*
	(2.0920)	(1.6934)	(4.3504)	(5.8846)	(1.6948)
GBP	0.0017	0.0405**	0.0597*	0.0763*	0.0774*
	(0.0722)	(2.9275)	(1.5969)	(1.6035)	(1.7966)
AUD	0.0291	0.0695*	0.0966*	0.0896	0.1102
	(1.0025)	(1.6248)	(1.5286)	(1.3848)	(1.3692)
CAD	0.0258	0.0334	0.0252	0.1061	0.1028
	(0.7774)	(0.9083)	(0.3803)	(1.0474)	(0.9157)
CHF	0.0269	-0.0011	0.0319	0.0295	0.0339
	(1.2007)	(-0.0215)	(0.3846)	(0.2890)	(0.3002)

Notes:

1. Panel A and B report the test results using the orthonormal series long-run variance estimators of $T_{b,n}$. Panel A and B use 4 and 6 for smoothing parameter (M), respectively.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from student t-distributions with degree of freedom 4 and 6 distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts described in the notes to Table 2

Table 14: DMW test: OS LRV estimators

This table presents the results of DMW test of the null of equal MSPEs between random walk without a drift and our forecasts.
For each forecasting horizon, the following statistics is reported:

$$\frac{\sqrt{n_1^{(i)}}DMW_{h,n}^{(i)}}{\sqrt{V_{DMW_{h,n}^{(i)}}}}$$

Currency	Forecasting Horizon (h)				
	$1m$	$3m$	$6m$	$9m$	$12m$
			Panel A: $M = 4$		
EUR	−0.619	2.297**	2.219**	2.187**	1.481
	(0.715)	(0.021)	(0.047)	(0.047)	(0.106)
JPY	0.642	0.965	1.553*	1.277	0.7711
	(0.278)	(0.195)	(0.095)	(0.135)	(0.258)
GBP	0.003	0.993	1.296	0.954	0.519
	(0.499)	(0.189)	(0.132)	(0.197)	(0.316)
AUD	1.474	1.761*	1.710*	1.773*	1.771*
	(0.107)	(0.077)	(0.081)	(0.075)	(0.076)
CAD	0.591	1.084	1.292	1.515	1.558*
	(0.293)	(0.170)	(0.133)	(0.102)	(0.097)
CHF	−0.180	−0.816	−0.840	−0.453	−0.681
	(0.499)	(0.189)	(0.132)	(0.197)	(0.316)
			Panel A: $M = 6$		
EUR	−0.621	1.577*	1.563*	1.938**	1.624*
	(0.721)	(0.083)	(0.084)	(0.050)	(0.078)
JPY	0.752	0.723	1.261	1.302	0.762
	(0.240)	(0.248)	(0.127)	(0.120)	(0.238)
GBP	0.003	0.985	1.295	1.039	0.625
	(0.499)	(0.181)	(0.121)	(0.169)	(0.277)
AUD	1.760*	1.857*	1.767*	1.840*	1.544*
	(0.064)	(0.056)	(0.064)	(0.058)	(0.087)
CAD	0.706	1.263	1.486*	1.815*	1.899*
	(0.253)	(0.127)	(0.094)	(0.060)	(0.053)
CHF	−0.169	−0.523	−0.560	−0.351	−0.485
	(0.564)	(0.690)	(0.702)	(0.631)	(0.678)

Notes:

1. Panel A and B report the test results using the orthonormal series based long-run variance estimators of $\sqrt{n_1^{(i)}}DMW_{h,n}^{(i)}$. Panel A and B use 4 and 6 for smoothing parameter (M), respectively.

2. p-values are in parentheses. We use the test as an one-sided test. Critical values from student t-distributions with degree of freedom 4 and 6 distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our point forecasts is described in the notes to Table 8.

Table 15: CW test: OS LRV estimators

This table presents the results of Clark and West (2006) test of the null of equal predictive power under the martingale assumption.

For each forecasting horizon, the following statistics is reported:

$$\frac{\sqrt{n_1^{(i)}}CW_{h,n}^{(i)}}{\sqrt{V_{CW_{h,n}^{(i)}}}}$$

Currency	Forecasting Horizon (h) 1m	3m	6m	9m	12m
	Panel A: $M = 4$				
EUR	−0.003	2.917**	2.139**	2.125*	1.533*
	(0.501)	(0.022)	(0.050)	(0.050)	(0.091)
JPY	1.025	1.062	1.806*	1.509	0.831
	(0.182)	(0.174)	(0.073)	(0.103)	(0.226)
GBP	0.424	1.040	1.424	1.094	0.611
	(0.347)	(0.179)	(0.114)	(0.168)	(0.287)
AUD	1.649*	1.790*	1.781*	1.838*	1.809*
	(0.087)	(0.074)	(0.075)	(0.070)	(0.072)
CAD	0.944	1.130	1.439	1.613*	1.612*
	(0.148)	(0.117)	(0.071)	(0.050)	(0.048)
CHF	0.520	−0.690	−0.564	−0.206	−0.514
	(0.315)	(0.736)	(0.699)	(0.576)	(0.683)
	Panel A: $M = 6$				
EUR	−0.003	1.611*	1.617*	1.909*	1.659*
	(0.501)	(0.079)	(0.078)	(0.052)	(0.074)
JPY	1.203	0.793	1.498*	1.562*	0.897
	(0.137)	(0.229)	(0.092)	(0.085)	(0.202)
GBP	0.392	1.027	1.400	1.170	0.730
	(0.354)	(0.172)	(0.106)	(0.143)	(0.246)
AUD	1.976**	1.890*	1.848*	1.914*	1.587*
	(0.048)	(0.054)	(0.057)	(0.052)	(0.082)
CAD	1.143	1.323	1.687*	1.949**	1.967**
	(0.148)	(0.117)	(0.071)	(0.050)	(0.048)
CHF	0.523	−0.450	−0.391	−0.166	−0.377
	(0.310)	(0.666)	(0.645)	(0.563)	(0.640)

Notes:

1. Panel A and B report the test results using the orthonormal series based long-run variance estimators to control for auto-correlation. Panel A and B use 4 and 6 for smoothing parameter (M), respectively .

2. p-values are in parentheses. We use the test as an one-sided test. Critical values from student t-distributions with degree of freedom 4 and 6 distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our point forecasts is described in the notes to Table 8.

Table 16: Directional test weighted by the magnitude of exchange rate changes against random walk with a drift: No control for autocorrelation

This table test the null that our directional forecasts are uncorrelated with future exchange rate changes controlling for the exchange rate trend in the sample period:

$$E[D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)} - \bar{e}_{n,h}^{(i)})] = 0$$

For each forecasting horizon, the following statistics is reported: $T_{c,n}^{(i)} = \frac{\sum_{t=n_0^{(i)}}^{n^{(i)}-h} D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)} - \bar{e}_{n,h}^{(i)})}{n_1^{(i)}}$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
EUR	-0.0001	0.0021***	0.0048***	0.0066***	0.0057***
	(-0.0429)	(2.5462)	(4.2382)	(4.3505)	(3.4551)
JPY	0.0020***	0.0024**	0.0072***	0.0119***	0.0102***
	(2.5704)	(1.7512)	(3.9744)	(5.6914)	(3.9309)
GBP	0.0002	0.0023***	0.0040***	0.0057***	0.0061***
	(0.3834)	(3.3570)	(4.6584)	(5.5802)	(4.4582)
AUD	0.0015**	0.0025**	0.0079***	0.0124***	0.0138***
	(2.1346)	(2.1259)	(4.6693)	(6.6265)	(6.1817)
CAD	0.0006*	0.0019***	0.0013	0.0070***	0.0105***
	(1.3401)	(2.5669)	(1.2412)	(5.6891)	(7.6087)
CHF	0.0017***	-0.0003	-0.0004	0.0042**	-0.0002
	(2.3506)	(-0.2142)	(-0.2483)	(2.1188)	(-0.0969)

Notes:

1. This table presents the test results without controlling for auto-correlation induced by overlapping observations in the forecasts.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 17: Directional test weighted by the magnitude of exchange rate changes against random walk with a drift: Control for autocorrelation

This table test the null that our directional forecasts are uncorrelated with future exchange rate changes controlling for the exchange rate trend in the sample period:

$$E[D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)} - \bar{e}_{n,h}^{(i)})] = 0$$

For each forecasting horizon, the following statistics is reported: $T_{c,n}^{(i)} = \frac{\sum_{t=n_0^{(i)}}^{n^{(i)}-h} D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)} - \bar{e}_{n,h}^{(i)})}{n_1^{(i)}}$

Currency	Forecasting Horizon (h)				
	$1m$	$3m$	$6m$	$9m$	$12m$
	Panel A: Newey-West				
EUR	−0.0001	0.0021*	0.0048***	0.0066***	0.0057***
	(−0.0282)	(1.3678)	(2.4090)	(2.8658)	(2.5081)
JPY	0.0020**	0.0024	0.0072**	0.0119**	0.0102*
	(1.7655)	(0.7862)	(1.6993)	(2.4438)	(1.6185)
GBP	0.0002	0.0023**	0.0040**	0.0057***	0.0061**
	(0.2467)	(1.6851)	(2.1444)	(2.5322)	(2.0439)
AUD	0.0015*	0.0025	0.0079**	0.0124***	0.0138***
	(1.4507)	(1.0056)	(2.1199)	(2.9050)	(2.5781)
CAD	0.0006	0.0019	0.0013	0.0070**	0.0105**
	(0.8580)	(1.2125)	(0.5694)	(2.8479)	(3.3878)
CHF	0.0017*	−0.0003	−0.0004	0.0042	−0.0002
	(1.3642)	(−0.0976)	(−0.1086)	(0.9151)	(−0.0409)
	Panel B: Andrews				
EUR	−0.0001	0.0021	0.0048**	0.0066***	0.0057***
	(−0.0279)	(1.1674)	(2.0876)	(2.7570)	(2.4876)
JPY	0.0020**	0.0024	0.0072	0.0119*	0.0102
	(1.6535)	(0.6035)	(1.1957)	(1.6374)	(1.0312)
GBP	0.0002	0.0023*	0.0040*	0.0057**	0.0061*
	(0.2410)	(1.4749)	(1.6394)	(1.8042)	(1.5611)
AUD	0.0015*	0.0025	0.0079*	0.0124**	0.0138**
	(1.4267)	(0.8603)	(1.5176)	(2.0004)	(1.6816)
CAD	0.0006	0.0019	0.0013	0.0070**	0.0105***
	(0.8490)	(1.0341)	(0.4522)	(2.2548)	(2.3498)
CHF	0.0017*	−0.0003	−0.0004	0.0042	−0.0002
	(1.6052)	(−0.0961)	(−0.0837)	(0.6953)	(−0.0296)

Notes:

1. Panel A and B report the test results using Newey-West and Andrews LRV estimators to control for autocorrelation, respectively.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 18: Directional test weighted by the magnitude of exchange rate changes against random walk with a drift: OS LRV estimators

This table test the null that our directional forecasts are uncorrelated with future exchange rate changes controlling for the exchange rate trend in the sample period:

$$E[D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)} - \bar{e}_{n,h}^{(i)})] = 0$$

For each forecasting horizon, the following statistics is reported: $T_{c,n}^{(i)} = \frac{\sum_{t=n_0^{(i)}}^{n^{(i)}-h} D_{t,h}^{(i)}(e_{t+h}^{(i)} - e_t^{(i)} - \bar{e}_{n,h}^{(i)})}{n_1^{(i)}}$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
			Panel A: $M = 4$		
EUR	−0.0001	0.0021	0.0048	0.0066*	0.0057*
	(−0.0833)	(1.2042)	(1.4904)	(1.8258)	(1.7403)
JPY	0.0020**	0.0024*	0.0072***	0.0119**	0.0102
	(2.3087)	(1.6015)	(4.3011)	(2.6997)	(1.2261)
GBP	0.0002	0.0023*	0.0040**	0.0057**	0.0061*
	(0.3164)	(2.0548)	(3.2298)	(2.7021)	(1.6097)
AUD	0.0015	0.0025	0.0079*	0.0124	0.0138*
	(1.5261)	(1.4047)	(1.4054)	(1.3842)	(1.5826)
CAD	0.0006	0.0019	0.0013	0.0070*	0.0105*
	(0.7383)	(0.9900)	(0.5225)	(1.2818)	(1.2297)
CHF	0.0017**	−0.0003	−0.0004	0.0042	−0.0002
	(2.2195)	(−0.1300)	(−0.0713)	(0.5148)	(−0.0264)
			Panel A: $M = 6$		
EUR	−0.0001	0.0021	0.0048*	0.0066*	0.0057*
	(−0.0792)	(1.1426)	(1.3401)	(1.5856)	(1.5876)
JPY	0.0020*	0.0024	0.0072**	0.0119**	0.0102
	(1.5959)	(0.7447)	(2.0145)	(2.5186)	(1.2106)
GBP	0.0002	0.0023**	0.0040**	0.0057**	0.0061*
	(0.3484)	(2.4638)	(2.6707)	(2.0286)	(1.4797)
AUD	0.0015*	0.0025	0.0079*	0.0124*	0.0138*
	(1.5235)	(1.1234)	(1.5738)	(1.5637)	(1.5204)
CAD	0.0006	0.0019	0.0013	0.0070*	0.0105*
	(0.8014)	(1.0015)	(0.4838)	(1.5298)	(1.4923)
CHF	0.0017**	−0.0003	−0.0004	0.0042	−0.0002
	(2.4572)	(−0.1532)	(−0.0860)	(0.6272)	(−0.0284)

Notes:

1. Panel A and B report the test results using the orthonormal series long-run variance estimators of $T_{c,n}^{(i)}$. Panel A and B use 4 and 6 for smoothing parameter (M), respectively.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from student t-distributions with degree of freedom 4 and 6 distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 19: Binomial directional test against random walk with a drift: No control for autocorrelation

This table tests the null that our directional forecasts are uncorrelated with the future direction of the exchange rate controlling for the exchange rate trend in the sample period::

$$Cov(D_{t,h}^{(i)}, \bar{R}_{t,h}^{(i)}) = 0$$

For each forecasting horizon, the following statistics is reported:

$$T_{d,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} \hat{R}_{t,h}^{(i)} - [\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)}][\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} \hat{R}_{t,h}^{(i)}]$$

	Forecasting Horizon (h)				
Currency	$1m$	$3m$	$6m$	$9m$	$12m$
EUR	0.0070	0.0300*	0.0802***	0.0911***	0.0623***
	(0.3820)	(1.6226)	(4.5041)	(5.3903)	(3.7952)
JPY	0.0684***	0.0764***	0.1320***	0.1530***	0.0914***
	(2.8746)	(3.1085)	(5.3581)	(6.1649)	(3.6255)
GBP	0.0017	0.0405***	0.0596***	0.0761***	0.0772***
	(0.0868)	(1.9751)	(2.8793)	(3.6452)	(3.6485)
AUD	0.0289**	0.0618***	0.0908***	0.0793***	0.1091***
	(1.6573)	(3.4508)	(5.0595)	(4.3982)	(6.2030)
CAD	0.0183	0.0444**	0.0330*	0.1130***	0.1333***
	(0.9008)	(2.1172)	(1.5495)	(5.3513)	(6.2698)
CHF	0.0232	0.0048	0.0147	0.0812***	0.0963***
	(0.9471)	(0.1882)	(0.5643)	(3.1099)	(3.6844)

Notes:

1. This table presents the test results without controlling for auto-correlation induced by overlapping observations in the forecasts.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively. Positive and statistically significant test statistics indicate that our forecasts have predictive power over the future exchange rate movement controlling for the exchange rate trend in the sample period.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 20: Binomial directional test against random walk with a drift: Control for autocorrelation

This table tests the null that our directional forecasts are uncorrelated with the future direction of the exchange rate controlling for the exchange rate trend in the sample period::

$$Cov(D_{t,h}^{(i)}, \bar{R}_{t,h}^{(i)}) = 0$$

For each forecasting horizon, the following statistics is reported:

$$T_{d,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0}^{n-h} D_{t,h}^{(i)} \hat{R}_{t,h}^{(i)} - [\frac{1}{n_1^{(i)}} \sum_{t=n_0}^{n-h} D_{t,h}^{(i)}][\frac{1}{n_1^{(i)}} \sum_{t=n_0}^{n-h} \hat{R}_{t,h}^{(i)}]$$

	Forecasting Horizon (h)				
Currency	1m	3m	6m	9m	12m
	Panel A: Newey-West				
EUR	0.0070	0.0300	0.0802***	0.0911***	0.0623***
	(0.2599)	(0.9824)	(2.4663)	(3.3112)	(2.6545)
JPY	0.0684**	0.0764*	0.1320***	0.1530***	0.0914*
	(2.0455)	(1.6318)	(2.6245)	(2.7721)	(1.5774)
GBP	0.0017	0.0405	0.0596*	0.0761**	0.0772**
	(0.0647)	(1.0472)	(1.5362)	(1.7713)	(1.7203)
AUD	0.0289	0.0618**	0.0908***	0.0793**	0.1091***
	(1.0656)	(1.9602)	(2.4993)	(2.1393)	(2.9552)
CAD	0.0183	0.0444	0.0330	0.1130***	0.1333***
	(0.6379)	(1.0758)	(0.7216)	(2.5787)	(2.8721)
CHF	0.0232	0.0048	0.0147	0.0812*	0.0963*
	(0.6353)	(0.0973)	(0.2599)	(1.4246)	(1.5929)
	Panel B: Andrews				
EUR	0.0070	0.0300	0.0802**	0.0911***	0.0623***
	(0.2538)	(0.9034)	(2.0274)	(3.0011)	(2.5909)
JPY	0.0684**	0.0764*	0.1320**	0.1530**	0.0914
	(2.0239)	(1.3860)	(2.0476)	(1.9759)	(1.0839)
GBP	0.0017	0.0405	0.0596*	0.0761*	0.0772*
	(0.0638)	(0.9460)	(1.3339)	(1.3989)	(1.3501)
AUD	0.0289	0.0618**	0.0908**	0.0793**	0.1091**
	(1.0825)	(1.8471)	(1.9679)	(1.6812)	(2.0672)
CAD	0.0183	0.0444	0.0330	0.1130**	0.1333**
	(0.6394)	(0.9365)	(0.5799)	(2.0892)	(2.1278)
CHF	0.0232	0.0048	0.0147	0.0812	0.0963
	(0.6624)	(0.0969)	(0.1985)	(1.1009)	(1.1535)

Notes:

1. Panel A and B report the test results using Newey-West and Andrews LRV estimators to control for autocorrelation, spectively.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 21: Binomial directional test against random walk with a drift: OS LRV estimators

This table tests the null that our directional forecasts are uncorrelated with the future direction of the exchange rate controlling for the exchange rate trend in the sample period::

$$Cov(D_{t,h}^{(i)}, \bar{R}_{t,h}^{(i)}) = 0$$

For each forecasting horizon, the following statistics is reported:

$$T_{d,n}^{(i)} = \frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)} \hat{R}_{t,h}^{(i)} - [\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} D_{t,h}^{(i)}][\frac{1}{n_1^{(i)}} \sum_{t=n_0^{(i)}}^{n-h} \hat{R}_{t,h}^{(i)}]$$

	Forecasting Horizon (h)				
Currency	1m	3m	6m	9m	12m
			Panel A: $M = 4$		
EUR	0.0070	0.0300**	0.0802	0.0911*	0.0623
	(0.8215)	(3.0114)	(1.2709)	(1.7922)	(1.4906)
JPY	0.0684**	0.0764*	0.1320***	0.1530***	0.0914*
	(2.7359)	(2.0465)	(5.7715)	(6.1903)	(1.6118)
GBP	0.0017	0.0405**	0.0596*	0.0761	0.0772*
	(0.0715)	(2.4183)	(2.0450)	(1.5245)	(1.5489)
AUD	0.0289	0.0618**	0.0908*	0.0793	0.1091**
	(1.3598)	(2.8580)	(1.9213)	(1.4756)	(2.2726)
CAD	0.0183	0.0444**	0.0330	0.1130**	0.1333*
	(1.0362)	(2.4526)	(1.1849)	(3.0655)	(1.8689)
CHF	0.0232	0.0048	0.0147	0.0812	0.0963
	(1.1897)	(0.0889)	(0.1656)	(0.7511)	(0.9897)
			Panel A: $M = 6$		
EUR	0.0070	0.0300	0.0802	0.0911*	0.0623*
	(0.8287)	(1.2738)	(1.4378)	(1.6960)	(1.6042)
JPY	0.0684**	0.0764*	0.1320***	0.1530***	0.0914*
	(1.9663)	(1.7751)	(4.6714)	(5.6426)	(1.6103)
GBP	0.0017	0.0405**	0.0596*	0.0761*	0.0772*
	(0.0722)	(2.9275)	(1.5944)	(1.6006)	(1.7933)
AUD	0.0289	0.0618*	0.0908*	0.0793*	0.1091*
	(1.0388)	(1.7302)	(1.5803)	(1.4909)	(1.4531)
CAD	0.0183	0.0444	0.0330	0.1130*	0.1333
	(0.6959)	(1.3671)	(0.6037)	(1.5100)	(1.4358)
CHF	0.0232	0.0048	0.0147	0.0812	0.0963
	(0.9385)	(0.1153)	(0.1813)	(0.9955)	(0.9708)

Notes:

1. Panel A and B report the test results using the orthonormal series long-run variance estimators of $T_{d,n}^{(i)}$. Panel A and B use 4 and 6 for smoothing parameter (M), respectively.

2. t-values are in parentheses. We use the test as an one-sided test. Critical values from student t-distributions with degree of freedom 4 and 6 distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our directional forecasts is described in the notes to Table 2.

Table 22: DMW test against random walk with a drift

This table presents the results of DMW test of the null of equal MSPEs between random walk with a drift and our forecasts
For each forecasting horizon, the following statistics is reported:

$$\frac{\sqrt{n_1^{(i)}}DMW_{h,n}^{(i)}}{\sqrt{V_{DMW_{h,n}^{(i)}}}}$$

Currency	Forecasting Horizon (h) 1m	3m	6m	9m	12m
	Panel A: Newey-West				
EUR	2.202**	2.300**	3.021***	3.597***	4.258***
	(0.014)	(0.011)	(0.001)	(0.000)	(0.000)
JPY	1.744**	1.522*	2.964***	4.127***	4.244***
	(0.041)	(0.064)	(0.002)	(0.000)	(0.000)
GBP	0.411	0.524	0.931	1.051	1.251
	(0.341)	(0.300)	(0.176)	(0.147)	(0.105)
AUD	2.842***	1.841**	2.576***	3.305***	3.817***
	(0.002)	(0.033)	(0.005)	(0.000)	(0.000)
CAD	2.482***	2.543***	3.208***	4.140***	4.959***
	(0.007)	(0.005)	(0.001)	(0.000)	(0.000)
CHF	2.088**	2.413***	3.038***	4.293***	5.666***
	(0.018)	(0.008)	(0.001)	(0.000)	(0.000)
	Panel B: Andrews				
EUR	1.213	1.813**	1.985**	1.914**	1.901**
	(0.113)	(0.035)	(0.024)	(0.028)	(0.029)
JPY	0.901	1.222	1.846**	1.833**	1.585*
	(0.184)	(0.111)	(0.032)	(0.033)	(0.056)
GBP	0.212	0.373	0.551	0.516	0.537
	(0.416)	(0.355)	(0.291)	(0.303)	(0.295)
AUD	1.528*	1.364*	1.690**	1.875**	1.921**
	(0.063)	(0.086)	(0.046)	(0.030)	(0.027)
CAD	1.432*	1.818**	2.159**	2.379***	2.583***
	(0.076)	(0.035)	(0.015)	(0.009)	(0.005)
CHF	1.287*	1.865**	1.946**	2.339***	2.898***
	(0.099)	(0.031)	(0.026)	(0.010)	(0.002)

Notes:

1. Panel A and B report the test results using Newey-West and Andrews LRV estimators to control for autocorrelation.

2. p-values are in parentheses. We use the test as an one-sided test. Critical values from a standard normal distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively. Positive and statistically significant test statistics indicate that our forecasts outperform the random walk with a drift in forecasting the future exchange rate.

3. The information on our point forecasts is described in the notes to Table 8.

Table 23: DMW test against random walk with a drift: OS LRV estimators

This table presents the results of DMW test of the null of equal MSPEs between random walk with a drift and our forecasts
For each forecasting horizon, the following statistics is reported:

$$\frac{\sqrt{n_1^{(i)}}DMW_{h,n}^{(i)}}{\sqrt{V_{DMW_{h,n}^{(i)}}}}$$

Currency	Forecasting Horizon (h) 1m	3m	6m	9m	12m
	Panel A: $M = 4$				
EUR	1.236	1.721*	1.830*	1.786*	1.799*
	(0.142)	(0.080)	(0.071)	(0.074)	(0.073)
JPY	0.789	0.797	1.218	1.250	1.150
	(0.237)	(0.235)	(0.145)	(0.140)	(0.157)
GBP	0.300	0.381	0.562	0.521	0.540
	(0.390)	(0.361)	(0.302)	(0.315)	(0.309)
AUD	1.549*	1.343	1.588*	1.709*	1.778*
	(0.098)	(0.125)	(0.094)	(0.081)	(0.075)
CAD	1.213	1.865*	1.887*	1.962*	2.146**
	(0.146)	(0.068)	(0.066)	(0.061)	(0.049)
CHF	1.230	1.816*	1.721*	1.875*	2.363**
	(0.143)	(0.072)	(0.080)	(0.067)	(0.039)
	Panel A: $M = 6$				
EUR	1.093	1.558*	1.567*	1.542*	1.610*
	(0.158)	(0.085)	(0.084)	(0.087)	(0.079)
JPY	0.951	0.892	1.358	1.361	1.228
	(0.189)	(0.203)	(0.112)	(0.111)	(0.133)
GBP	0.268	0.333	0.494	0.442	0.446
	(0.399)	(0.375)	(0.320)	(0.337)	(0.336)
AUD	1.803*	1.297	1.432	1.480*	1.456*
	(0.061)	(0.121)	(0.101)	(0.095)	(0.098)
CAD	1.474*	2.162**	2.180**	2.183**	2.261**
	(0.095)	(0.037)	(0.036)	(0.036)	(0.032)
CHF	1.203	1.644*	1.565*	1.757*	2.094**
	(0.137)	(0.076)	(0.084)	(0.065)	(0.041)

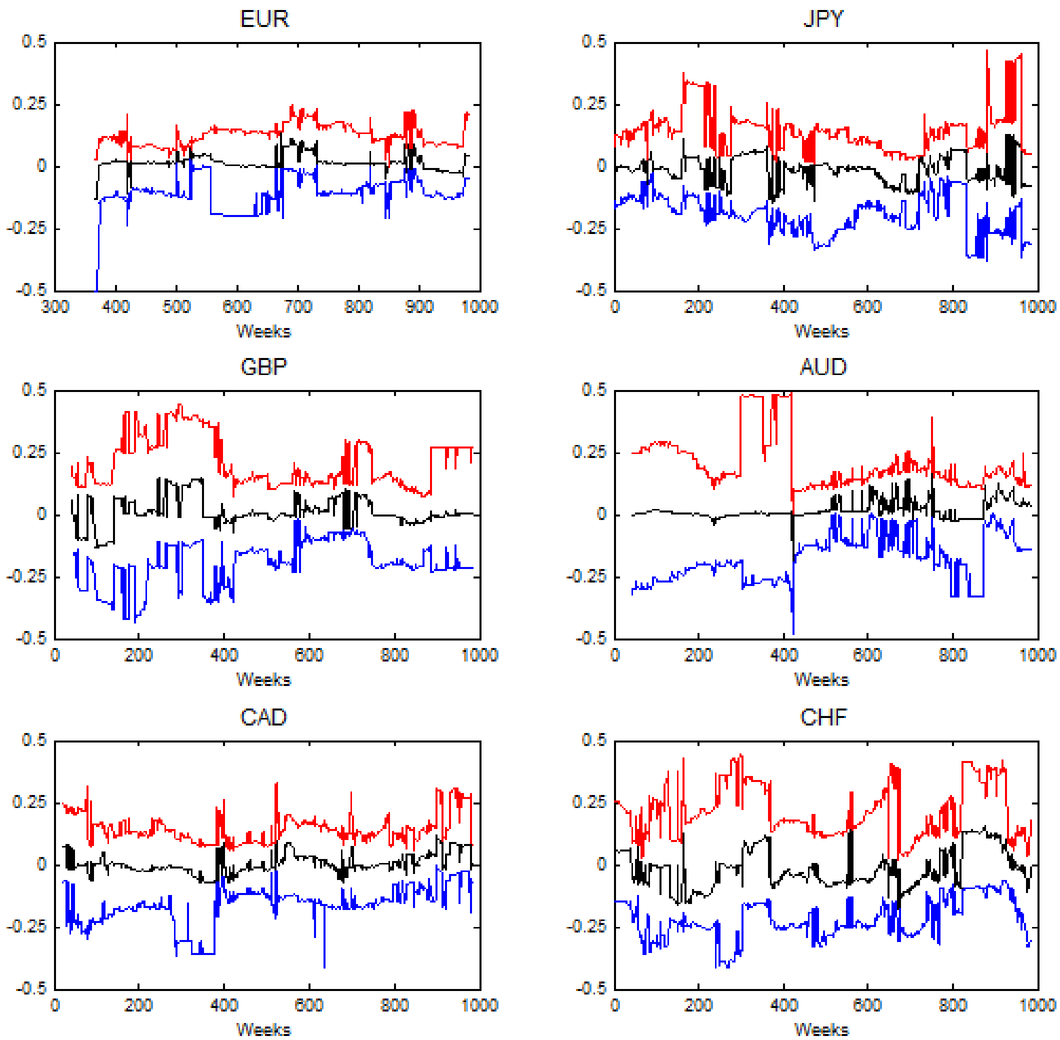
Notes:

1. Panel A and B report the test results using the orthonormal series based long-run variance estimators. Panel A and B use 4 and 6 for smoothing parameter (M), respectively.

2. p-values are in parentheses. We use the test as an one-sided test. Critical values from student t-distributions with degree of freedom 4 and 6 distribution are used for inference. *, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

3. The information on our point forecasts is described in the notes to Table 8.

Figure 4: μ estimates

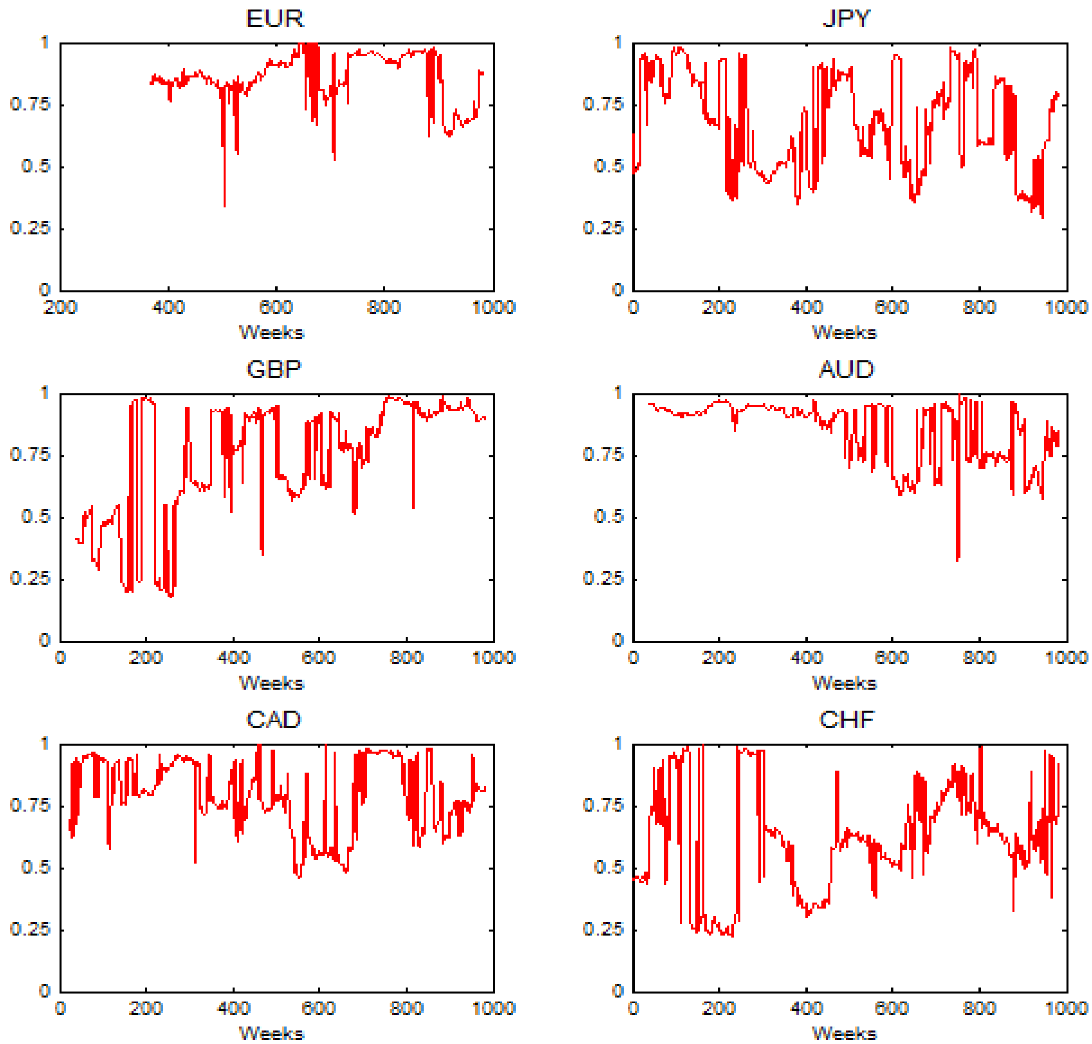


Notes:

1. This graph presents the estimated means of each state in the AR(1) Markov switching model of the net position for all currencies. The red solid line(blue line) depicts the estimated mean of the up (down) state, while the black line describes the estimated mean of the range state.

2. The rolling window size in the estimation of the Markov switching model is 120 weeks for EUR, GBP and AUD, 100 weeks for CAD, and 80 weeks for JPY and CHF. The estimation begins on 01/20/1995 for GBP and AUD, on 09/01/1994 for CAD, on 04/15/1994 for JPY and CHF, and on 05/04/2001 for EUR.

Figure 5: θ estimates

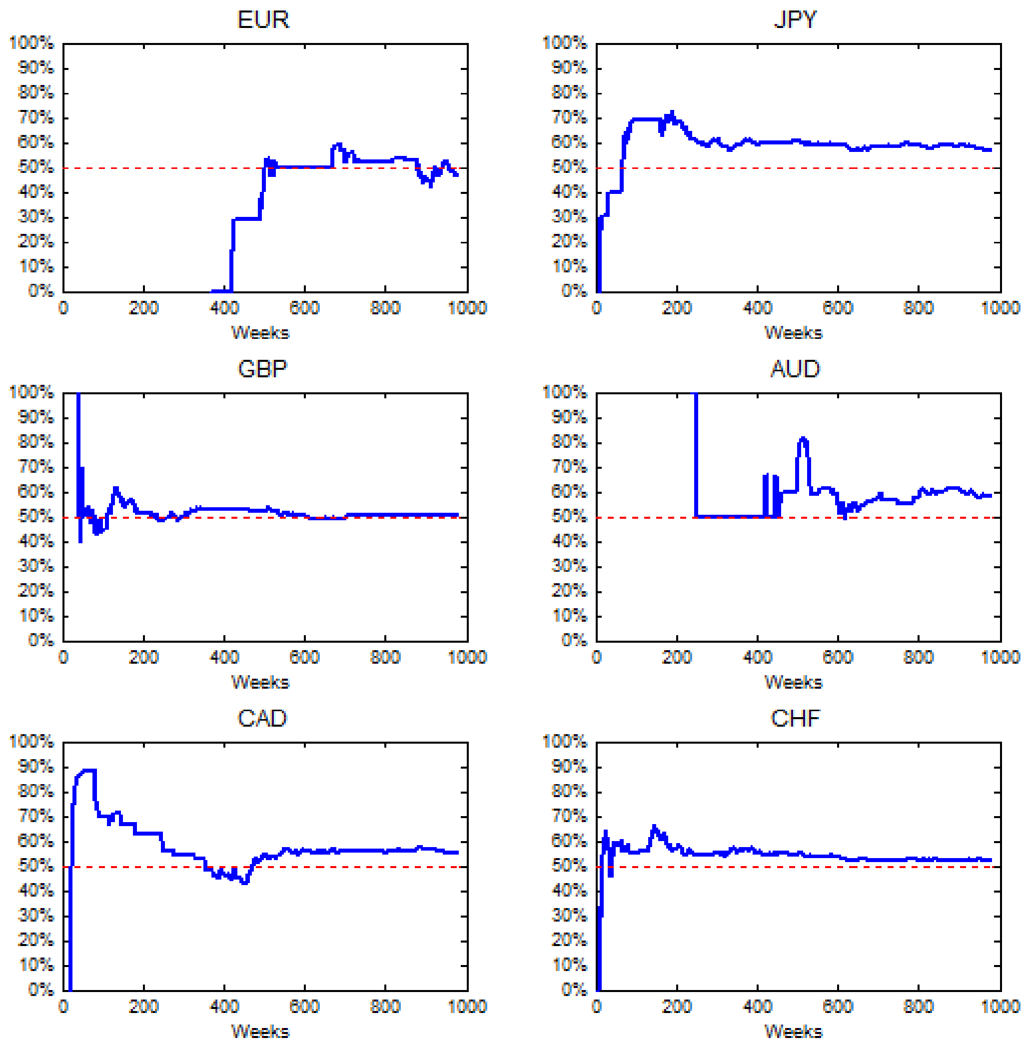


Notes:

1. This graph presents the estimated AR(1) coefficient of the Markov switching model of the net position for all currencies. The red solid line depicts the estimated AR(1) coefficient.

2. The information on the rolling window sizes in the estimation of the Markov switching model are described in the notes to Figure 4.

Figure 6: Evolution of cumulative forecast success ratio: $h = 1m$ (4 weeks)

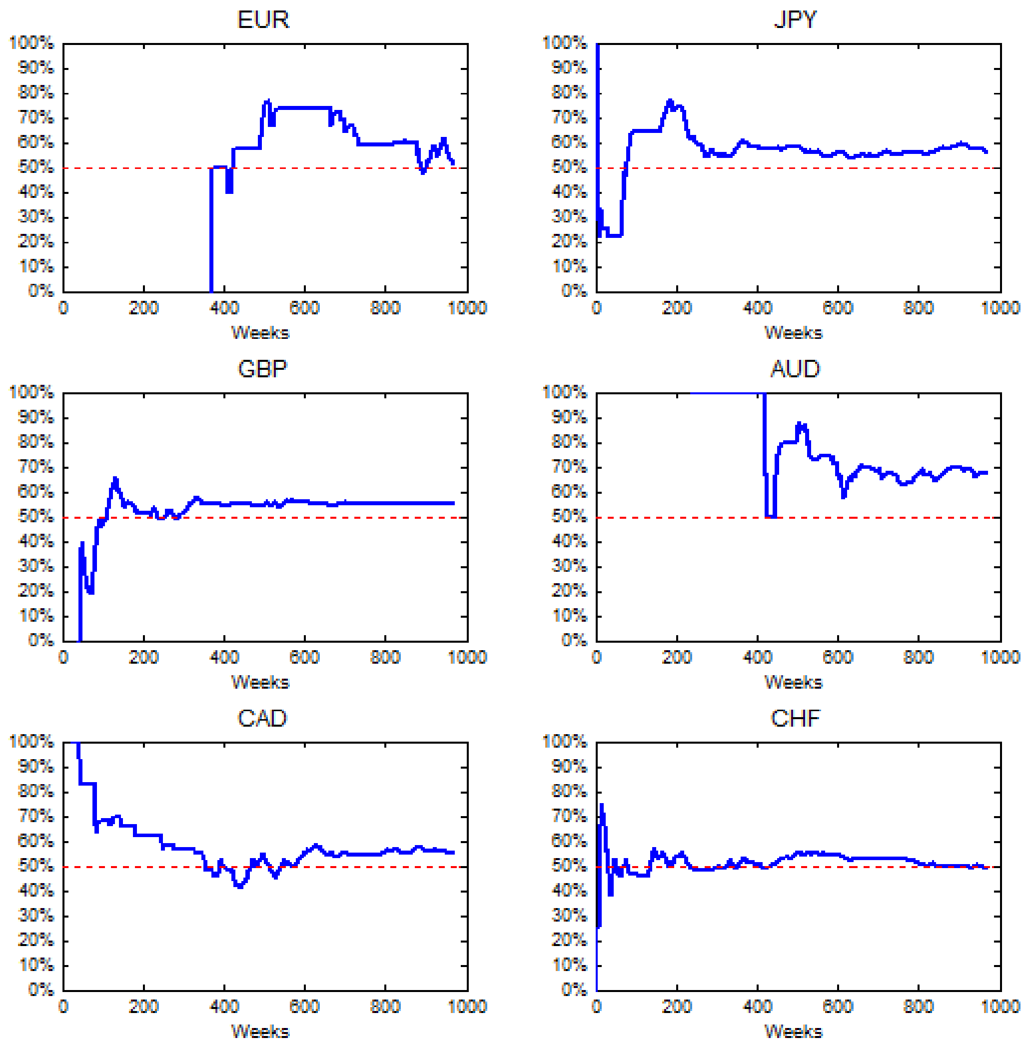


Notes:

1. t=0 is the first week in which h month ahead forecasts are generated.

2.The forecast success ratio is defined the number of successful depreciation or appreciation forecasts divided by the total number of depreciation and appreciation forecasts. When we predict no change ($D_{t,h} = 0$, we do not count it in the calculation of forecast success ratio

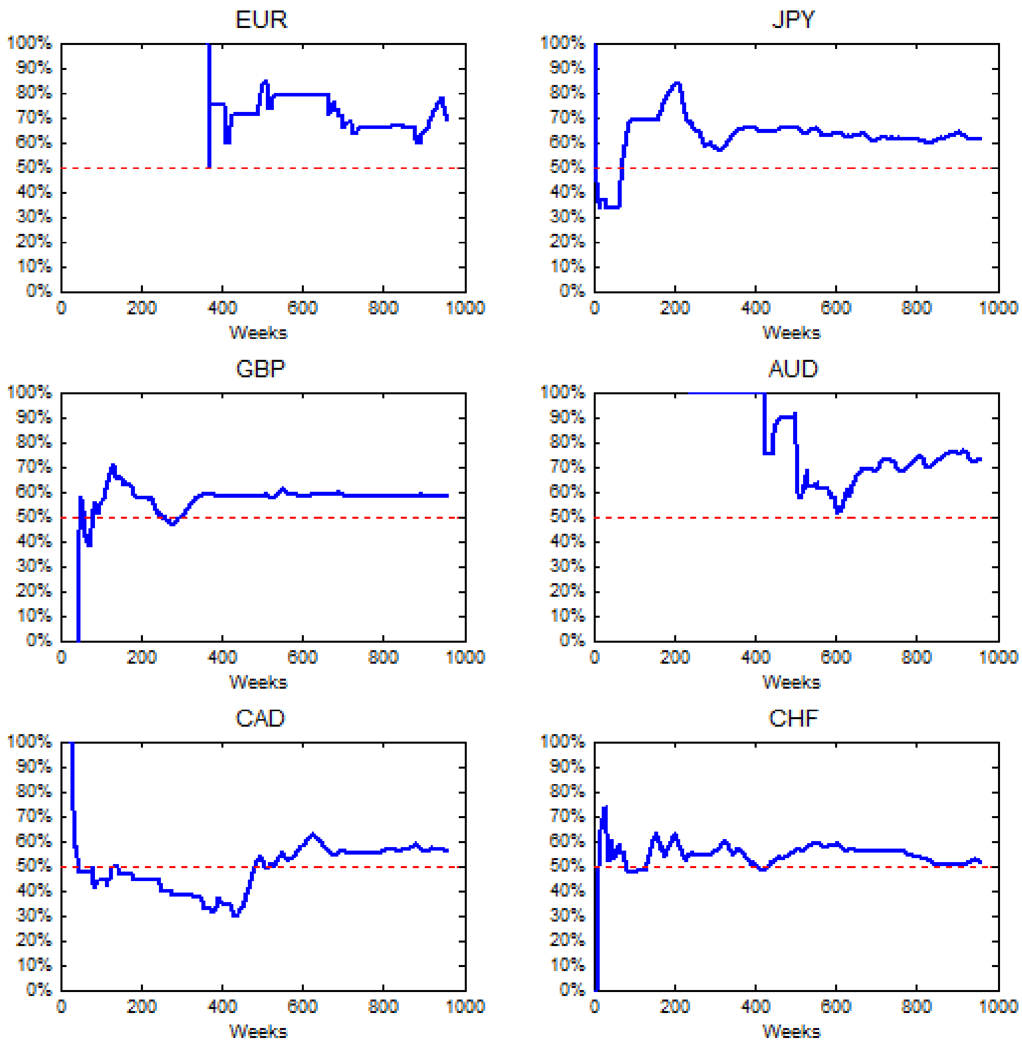
Figure 7: Evolution of cumulative forecast success ratio: $h = 3m$ (13 weeks)



Notes:

1. The information on the cumulative forecast success ratio is described in the notes to Figure 6.

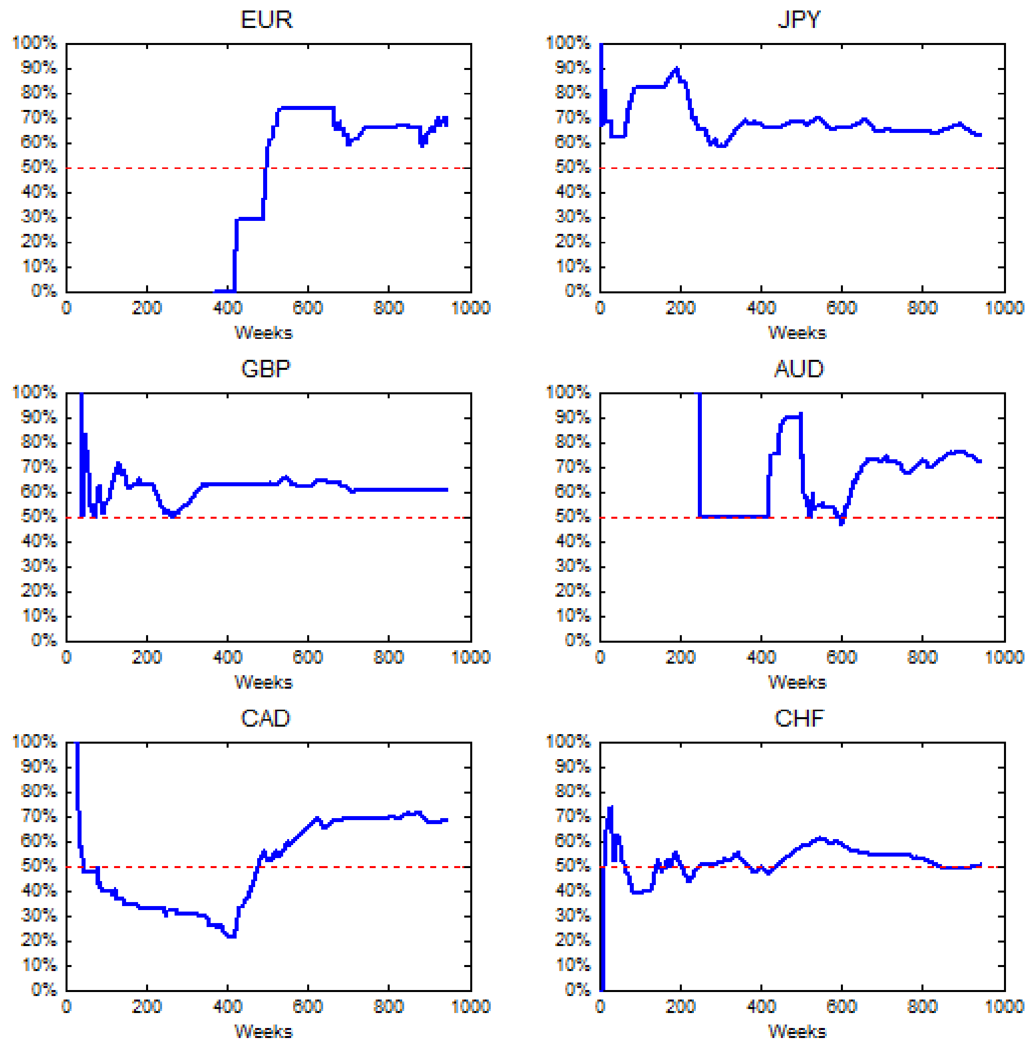
Figure 8: Evolution of cumulative forecast success ratio: $h = 6m$ (25 weeks)



Notes:

1. The information on the cumulative forecast success ratio is described in the notes to Figure 6.

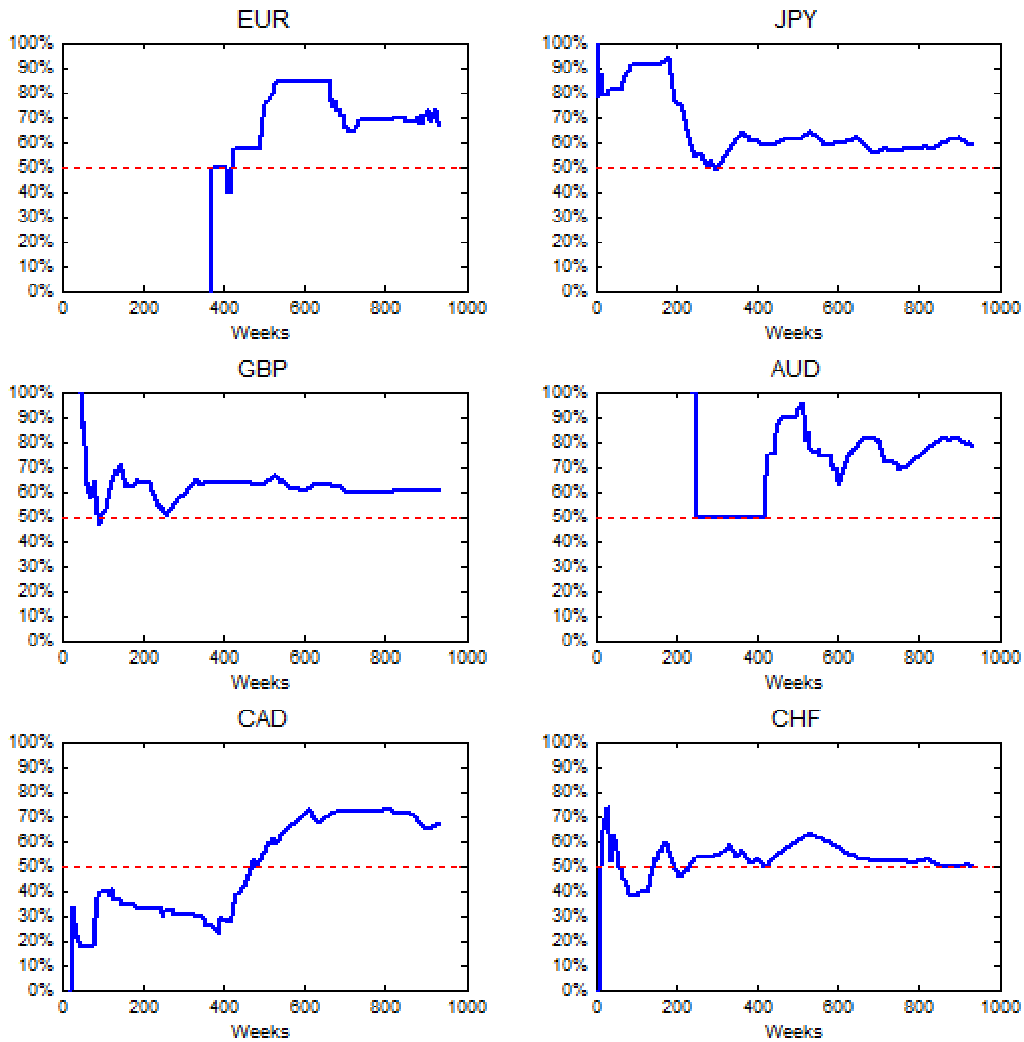
Figure 9: Evolution of cumulative forecast success ratio: $h = 9m$ (38 weeks)



Notes:

1. The information on the cumulative forecast success ratio is described in the notes to Figure 6.

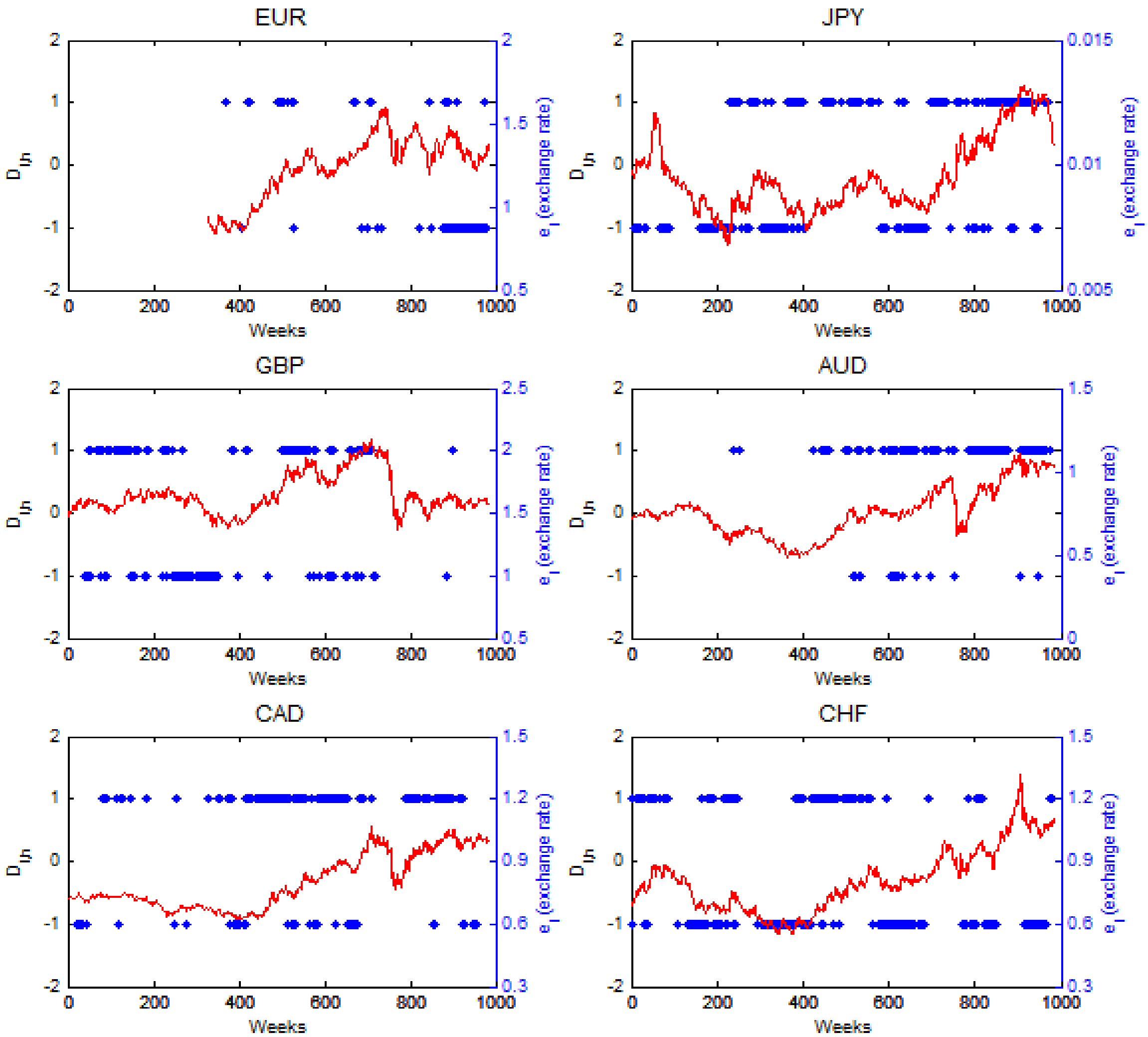
Figure 10: Evolution of cumulative forecast success ratio: $h = 12m$ (50 weeks)



Notes:

1. The information on the cumulative forecast success ratio is described in the notes to Figure 6.

Figure 11: $D_{t,h}^{(i)}$: $h = 1m$ (4 weeks)

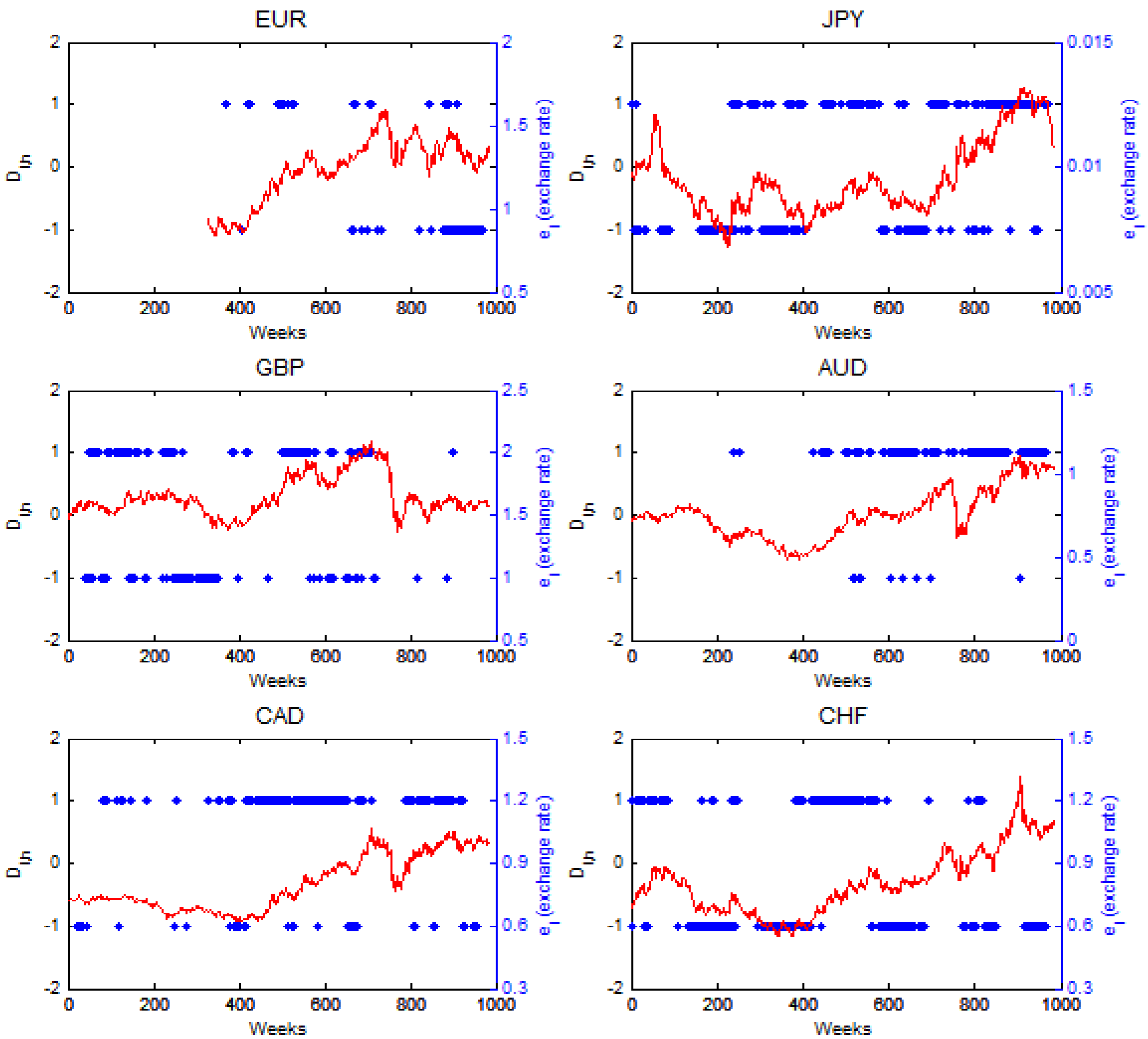


Notes:

1. This graph presents the $D_{t,h}^{(i)}$ on which our directional forecasts are based. $D_{t,h}^{(i)}$ (blue scatter plot) is on the left axis and the exchange rate (red line) on the right axis.

2. Blue scatter plots can take values -1 or 1. No scatter plots on the given weeks indicate $D_{t,h}^{(i)} = 0$. -1 (1) predicts depreciation (or appreciation) of the given currency against US Dollar over the h month forecasting horizon. No scatter plots on the given weeks mean that our directional forecasts predict no change over the same forecasting horizon.

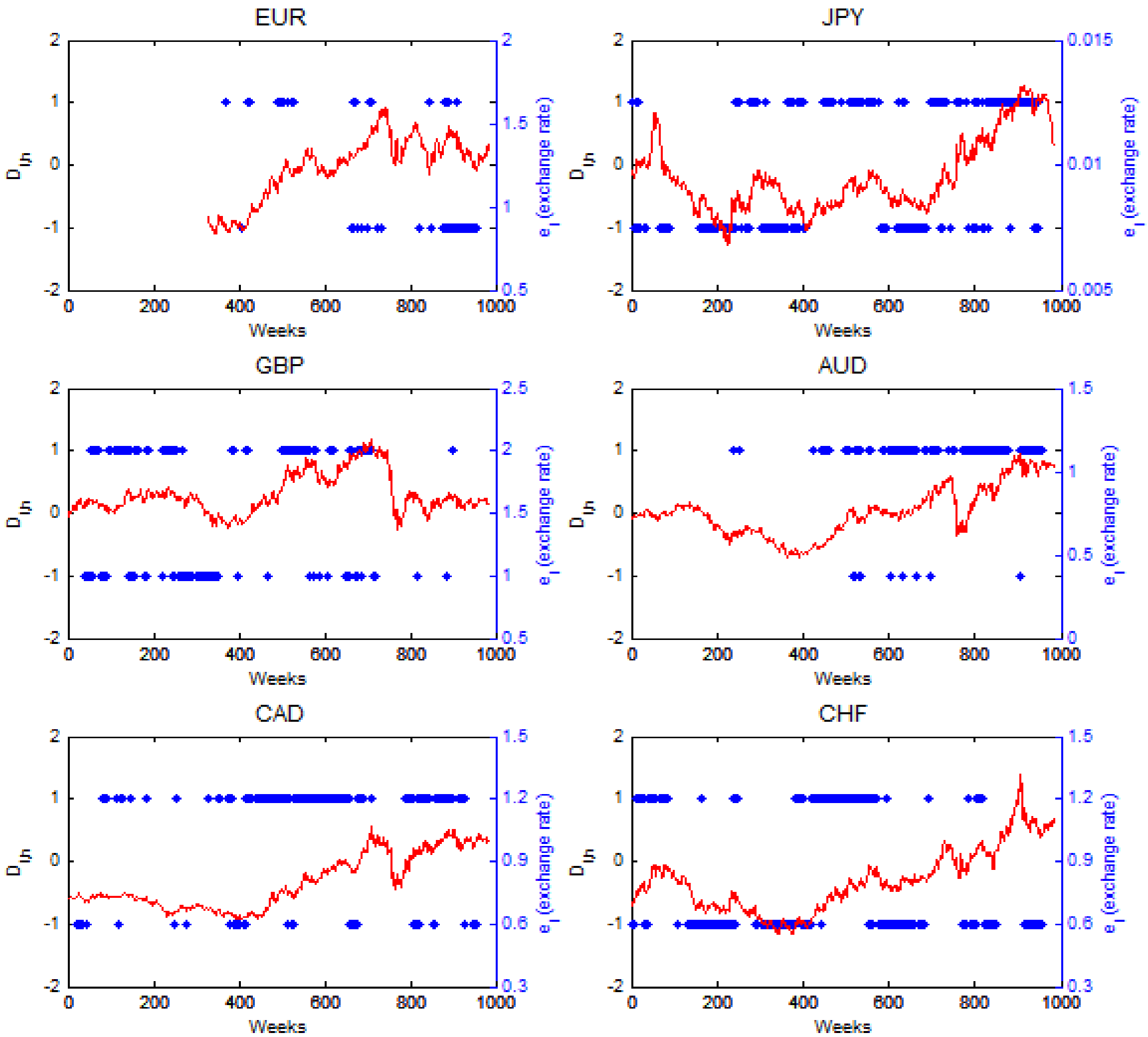
Figure 12: $D_{t,h}^{(i)}$: $h = 3m$ (13 weeks)



Notes:

1. The information on the graph is described in the notes to Figure 11.

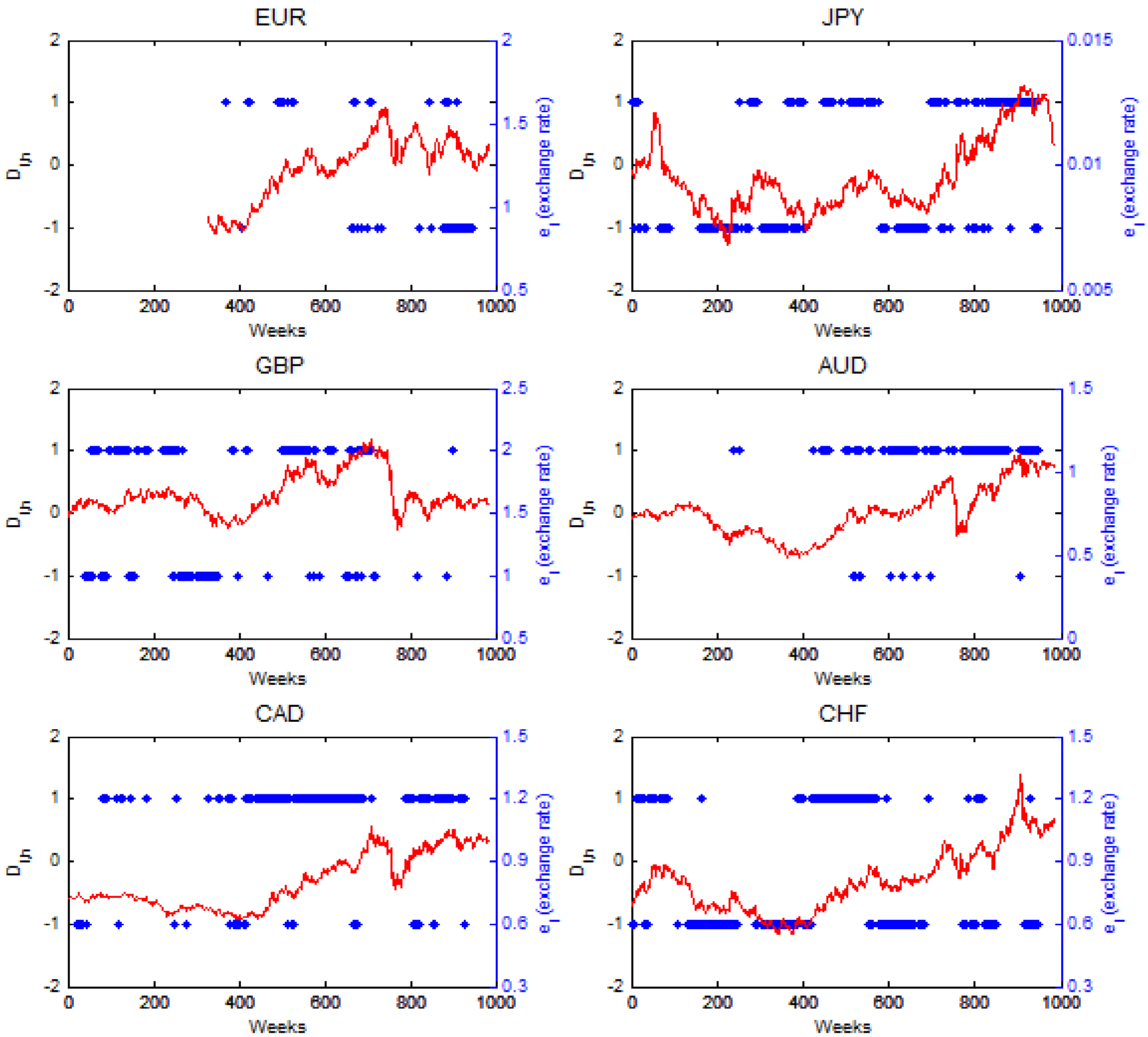
Figure 13: $D_{t,h}^{(i)}$: $h = 6m$ (25 weeks)



Notes:

1. The information on the graph is described in the notes to Figure 11.

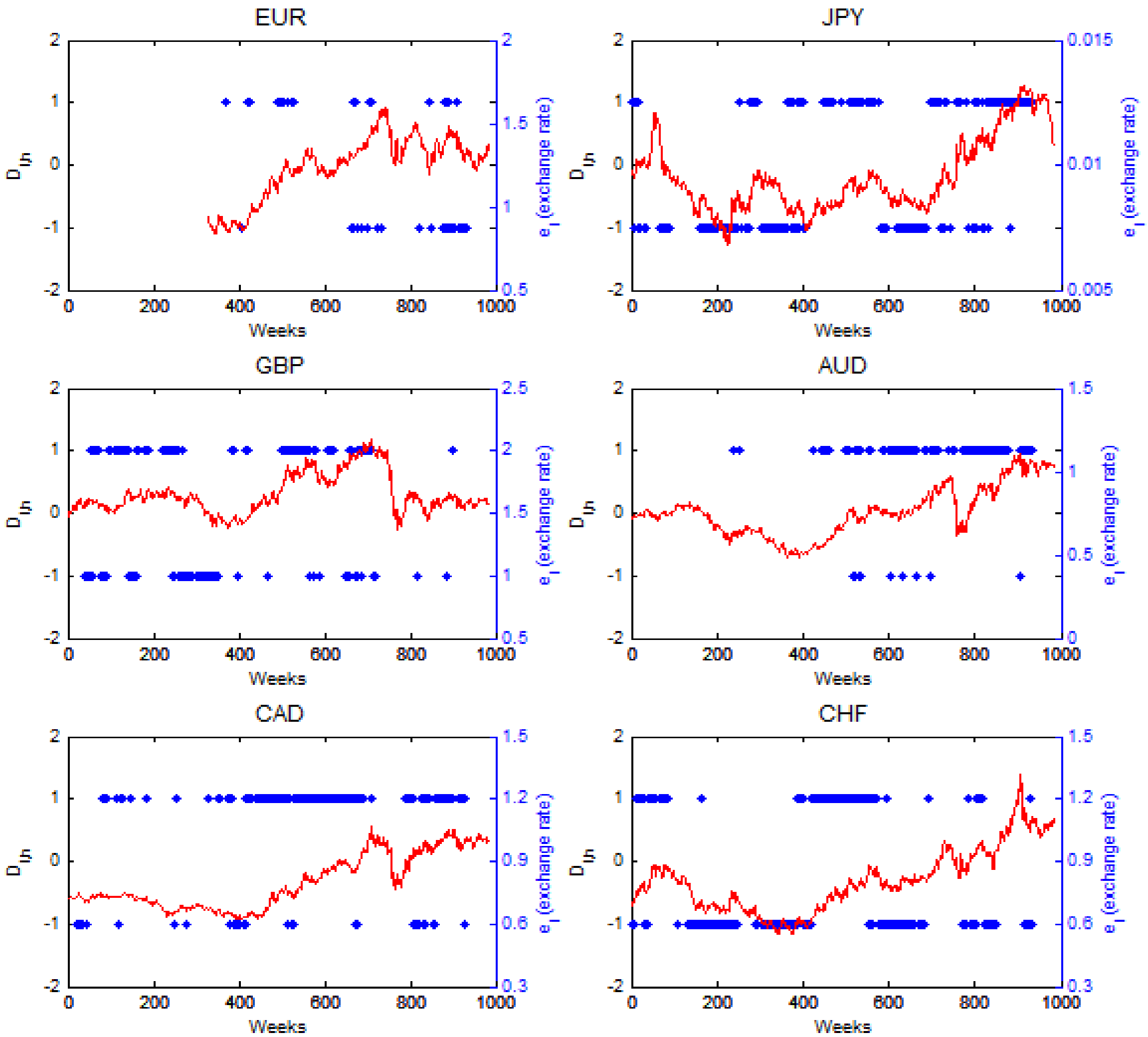
Figure 14: $D_{t,h}^{(i)}$: $h = 9m$ (38 weeks)



Notes:

1. The information on the graph is described in the notes to Figure 11.

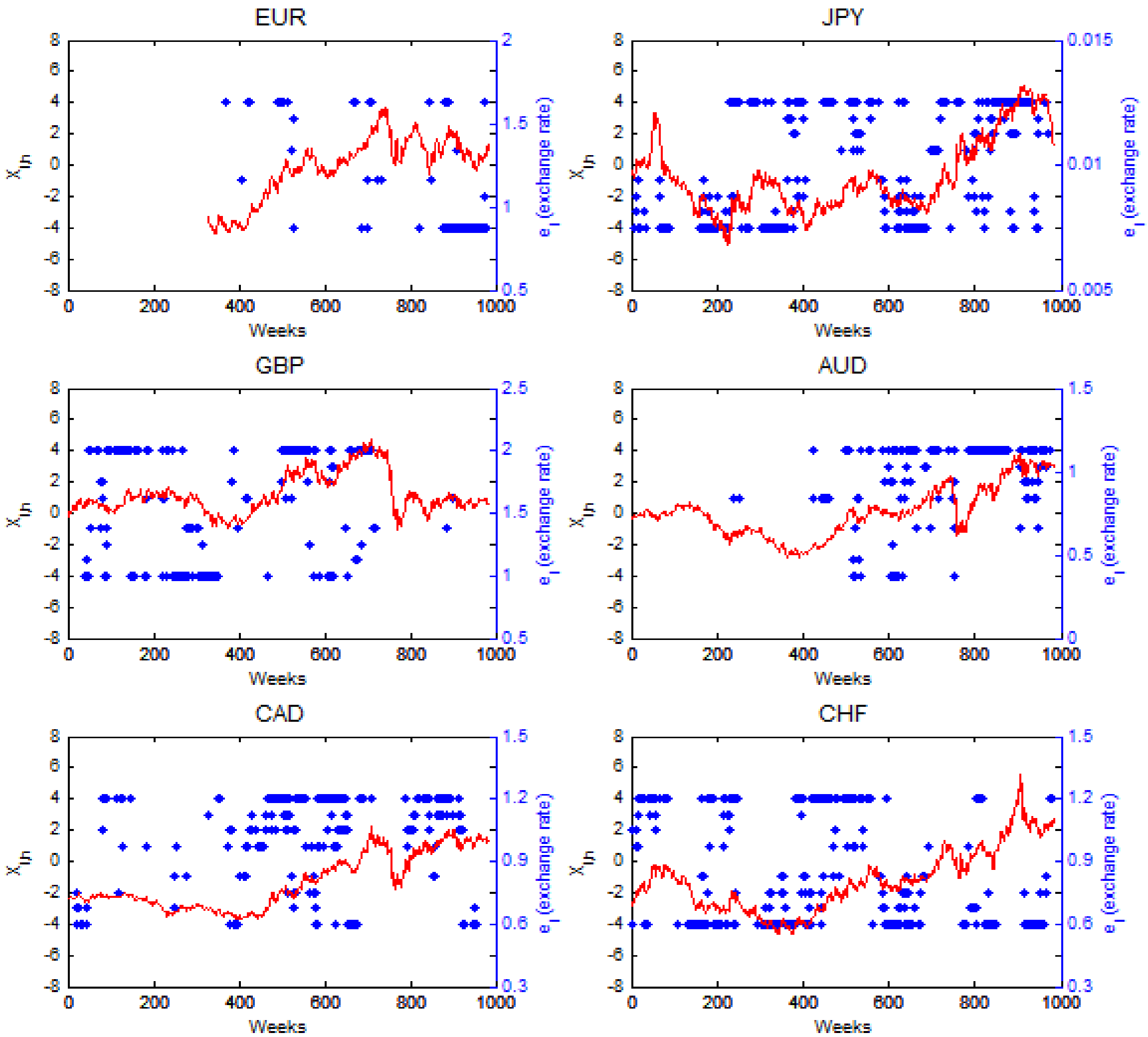
Figure 15: $D_{t,h}^{(i)}$: $h = 12m$ (50 weeks)



Notes:

1. The information on the graph is described in the notes to Figure 11.

Figure 16: $X_{t,h}^{(i)}$: $h = 1m$ (4 weeks)

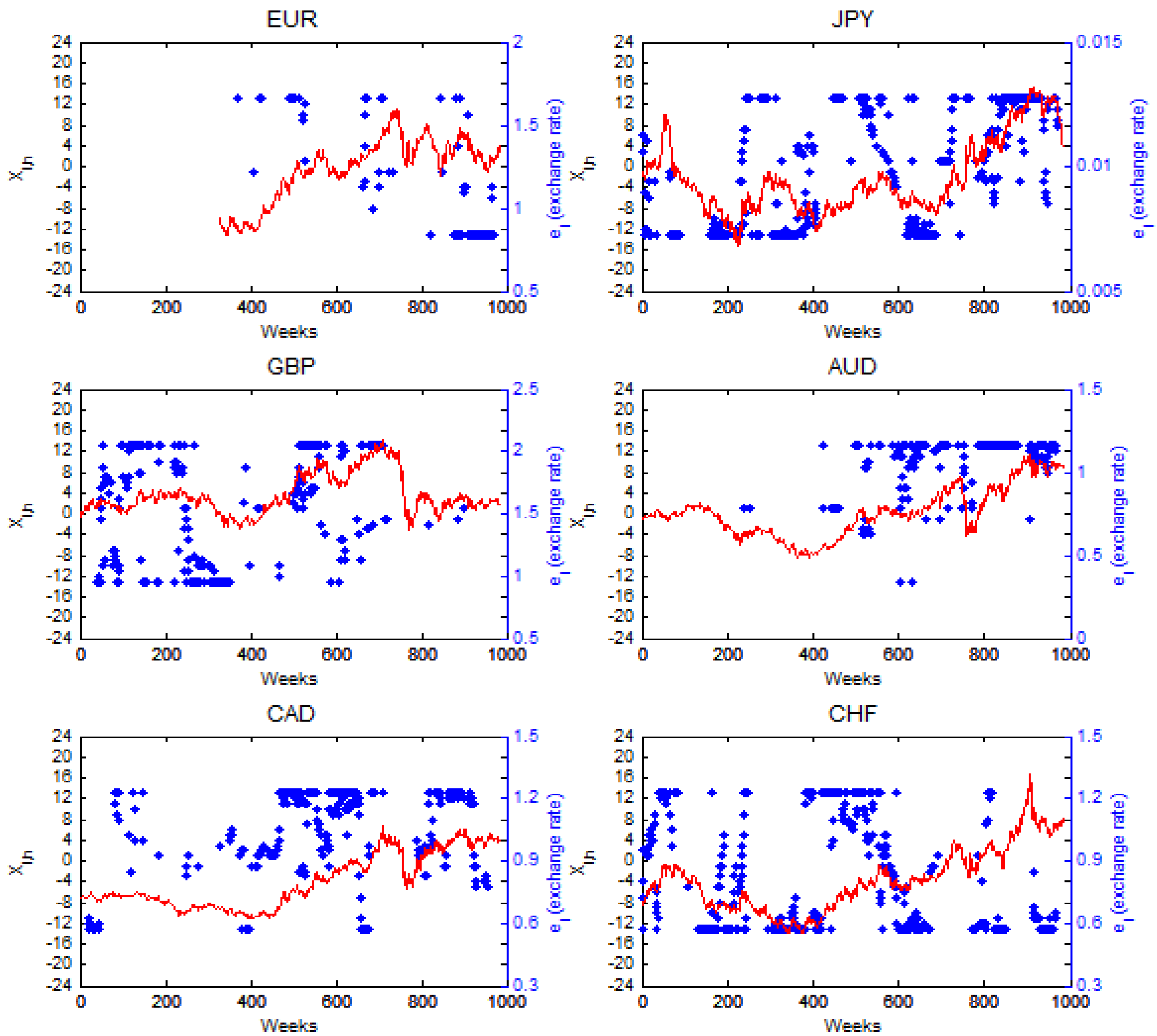


Notes:

1. This graph presents the $X_{t,h}^{(i)}$, which is the net number of periods with predicted speculators' accumulation (decumulation) over the following h months. $X_{t,h}^{(i)}$ (blue scatter plot) is on the left axis and the exchange rate (red line) on the right axis.

2. Blue scatter plots can take values from -h to h except for 0, No scatter plots on the given weeks indicate $X_{t,h}^{(i)} = 0$. -h (or h) indicates the magnitude of depreciation (or appreciation) over the h forecasting horizon. No scatter plots on the given weeks mean that our directional forecasts predict no change over the same forecasting horizon.

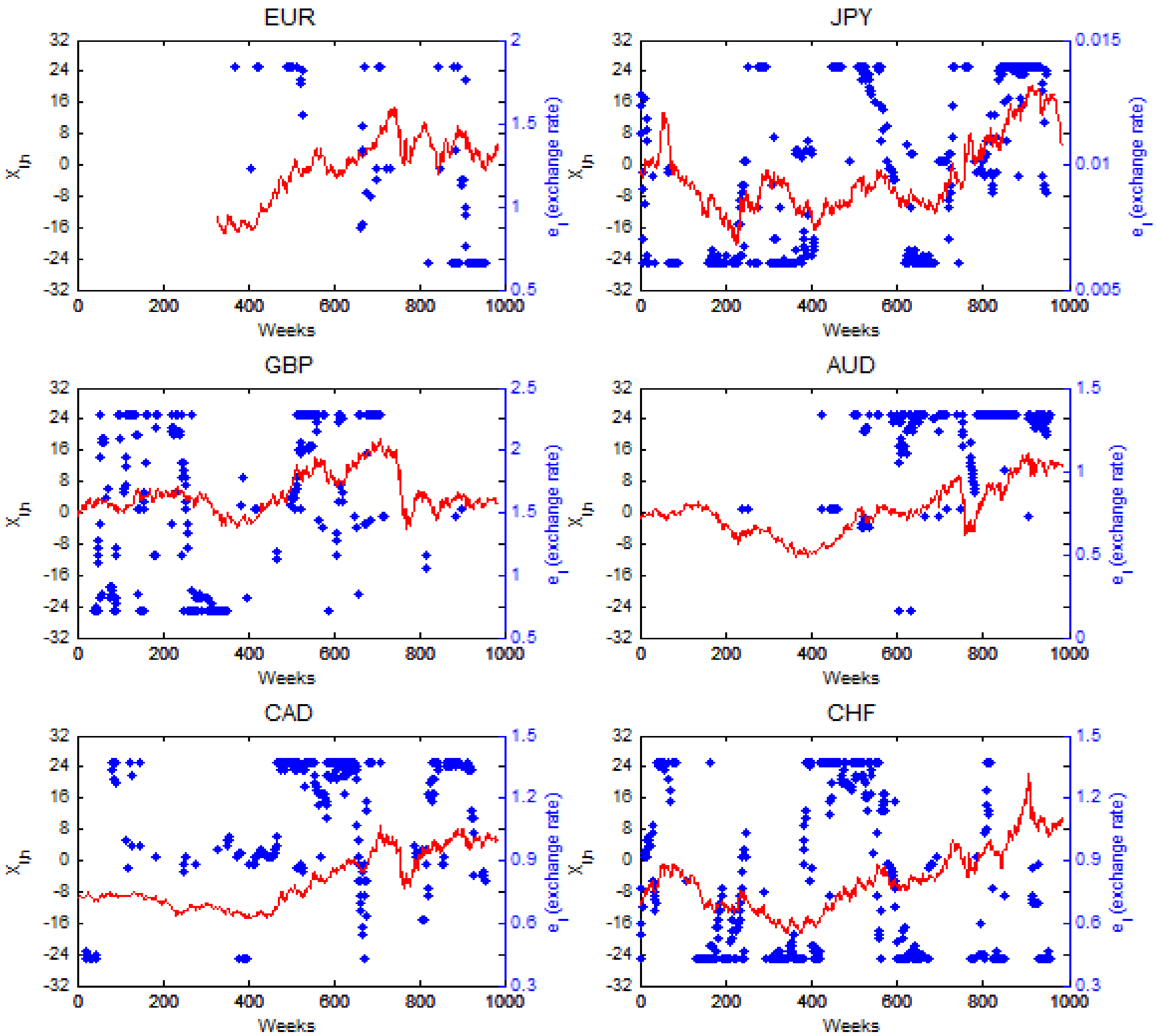
Figure 17: $X_{t,h}^{(i)}$: $h = 3m$ (13 weeks)



Notes:

1. The information on the graph is described in the notes to Figure 16.

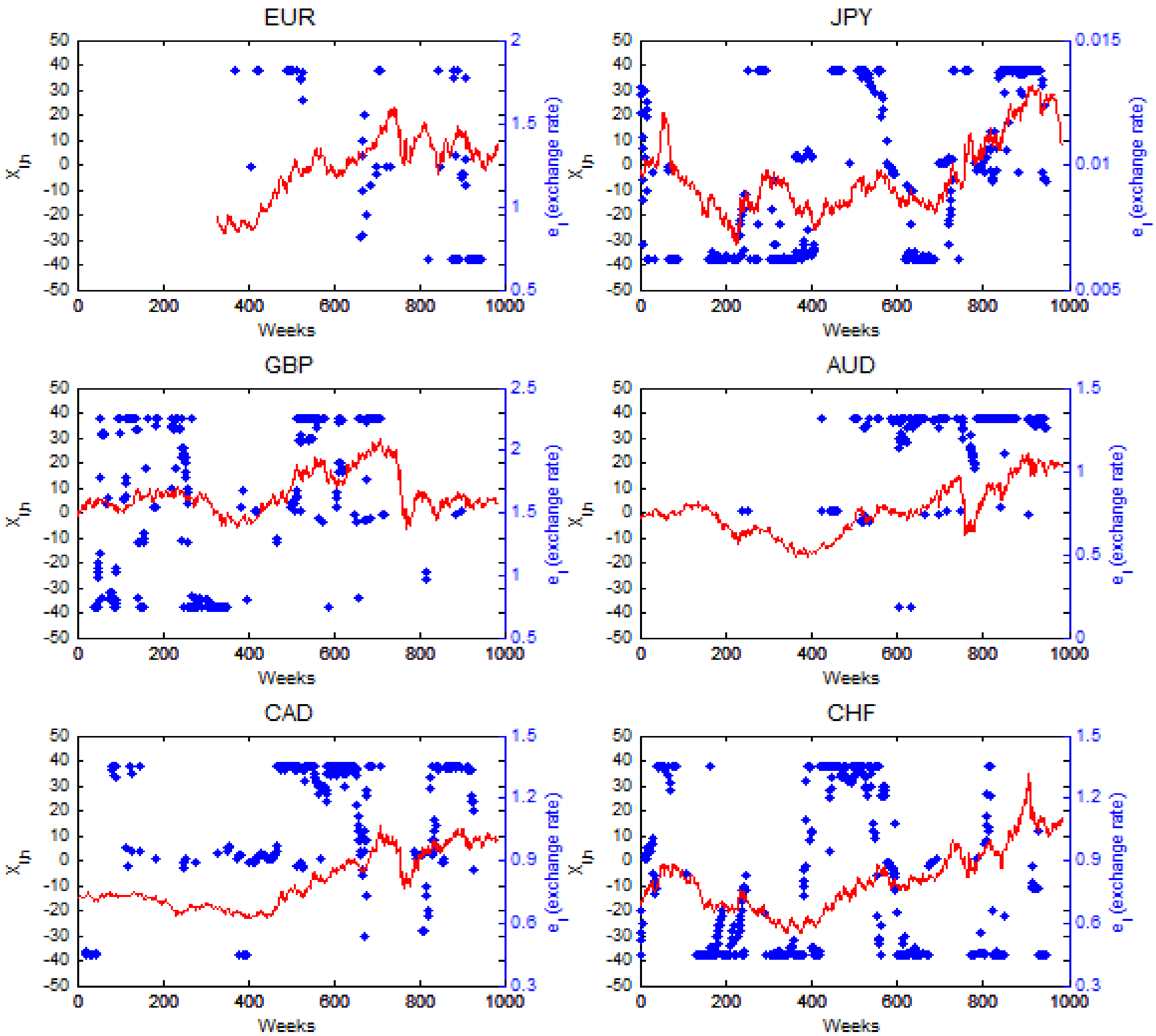
Figure 18: $X_{t,h}^{(i)}$: $h = 6m$ (25 weeks)



Notes:

1. The information on the graph is described in the notes to Figure 16.

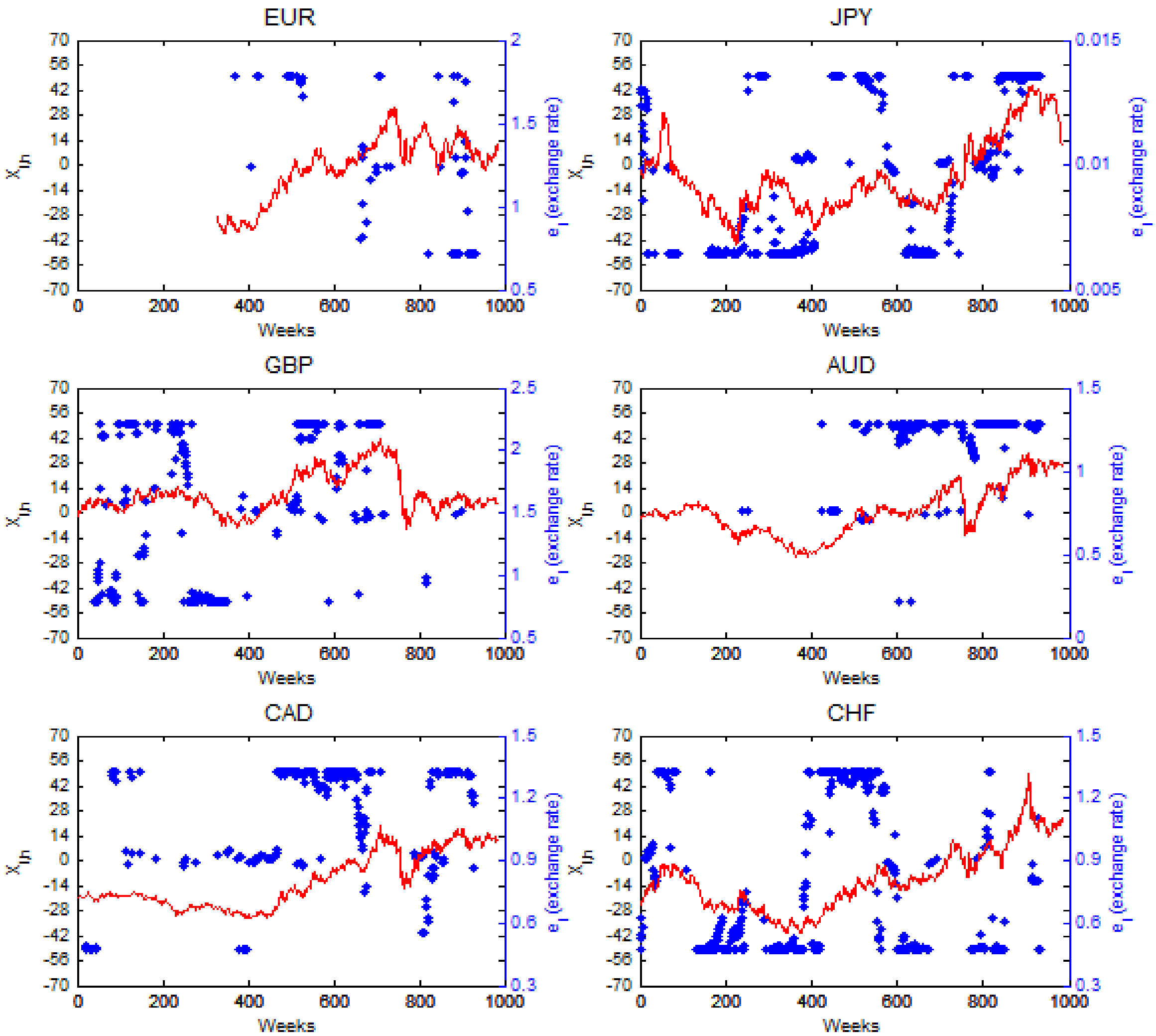
Figure 19: $X_{t,h}^{(i)}$: $h = 9m$ (38 weeks)



Notes:

1. The information on the graph is described in the notes to Figure 16.

Figure 20: $X_{t,h}^{(i)}$: $h = 12m$ (50 weeks)



Notes:

1. The information on the graph is described in the notes to Figure 16.

2 Emerging Market Business Cycles: Financial Frictions vs Permanent Shocks

2.1 Introduction

Business cycles in emerging economies exhibit notable differences from those in developed economies: the volatility of consumption relative to output is on average greater than one and trade balance is strongly counter-cyclical. Current theoretical explanations of these divergences of business cycle features between emerging economies and developed economies fall into two leading approaches.

The first approach, represented by Aguiar and Gopinath (2007), argues that a frictionless standard real business cycle model driven mainly by shocks to trend growth (permanent shocks to total factor productivity (TFP)) can explain all defining features of business cycles in emerging economies. According to this view, emerging countries, in contrast to developed countries, experience frequent regime changes because of the sudden swings in economic policies. Therefore, shocks to trend growth are the main source of economic fluctuations in these economies, unlike developed economies whose fluctuations are primarily driven by transitory shocks to TFP. The second approach, exemplified by Neumeyer and Perri (2005) and Uribe and Yue (2006), argues that in order to explain economic fluctuations in emerging economies, one should take into account the roles of financial imperfections and external shocks which asymmetrically affect these countries. This line of research, for example, introduces foreign interest rate shocks coupled with financial frictions such as working capital into a standard small open economy model.

To test the hypotheses implied by these two approaches from an empirical perspective, we need to distinguish transitory shocks from permanent shocks in the data and measure the relative importance of these two shocks in economic fluctuations in emerging economies. Recent related empirical literature, encouraged by the developments in the theory and implementation of Bayesian methods, has focused on estimating the parameters of the exogenous shock processes to test the empirical performance of these two approaches. The results of recent studies are in favor of the role of financial frictions and against that of shocks to trend growth. Garcia-Cicco, Pancrazi and Uribe (2009) estimate the Aguiar and Gopinath (AG) model, using Argentine and Mexican data over the period 1900-2005. They find that the AG model does a poor job at explaining the observed business cycles in Argentina and Mexico. Instead, an augmented version of the AG model, which incorporates preference shocks and country risk premium shocks into the AG model, mimics well the observed business cycles in emerging countries. Furthermore the augmented model assigns a negligible role to permanent productivity shocks. Chang and Fernandez (2010) compare the performance of the AG model with that of encompassing model which combines shocks to trend growth with interest rate shocks and financial frictions, using the Mexican data of Aguiar and Gopinath (2007). Their results are also supportive of the view that explaining fluctuations in emerging economies requires the assumption of financial imperfections that amplify transitory shocks. In their study, permanent shocks play an insignificant role if financial frictions are present.

However, it is too early to make conclusions since most empirical studies are centered on Latin American countries. In this paper, I instead focus on Korea, which shares the same features of macroeconomic fluctuations observed in other emerging countries but has gone through a different economic development process. I follow the encompassing model developed by Chang and Fernandez (2010) as an alternative model to the AG model. I employ the Korean data over the same period of 1980:1Q-2003:2Q as in Aguiar and Gopinath (2007) and Chang and Fernandez (2010), thus ensuring that my results can be directly compared with their findings for Latin American countries. My work differs from Chang and Fernandez (2010) in several dimensions. First, using reliable capital stock data, I explore the transitional dynamics in Korea and its implications for the estimation results. Second, with country spread data unavailable in Korea, I calibrate and estimate the parameters using different methods.

As a result of Bayesian estimations of the two models, my findings are quite contrary to those from previous studies. First, when we estimate the underlying productivity parameter, the magnitude of permanent shocks is much larger than that of transitory shocks. The estimated posterior mode ratio of volatilities between transitory and permanent shocks is 0.59 in the AG model, which is very close to the value of 0.37 obtained in Aguiar and Gopinath (2007). Furthermore, the relative importance of permanent shocks does not subside even when financial frictions are present. The ratio is 0.1 in the encompassing model, which is in stark contrast with the findings of Chang and Fernandez (2010) that the volatility of innovations is much smaller in the permanent technology process than in the transitory one. In their results, the ratio is 5.5. Moreover, the random walk component of the Solow residual, a measure of the relative importance of trend shocks, is as high as what Aguiar and Gopinath (2007) obtained. This is at odds with the findings of Chang and Fernandez (2010), and Garcia-Cicco, Pancrazi and Uribe (2009).

Second, the comparison of theoretical second moments of the two models with the moments of Korean data also shows that the AG model delivers a closer match to the moments calculated from the data. The AG model estimates the ratio of consumption volatility relative to output as 1.13, which is almost equal to the value of 1.11 generated from the data. On the other hand, the encompassing model severely overestimates the ratio. Furthermore, the ratio of trade balance share volatility relative to output estimated by the AG model is exactly the same as that calculated from the data.

Lastly, when I evaluate the relative contribution of the different shocks to aggregate fluctuations using the variance decomposition, I find that the permanent productivity shocks are responsible for the bulk of the macroeconomic fluctuations. The striking result is that the contribution of transitory shocks and world interest rate shocks to business cycles in Korea is predicted to be too trivial. They play virtually no role in explaining movements in output and consumption growth and a minor role in explaining the variance of investment growth and the change in trade balance share. All four of these variables are mainly driven by permanent shocks.

However, these results should be interpreted with caution, because the downward trend of the growth rate during the transition path to the steady state in Korea might be captured as permanent shocks. As Section 2 indicates, Korea's economy was on the transition path to the steady state during most of the time of the sample period of 1980:1Q - 2003:2Q. This raises an issue in the empirical study of emerging market business cycles. No existing studies examine explicitly whether the samples they use for the estimation are generated from the transition or balanced growth path. In this regard, extending the time series of data back in time as in Garcia-Cicco, Pancrazi and Uribe (2009) without considering this issue might not be useful since it might be only in the recent decades that emerging countries economies have been in the steady state.

The rest of this paper is organized as follows. Section 2 examines the transition dynamics and the key moments of business cycle in Korea. Section 3 presents the competing models under study. Section 4 calibrates the models using Korean data and discusses the methodology of Bayesian estimation. Section 5 presents and discusses the results. Section 6 concludes.

2.2 Transitional Dynamics and Business Cycle Properties in Korea

In this Section, I briefly explore the role of transitional dynamics in explaining Korea's economic growth. I confirm that before the Asian crisis, Korea's economy was on convergence path to the steady state and thus its economic growth rate had declined gradually over time. Also, I provide the second moment properties of the Korean business cycle over the period of 1970-2008. Korea's economy shares the business cycle properties common to other emerging economies as noted in Neumeyer and Perri (2005): consumption is more volatile than output and trade balance is strongly countercyclical.

2.1 Transition Dynamics

Figure 21 shows the historical behaviors of the logarithm of GDP per capita, labor share, capital to output ratio and real rate of return to capital in Korea over the period 1970-2008, which are depicted on a quarterly basis. As we can see, the Korean labor share gradually increased from 40% in 1970 and converged to 60% in mid-1990s. The real rate of return to capital declined from about 12% to 2% over the period 1970 - the mid-1990s. The capital-output ratio continued to rise until the early 2000s and has been stable around 10 since then. The trajectory of the logarithm of GDP per capita implies that the growth rate of output gradually declined from the early 1990s. This evidence suggests that Korea's economy featured the transition dynamics and gradually converged to the balanced growth path from 1970 to the mid-1990s. This confirms Young (1994, 1995)'s findings that increasing investment rates and factor input accumulation mainly contributes to growth in the Asian growth miracles.

2.2 Business Cycle Properties

Table 24 presents the volatilities of the data, in terms of standard deviations, volatilities relative to output, correlations with output and trade balance, and autocorrelations. It uses the data in log differences except for the trade balance relative to output (trade balance share) for which level differences are used. The column 1 of Table 24 uses the same period (1980:1Q- 2003: 2Q) as in Aguiar and Gopinath (2007), and Chang and Fernandez (2010) so that my results can be compared with the findings for Mexico and other emerging countries. Column 2 uses the period (1998:1Q-2008:4Q) during which, arguably, Korea's economy is in the steady state. Column 3 employs the entire sample period (1970:1Q - 2008:4Q). Moments were calculated using generalized method of moments (GMM), and standard errors are reported in parentheses.

Panel A of column 1 reports the volatility of log difference in the variables (output, consumption, investment and first difference in trade balance share) for Korea's economy. Compared to the findings for Mexico as reported in Aguiar and Gopinath (2007), and Chang and Fernandez (2010), Korea's output and consumption are more volatile but its investment and trade balance share are more stable. Panel B of column 1 reports the volatility of the variables relative to output. As we can see, consumption is more volatile than output. The ratio of consumption volatility relative to output is 1.1, which is smaller than that of Mexico (1.27). Panel C of column 1 presents the correlation of the variables with output. It shows strong counter-cyclicality of trade balance in Korea, which is also present in Mexico. Panel E of column 1 reports autocorrelation of the variables. A notable difference between Korea and Mexico is that the autocorrelation of output in Korea is almost zero while in Mexico it is 0.27.

The comparison across the columns in Table 24 reveals the changes in second moments of Korea's business cycle properties before and after the Asian crisis. After the crisis, output and consumption volatilities increased while investment and trade balance volatilities declined. Interestingly, the relative volatility of consumption to output increased from 1.11 to 1.37 while investment became less volatile relative to output.

2.3 Models

In this section, I briefly introduce two models: the stochastic trend model developed by Aguiar and Gopinath (2007) and encompassing model in Chang and Fernandez (2010).

2.1 The Stochastic Trend (AG) Model

Aguiar and Gopinath (2007) have recently emphasized that the empirical failures of the standard emerging market model can be fixed by allowing labor augmenting growth to be random. In this section, I briefly introduce their model. Technology is characterized by a Cobb-Douglas production function that uses capital(K_t) and labor(N_t) as inputs:

$$Y_t = e^{z_t} K_t^{1-\alpha} (\Gamma_t N_t)^{\alpha} \tag{52}$$

where α represents labor share of output. z_t and Γ_t represent the productivity processes. The two productivity processes are characterized by different stochastic components. Specifically, z_t is an AR(1) process:

$$z_t = \rho_z z_{t-1} + \epsilon_t^z$$

with $|\rho_z| < 1$, ϵ_t^z is an i.i.d. process with $N(0, \sigma_z)$.

Γ_t represents the cumulative product of growth shocks. In particular,

$$\Gamma_t = g_t \Gamma_{t-1} = \prod_{s=0}^{t} g_s \tag{53}$$

$$\ln(g_{t+1}/\mu_g) = \rho_g \ln(g_t/\mu_g) + \epsilon_t^g \tag{54}$$

with $|\rho_g| < 1$, ϵ_t^g is an i.i.d. process with $N(0, \sigma_g)$. μ_g is the long run mean growth rate of the economy.

Since realization of g permanently influences Γ, output is nonstationary with a stochastic trend. Further on the Γ_t process is:

$$\ln \Gamma_t = \ln g_t + \ln \Gamma_{t-1}$$

So, we clearly see that this process is permanent in levels of Γ_t, while transitory in growth rates of Γ_t which is g_t.

I focus on GHH (1998) preferences in stead of Cobb-Douglas preferences in the original AG model. GHH preferences are widely known to help reproduce some emerging economies business cycles facts by making the labor supply not depend on income levels. GHH preferences take the form as follows,

$$U_t = \frac{(C_t - \tau \Gamma_{t-1} N_t^{\upsilon})^{1-\sigma}}{1-\sigma} \tag{55}$$

where $\upsilon > 1$ and $\tau > 0$. The elasticity of labor supply is given by $\frac{1}{\upsilon - 1}$, and the intertemporal elasticity of substitution is given by $\frac{1}{\sigma}$. To ensure that labor supply remains bounded along the growth path, cumulative growth in the disutility of labor is included. For utility to be well defined, $\beta \mu_g^{1-\sigma}$ must be less than 1.

The per period resource constraint is

$$C_t + X_t = Y_t - B_t + q_t B_{t+1}$$

International financial transactions are restricted to one-period, risk-free bonds. The level of debt due in period t is denoted B_t, and q_t is the time t price of debt due in period $t+1$. The price of debt is sensitive to the level of outstanding debt, taking the form used in Schnitt-Grohe and Uribe (2003). This is needed for the level of bond holdings to be stationary and one of six methods imposing stationarity of bond holdings.

$$\frac{1}{q_t} = 1 + r_t = 1 + r^* + \psi \left[e^{\frac{B_{t+1}}{\Gamma_t} - b} - 1 \right] \tag{56}$$

where r^* is the world interest rate, b represents the steady-state level of debt, and $\psi > 0$ governs the elasticity of the interest rate to change in indebtness.

In choosing the optimal amount of debt, the representative agent does not internalize the fact that she faces an upward-sloping supply of loans, i.e. she is still a price taker.

Capital accumulates according to

$$K_{t+1} = X_t + (1-\delta)K_t - \frac{\phi}{2}(\frac{K_{t+1}}{K_t} - \mu_g)^2 K_t$$

Capital depreciates at the rate δ, and changes to the capital stock includes capital adjustment cost $\frac{\phi}{2}(\frac{K_{t+1}}{K_t} - \mu_g)^2 K_t$.

For any variable, we can normalize by trend productivity in period $t-1$. A hat is introduced to denote its detrended counterpart.

$$\widehat{x}_t = \frac{x_t}{\Gamma_{t-1}}$$

In normalized form, the representative agent's problem can be stated recursively.

$$V(\widehat{K}_t, \widehat{B}_t, z_t, g_t) = \max_{\widehat{C}_t, N_t, \widehat{K}_{t+1}, \widehat{B}_{t+1}} U(\widehat{C}_t, N_t) + \beta g_t^{1-\sigma} E_t V(\widehat{K}_{t+1}, \widehat{B}_{t+1}, z_{t+1}, g_{t+1}) \quad (57)$$

where $U(\widehat{C}_t, N_t) = \frac{(\widehat{C}_t - \tau N_t^{\upsilon})^{1-\sigma}}{1-\sigma}$

The optimization is subject to the budget constraint

$$\widehat{C}_t + g_t \widehat{K}_{t+1} = \widehat{Y}_t + (1-\delta)\widehat{K} - \frac{\phi}{2}(g_t \frac{\widehat{K}_{t+1}}{\widehat{K}_t} - \mu_g)^2 \widehat{K_t} - \widehat{B}_t + g_t q_t \widehat{B}_{t+1} \quad (58)$$

The accumulation of the capital stock, production function and net export are given by

$$g_t \widehat{K}_{t+1} = \widehat{X_t} + (1-\delta)\widehat{K_t} - \frac{\phi}{2}(\frac{\widehat{K}_{t+1}}{\widehat{K}_t} - \mu_g)^2 \widehat{K}_t$$

$$\widehat{Y}_t = e^{z_t} \widehat{K}_t^{1-\alpha} (g_t N_t)^{\alpha}$$

$$\widehat{NX}_t = \widehat{Y}_t - \widehat{X_t} - \widehat{C}_t$$

2.2 Encompassing Model

I follow the encompassing model developed by Chang and Fernandez (2010), which basically introduced financial frictions into the AG model in the previous subsection. First, they include two financial frictions (*Assumption of a country spread linked to expected productivity* and *Working capital assumption)* into the AG model as follows.

1. *Assumption of a country spread linked to expected productivity*

The price of the agent's debt is assumed to be given from the equation (56)

$$1/q_t = R_t + \psi \left[e^{\frac{B_{t+1}}{\Gamma_t} - b} - 1 \right] \tag{59}$$

where R_t is a country specific rate,

$$R_t = S_t R_t^* \tag{60}$$

where R_t^* is the world interest rate and S_t a country spread.

Unlike the AG model, The world interest rate is now assumed to be random. The process R_t^* is given by

$$\ln(R_t^*/R_{t-1}^*) = \rho_R \ln(R_{t-1}^*/R^*) + \epsilon_t^R \tag{61}$$

where $|\rho_R| < 1$ and ϵ_t^R is i.i.d. Innovation with mean 0 and standard deviation σ_R.

As in Neumeyer and Perri (2005), they let the deviations of the country spread from its long-run level depend on expected future productivity as follows

$$\ln(S_t/S) = -\eta E_t \ln z_{t+1} \tag{62}$$

2. Working capital assumption

Another financial friction they introduce comes from Neumeyer and Perri (2005) and Uribe and Yue (2006), which assume that firms in emerging economies should finance a fraction of their labor cost in advance. In this case, the labor market equilibrium condition requires

$$W_t \left[1 + \theta(R_{t-1} - 1)\right] = \alpha \frac{\widehat{Y}_t}{N_t} \tag{63}$$

This implies that firms are assumed to finance their labor cost from households and forced to pay a fraction θ of the labor cost before production.

Second, Chang and Fernandez (2010) allowed the country spread to depend on permanent technology shocks as well as transitory technology shocks in their encompassing model. To carry out this idea, they modify the assumption (3.13) on country risk and allow for stochastic trend shocks to also affect the spreads.

$$\ln(S_t/S) = -\eta_1 E_t \ln z_{t+1} - \eta_2 E_t \ln(g_{t+1}/\mu_g)$$

One particular version of this, which they use, assumes that the spread is given by (2.12), except that the transitory productivity shock z_{t+1} is replaced by total factor productivity (Solow residual: SR_{t+1})

$$\ln(S_t/S) = -\eta E_t \ln(SR_{t+1}/SR) \tag{64}$$

where $SR_t = z_t g_t^\alpha$ and $SR = \mu_g^\alpha$.

Thus, their encompassing model is given by the country spread process in (64) along with the assumptions of stochastic interest rates (59,60 and 61), the working capital requirement (63), and trend shocks (53) and temporary productivity shocks (54)

2.4 Calibration and Estimation

For each model, I calibrate some parameters and estimate the rest using Korean data. Since I explore the relative importance of sources of business cycles fluctuations, I estimate the parameters of exogenous shocks processes. More specifically, the parameters of transitory and permanent productivity processes in both models are estimated. In the encompassing model, the parameters of world interest rate process are also estimated. To calibrate the parameter values discount factor (β) and long-run country spread $\overline{S}$ as in Chang and Fernandez (2010) and Aguiar and Gopinath (2007), I need Korea's gross interest rate data. Unfortunately, the data is not available for Korea. I instead use Korea's capital stock data to calibrate those parameter values. For some parameter values, there exist notable differences between Korea and other emerging countries.

2.1 Calibration

Table 25 reports the parameter values calibrated using the steady state equations or standard values from the literature. The time unit in the model is a quarter in my calibration. The parameter values in the GHH preferences (55) that I set to conventional values are the coefficients of relative risk aversion σ that I set to 2 and the curvature of labor υ that I set to 1.6 in both models.

I follow Schmitt-Grohe and Uribe (2003) and assign a small value 0.001 to the parameter ψ in the country's debt equation (59) for both models, measuring the sensitivity of the country interest rate premium to deviations of external debt from the trend.

For the other structural parameters, I calibrated μ_g, α, β, τ and δ so that the balanced growth paths in the model are consistent with the long-run averages in the data, using the Korean data for the period from 1980:1Q to 2003:2Q. In particular, I set the growth rate parameter μ_g for both models to 1.015 to match the average growth rate of 1.5% per quarter. I set the labor share parameter α in the production function (52) to 0.57 in the stochastic trend model to match an average labor share of income during the sample period, which is quite lower than that of other emerging countries. In the encompassing model, I set α to 0.58 in the encompassing model[28]. The labor parameter τ in the GHH preferences for the stochastic trend model is set to 3.004 to match average time spent working of 41.7% of total time (10 hours per day), which reflects that average hours worked per month in Korea is 210 hours during the period[29]. In the encompassing model, taking adjusted labor share into account, I set it to 2.8104.

For calibrating δ, notice that given the observations for the average investment to output ratio, the average capital to output ratio and the average growth rate calculated from Korean data, we can pindown depreciation rate of capital δ from the steady state equation. The average investment to output ratio and capital to output ratio are 0.308 and 8.03 respectively during the sample period. The average growth rate is 1.015. Therefore, depreciation rate of capital δ is calculated to 0.022 in both models. Given the values for μ_g, δ, α, σ and the average capital to output ratio, we can calibrate the discount rate β to 0.9982 using steady state debt Euler equation and capital Euler equation in the stochastic trend model. Also, $\overline{R^*}$ can be pin downed as 1.0321. In the encompassing model, in order to set β and $\overline{S}$, we need the gross country specific interest rate data. Unfortunately, those data are not available in Korea during the sample period. Instead, we have the real rate of return to capital and gross foreign interest rate $\overline{R^*}$ which is quarterly average US real interest rate during the sample period, 1.0025. Therefore, I set $\overline{R}$ and $\overline{S}$ ($\overline{R} - \overline{R^*}$) to 1.0305 and 1.028 respectively in the encompassing model. Accordingly, β is calculated to 0.9992. Data of debt to output ratio during the sample period is not available. I set b to 0.1

[28]In the encompassing model, α is not exactly equal to labor share, but it is $\alpha = \textit{labor share} \times [1 + (R-1)\theta]$. I compute the value using the posterior mode of $\theta, 0.83$.

[29]According to OECD (2008), over the period from 1980 to 2006, the average hours worked per year per employed person in Korea 2,669, which was much longer than 1,821 in the US and 1,833 of average in OECD countries.

in both models, considering steady state trade balance to output ratio and country specific interest rates $\overline{R}$.

2.2 Bayesian Estimation

I estimate the remaining parameters, using Bayesian methods and Korean data on aggregate output (Y), consumption (C), investment (I), and the trade balance to output ratio (TB/Y). For comparison with Latin American countries, the data are quarterly for the period from 1980:1Q to 2003:2Q, as in Aguiar and Gopinath (2007) and Chang and Fernandez (2010). Key parameters to be estimated are ρ_z, ρ_g, σ_z and σ_g governing the transitory and permanent productivity processed in both stochastic trend and encompassing model. In the encompassing model, I estimate the AR coefficient ρ_R and standard deviation of the innovations σ_R of the world interest rate process. In addition, the elasticity of the spread to expected productivity (η) and the working capital requirement parameter (θ) are also estimated in the encompassing model. In both cases, I estimate the parameter ϕ governing the capital adjustment cost. I also estimate four non-structural parameters representing the standard deviations of i.i.d. measurement errors on the four aggregate variables, $\sigma_C, \sigma_C, \sigma_I$ and $\sigma_{TB/Y}$.

My empirical implementation follows the methods of Chang and Fernandez (2010) which draw on An and Schorfheide (2007), Fernandez-Villaverde (2010) and etc. Once the model is linearized around its non-stochastic steady state, the system of equations can be characterized in the form of a transition equation

$$Z_t = PZ_{t-1} + Q\upsilon_t$$

where Z_t is a vector with model variables, υ_t is a vector of structural shocks, and P

and Q are system matrices.

The system of equations should be transformed into following measurement equation to implement Kalman filter.

$$D_t = F + GZ_t + \epsilon_t$$

where D_t is an observed data set and ϵ_t are exogenous i.i.d. measurement errors.

In this model, since the solutions of the model is characterized in terms of log-deviations from steady state, it is difficult to deal with the trend shock. So a transformation of data and model variables is needed as shown below.

$$\Delta \ln(D_t) = \ln \mu_g + (\widehat{d}_t - \widehat{d}_{t-1}) + \widehat{g}_t$$

where $\Delta \ln(D_t)$ denotes the first log difference of the data and a hat denotes log-deviations from steady state values.

Since trade balance to output ratio is not affected by trend shocks, we can directly map the observed data to the model based data. Moreover, we take a linear approximation (not log-linearization) to model-based measure of trade to output ratio, the mapping in terms of first difference is

$$\Delta(TB_t/Y_t) = (\widehat{tby}_t - \widehat{tby}_{t-1})$$

I repeat the maximization algorithm using random starting values for the parameters drawn from their prior support to find the posterior mode and check whether multiple modes exist. Then, I used the Random Walk Metropolis algorithm to generate 150,000 draws from the posterior distribution. The initial 50,000 draws were discarded.

2.5 Results

Since there are no earlier studies on Korea's business cycle, I use the same priors over the parameters to be estimated as in Chang and Fernandez (2010). Their priors are based on earlier studies on emerging market business cycles such as Aguiar and Gopinath (2004), Garcia-Cicco et al (2009), Neumeyer and Perri (2005) and Uribe and Yue (2006). Since Korean and Mexican economies share the same business cycles properties in many aspects, I believe that it is reasonable that I use the same priors for Mexico over the parameters of Korea's economy to be estimated.

2.1 Priors and Posteriors

The priors I use are described in Table 26. Key parameters to be estimated are those that govern the temporary and permanent technology processes: σ_z, σ_g, ρ_z and ρ_g. The relative magnitude of σ_z and σ_g is especially crucial to identifying the sources of emerging market business cycles. Unfortunately, prior studies on the relative magnitude of two shocks present mixed results. While Aguiar and Gopinath (2004) estimated a ratio of $\frac{\sigma_z}{\sigma_g} = \frac{0.41}{1.09} = 0.4$ for Mexico, Garcia-Cicco et al (2009) finding was ,$\frac{\sigma_z}{\sigma_g} = \frac{1.9}{1.7} = 1.1$. Chang and Fernandez (2010), which I follow, set their prior mean of 0.74 for σ_z and σ_g using the mean of the point estimates of σ_z and σ_g in Aguiar and Gopinath (2004).

Table 27 describes the estimated posterior distributions of the parameters of the AG and encompassing models. The first three columns present priors and posterior modes, means and 90 percent confidence intervals of the parameters in the AG model. The next two columns report posterior modes, means and 90 percent interval for the encompassing model. Figure 22 and 23 depict priors and posterior distributions for the AG and encompassing models, respectively.

Several results are worth mentioning:

1. The data are informative in the sense that the estimated posteriors provide more precise information than priors as measured by the width of the 90 percent confidence intervals. For example, the 90 percent interval of the posterior for ρ_g, the parameter that governs the persistence of the permanent technology process, becomes much narrower than that of the prior in the estimation of encompassing model. By contrast, the 90 percent interval of the posterior for ρ_z, the parameter that governs the persistence of the transitory technology process, shows no changes compared to that of the prior. This finding is quite at odds with Chang and Fernandez (2010) and Garcia-Cicco et al. (2009) who weakly identified the persistence of the trend shock to productivity.

2. The role of trend shocks in the encompassing model is more dominant than that implied by the prior. The estimated posterior mode ratio of volatilities between transitory and trend shocks, $\frac{\sigma_z}{\sigma_g} = \frac{0.13}{1.25} = 0.1$, is far below the value (5.5) estimated by Chang and Fernandez (2010). This result is more consistent with Aguiar and Gopinath's (2007) finding that the volatility of innovations is much larger in the permanent technology process than in the transitory one. To see this more clearly, I estimate the AG model shutting down both interest rate shocks and financial frictions. The ratio in the AG model, 0.59, is very close to the value (0.38) estimated by Aguiar and Gopinath's (2007) while it is quite below the value estimated by Chang and Fernandez (2010).

3. To confirm the relative importance of trend shocks, I calculate the random walk component (RWC) of the Solow residual defined as in Aguiar and Gopinath

(2007).

$$RWC = \frac{\alpha^2\sigma_g^2/(1-\rho_g)^2}{[2/(1+\rho_z)^2] + \left[\alpha^2\sigma_g^2/(1-\rho_g)\right]}$$

RWC for the encompassing model, 4.7, is far above the value of 0.2 estimated by Chang and Fernandez (2010), while that for the AG model, 4.6, is quite close to the value obtained by Aguiar and Gopinath (2007).

4. In contrast with the major role played by permanent shocks, transitory shocks play a minor role in the encompassing model. Interestingly, the volatility of innovation in the transitory technology process is much smaller in the encompassing model than in the AG model. However, the volatility of innovation in the permanent technology process are the same in both models.

5. The volatility of innovation in the country interest rate process, 0.25%, is below the value of 0.40% estimated by Chang and Fernandez (2010).

6. Posterior distributions of the parameters θ and η governing the degree of financial frictions in the encompassing model are positive. The posterior mode for θ is 0.68, which is very close to the 0.69 value estimated by Chang and Fernandez (2010). The posterior mode of 0.84 for η, which is higher than the 0.73 value in Chang and Fernandez (2010), reveals a significant elasticity of the spread to the expected movements in the country fundamentals, included in the Solow residual. Even though the data assign a non-negligible role to financial frictions, this does not necessarily mean that the encompassing model mimics well the observed business cycle in Korea. In the next subsection, I evaluate the two models comparing the sample moments from the data with the moments predicted by the two models.

2.2 Second Moments

The literature on the economies business cycles in emerging economies has emphasized some key moments in model evaluation. The counter-cyclicality of the trade balance and high volatility of consumption relative to output have drawn much attention in evaluating existing models. In this regard, Table 28 summarizes key moments of interest such as volatilities, correlations with output and trade balance, and serial correlations implied by the AG and encompassing models, along with filtered sample moments of Korean data. I filter the data using log-differences for output, consumption and investment, and first differences for the trade balance share. Model-based moments are computed using posterior mode estimates.

Table 28 shows that the AG model delivers a close match to the moments calculated from the data. First, the encompassing model severely underestimate the volatility of output and investment. By contrast, the AG model predicts more accurate investment and consumption volatilities in accordance with the data. Second, the AG model estimates the ratio of consumption volatility relative to output, 1.13, which is almost equal to the value of 1.11 generated from the data. On the other hand, the encompassing model severely overestimates the ratio. Furthermore, the ratio of trade balance share volatility relative to output estimated by the AG model is exactly the same as that calculated from the data. Third, the AG model also predicts that the correlation between trade balance share and output, a measure of counter-cyclicality of trade balance, is - 0.53, which is very close to the value of -0.43 in the data. Lastly, the AG model delivers a very close match to negative correlations of the trade balance share with consumption and investment in the data.

2.3 Variance Decomposition

Table 29 and 30 report the variance decomposition predicted by the AG and encompassing models, respectively. They assess the relative role of each structural shock in explaining macroeconomic fluctuations in Korea. I computed each share of structural shocks in both models in the variance of output growth (gY), consumption growth (gC), investment growth (gI) and the changes in the trade balance to GDP ratio (dTB/Y). Variance decompositions are computed from the estimation using above four variables and measurement errors. Numbers are reported using posterior means estimates and only the role of the structural shocks was taken into account.

Table 29, which reports the variance decomposition predicted by the AG model, shows that trend shocks play a major role in explaining the variance of all variables. Notably, trend shocks explain 80.1% and 98.6% of the variances of investment growth and the change in the trade balance to GDP ratio, respectively. On the other hand, the shares of transitory shocks in explaining the variance of each variable are all lower than those of permanent shocks.

In Table 30 which presents the variance decomposition predicted by the encompassing model, the dominant role of permanent shocks does not subside but grows. The notable result is that the contribution of transitory shocks and world interest rate shocks to business cycles in Korea is predicted to be too trivial. Transitory and world interest rate shocks play virtually no role in explaining movements in output and consumption growth. In addition, they play a minor role in explaining the variance of investment growth and the change in trade balance share. All four of these variables are driven by permanent shocks.

2.6 Conclusion

In this paper, I compare the performance of AG(stochastic trend) model and Chang and Fernandez (2010)'s encompassing model that combines stochastic trend with interest rate shocks and financial frictions, using the Korean data set over the period 1980-2003:1Q, which is the same period as in Aguiar and Gopinath (2007) and Chang and Fernandez (2010). In contrast to the results of Garcia-Cicco, Pancrazi and Uribe (2009) and Chang and Fernandez (2010) for Mexico and Argentina, the role of permanent shocks seems to be dominant in both models. The estimated posterior mode ratios of volatilities are $\frac{\sigma_z}{\sigma_g} = \frac{0.74}{1.25} = 0.59$ in the stochastic trend model and $\frac{\sigma_z}{\sigma_g} = \frac{0.13}{1.25} = 0.1$ in the encompassing model. Also, the random work components of the Solow residual are also high for both models.

These findings are also confirmed by the results of variance decompositions and the comparison of theoretical second moments of each model with the moments of the Korean data. The permanent productivity shocks play a dominant role in explaining macroeconomic fluctuations in Korea over the sample period. Also, the stochastic trend model delivers a closer match to the moments calculated from the data.

However, these results should be interpreted with caution, because the downward trend of the growth rate in the transition path could be captured as permanent shocks. As section 2 indicates, Korea's economy was in the transition path during most of the time in the sample period of 1980-2003:1Q. In fact, Korea's growth rate tended to keep going down gradually within the sample period until the Asian crisis in 1997 which, I believe, is the starting point of the balanced growth path in Korea.

2.7 Appendix

2.7.A Tables and Figures

Table 24: Second moments for Korea's economy

X	$80:1Q \sim 03:2Q$	$98:1Q \sim 08:4Q$	$70:1Q \sim 08:4Q$
		Standard Deviation (SD) (%)	
gY	1.82 (0.22)	1.99 (0.46)	1.84 (0.39)
gC	2.02 (0.54)	2.72 (0.78)	1.85 (0.59)
gI	4.34 (0.44)	4.06 (0.92)	6.09 (0.92)
dTB/Y	0.98 (0.21)	1.20 (0.34)	0.92 (0.22)
		$SD(gX \text{ or } dX)/SD(gY)$	
gC	1.11 (0.22)	1.37 (0.13)	1.01 (0.15)
gI	2.39 (0.19)	2.04 (0.17)	3.31 (0.53)
dTB/Y	0.54 (0.08)	0.61 (0.07)	0.50 (0.05)
		Correlation with gY	
gC	0.73 (0.12)	0.91 (0.05)	0.67 (0.11)
gI	0.66 (0.11)	0.88 (0.06)	0.51 (0.09)
dTB/Y	−0.43 (0.24)	−0.64 (0.21)	−0.27 (0.24)
		Correlation with dTB/Y	
gC	−0.73 (0.13)	−0.79 (0.13)	−0.49 (0.29)
gI	−0.52 (0.16)	−0.66 (0.18)	−0.38 (0.12)
		Serial correlation	
gY	0.01 (0.17)	0.18 (0.07)	−0.01 (0.11)
gC	0.32 (0.08)	0.08 (0.09)	0.21 (0.08)
gI	0.17 (0.13)	0.13 (0.06)	−0.07 (0.10)
dTB/Y	0.13 (0.10)	−0.05 (0.06)	0.05 (0.10)

Notes:

1. This table presents values of the second moments for Korea's economy over three different periods. Moments are calculated using GMM. The standard deivations are in parenthesis.

2. gX and dX denote log-differences and first differences in X = Y, C, I and TB/Y, respectively. For gX and dX, unfiltered data are used.

Table 25: Calibrated Parameters

Parameter	Description	Stochastic trend	Encompassing
σ	Intertemporal elasticity of substitution $(1/\sigma)$	2	2
β	Discount factor	0.9982	0.9992
τ	Labor parameter so that $\overline{N} = 0.417$	3.004	2.810
ν	Labor supply elasticity $[1/(\nu - 1)]$	1.6	1.6
μ_g	Growth rate	1.015	1.015
α	Labor share	0.57	0.58
δ	Depreciation rate	0.022	0.022
b	Debt to GDP ratio	0.1	0.1
ψ	Debt elastic interest rate parameter	0.001	0.001
$\overline{R^*}$	Gross foreign interest rate	1.0321	1.0025
$\overline{R}$	Gross country specific interest rate	-	1.0305
$\overline{S}$	Long-run country spread	-	1.0280

Notes:

1. α is given as labor share $*[1+(\overline{R^*} - 1)]\theta$ in the encompassing model. To calibrate α, I use the posterior mode of θ.

Table 26: Prior Distributions

Parameter	Range	Density	Mean	S.D(%)	90% C.I
	Parameters common to both models				
ρ_z	$[0,1)$	*beta* [356.2; 18.75]	0.95	1.12	[0.92; 0.97]
σ_z	R^+	*Gamma* [2.060; 0.004]	0.74	0.56	[0.12; 1.67]
ϕ	R^+	*Gamma* [3.000; 2.000]	6.00	346	[1.62; 12.6]
σ_X	R^+	*Gamma* [4.000; 0.005]	2.00	1.00	[0.67; 3.86]
ρ_g	$[0,1)$	*beta* [285.1; 110.9]	0.72	2.25	[0.68; 0.76]
σ_g	R^+	*Gamma* [2.060; 0.004]	0.74	0.56	[0.12; 1.67]
	Parameters specific to the encompassing model				
ρ_R	$[0,1)$	*beta* [44.26; 9.06]	0.83	5.10	[0.74; 0.91]
σ_R	R^+	*Gamma* [5.5552; 0.0013]	0.72	0.31	[0.30; 1.29]
θ	$[0,1)$	*Beta* [2.000; 2.000]	0.83	22.4	[0.13; 0.87]
η	R^+	*Gamma* [99.52; 0.010]	1.00	10.1	[0.84; 1.17]

Notes:

1. ρ_z is the AR(1) coefficient in the transitory technology process.
2. σ_z is the standard deviation(%) of transitory shock.
3. ϕ is the capital adjustment cost parameter.
4. σ_X is the standard deviation(%) of the measurement error in X = Y, C, I and TB/Y.
5. ρ_g is the AR(1) coefficient in the permanent technology process.
6. σ_g is the standard deviation of permanent shock(%).
7. ρ_R is the AR(1) coefficient in the foreign interest rate process.
8. σ_R is the standard deviation(%) of foreign interest shock.
9. θ is the working capital parameter.
10. η is the country spread elasticity.

Table 27: Posterior Distributions: Stochastic trend vs Encompassing model

Parameter	Prior	Stochastic trend		Encompassing	
		Mode	Mean & 90% C.I	Mode	Mean & 90% C.I
ρ_z	0.95 [0.92, 0.97]	0.95	0.95 [0.93, 0.96]	0.95	0.95 [0.93, 0.97]
ρ_g	0.72 [0.68, 0.76]	0.71	0.71 [0.68, 0.74]	0.65	0.65 [0.62, 0.68]
σ_z	0.74 [0.12, 1.67]	0.74	0.74 [0.51, 0.96]	0.13	0.11 [0.02, 0.23]
σ_g	0.74 [0.12, 1.67]	1.25	1.26 [1.10, 1.54]	1.25	1.26 [1.04, 1.50]
ϕ	6.00 [1.62, 12.6]	12.4	12.7 [9.4, 17.0]	34.9	35.2 [27.4, 43.9]
σ_Y	2.00 [0.67, 3.86]	0.87	0.88 [0.63, 1.12]	1.17	1.18 [1.03, 1.37]
σ_C	2.00 [0.67, 3.86]	0.86	0.86 [0.64, 1.07]	0.62	0.61 [0.33, 0.86]
σ_I	2.00 [0.67, 3.86]	3.04	3.08 [2.70, 3.51]	3.33	3.37 [2.98, 3.82]
$\sigma_{TB/Y}$	2.00 [0.67, 3.86]	0.44	0.43 [0.24, 0.61]	0.51	0.51 [0.32, 0.68]
ρ_R	0.83 [0.74, 0.91]			0.82	0.83 [0.73, 0.90]
σ_R	0.72 [0.30, 1.29]			0.26	0.25 [0.13, 0.40]
θ	0.50 [0.13, 0.87]			0.68	0.67 [0.23, 0.97]
η	1.00 [0.84, 1.17]			0.84	0.83 [0.67, 0.98]

Notes:

1. ρ_z is the AR(1) coefficient in the transitory technology process.
2. σ_z is the standard deviation(%) of transitory shock.
3. ϕ is the capital adjustment cost parameter.
4. σ_X is the standard deviation(%) of the measurement error in X = Y, C, I and TB/Y.
5. ρ_g is the AR(1) coefficient in the permanent technology process.
6. σ_g is the standard deviation(%) of permanent shock.
7. ρ_R is the AR(1) coefficient in the foreign interest rate process.
8. σ_R is the standard deviation(%) of foreign interest shock.
9. θ is the working capital parameter.
10. η is the country spread elasticity.

Table 28: Second moments: Data vs two alternative models

Variable	Korean data	Stochastic trend model	Encompassing model
		Standard Deviation (SD) (%)	
gY	1.82 (0.22)	1.63	1.20
gC	2.02 (0.54)	1.84	1.91
gI	4.34 (0.44)	3.15	2.62
dTB/Y	0.98 (0.21)	0.88	1.07
		$SD(gX \text{ or } dX)/SD(gY)$	
gC	1.11 (0.22)	1.13	1.59
gI	2.39 (0.19)	1.93	2.18
dTB/Y	0.54 (0.08)	0.54	0.89
		Correlation with gY	
gC	0.73 (0.12)	0.95	0.97
gI	0.66 (0.11)	0.92	0.83
dTB/Y	−0.43 (0.24)	−0.53	−0.70
		Correlation with dTB/Y	
gC	−0.73 (0.13)	−0.76	−0.86
gI	−0.52 (0.16)	−0.81	−0.97
		Serial correlation	
gY	0.01 (0.17)	0.11	0.21
gC	0.32 (0.08)	0.06	0.10
gI	0.17 (0.13)	0.01	−0.08
dTB/Y	0.13 (0.10)	−0.06	−0.11

Notes:

1. gX and dX denote log-differences and first differences in X = Y, C, I and TB/Y, respectively.

2. This table compares model based moments from two alternative models with histroical moments calculated using the Korean data, 1980:1Q- 2003:2Q. Historical moments are calculated using GMM. The standard deivations are in parenthesis.

3. Model based moments are computed using posterior mode. All estimations use measurement errors in all four variables.

Table 29: Forecast Error Variance Decomposition: Stochastic trend model

Structural shock	gY	gC	gI	dTB/Y
ϵ^g	50.9	76.4	80.1	98.6
Permanent productivity shock				
ϵ^z	49.1	23.6	19.9	1.4
Transitory productivity shock				

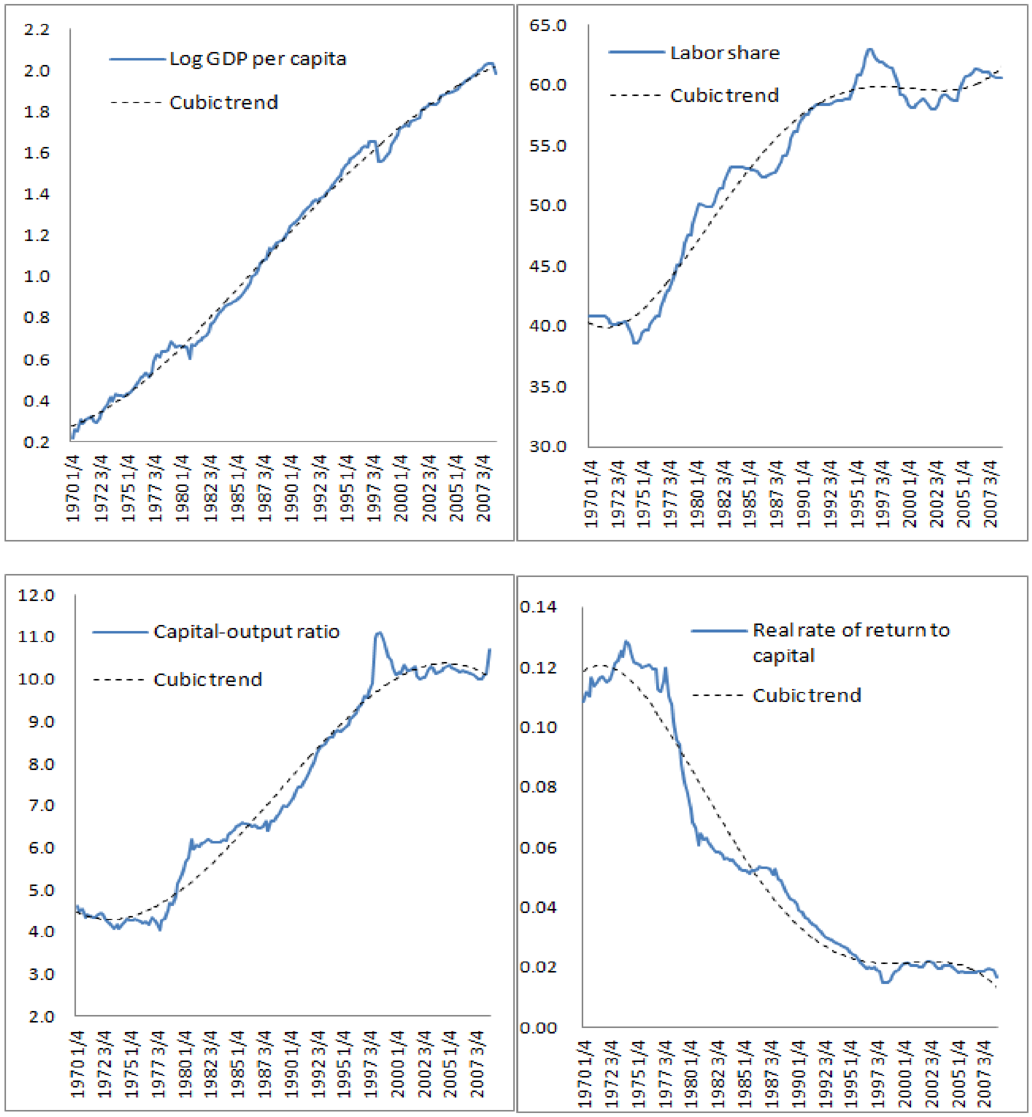
Notes:
1. gX and dX denote log-differences and first differences respectively. Variance decompositions computed from the estimation using four observables and measurement errors in all variables. Values are reported using posterior modes.

Table 30: Forecast Error Variance Decomposition: Encompassing model

Structural shock	gY	gC	gI	dTB/Y
ϵ^g	96.8	92.0	74.7	61.8
Permanent productivity shock				
ϵ^{R^*}	1.0	3.3	14.6	25.8
World interest rate shock				
ϵ^z	2.2	4.6	10.6	12.4
Transitory productivity shock				

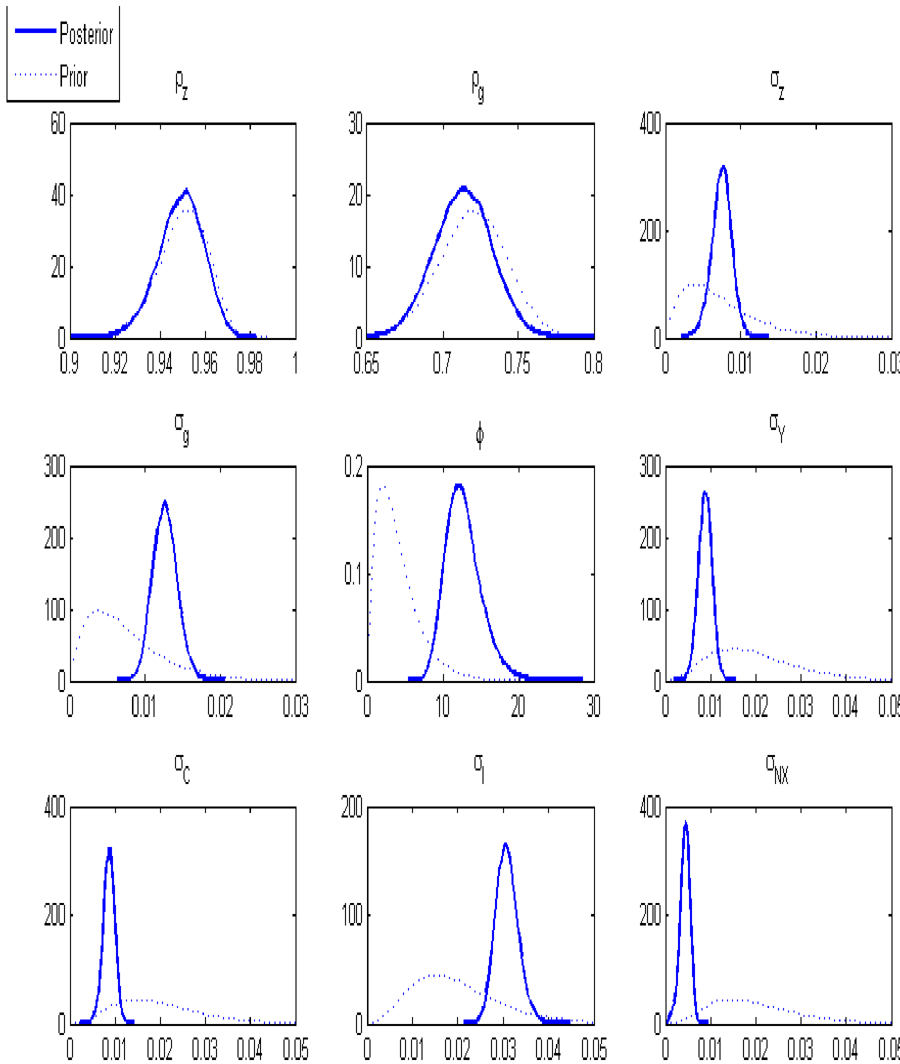
Notes:
1. gX and dX denote log-differences and first differences respectively. Variance decompositions computed from the estimation using four observables and measurement errors in all variables. Values are reported using posterior modes.

Figure 21: Transitional dynamics in Korea's economy



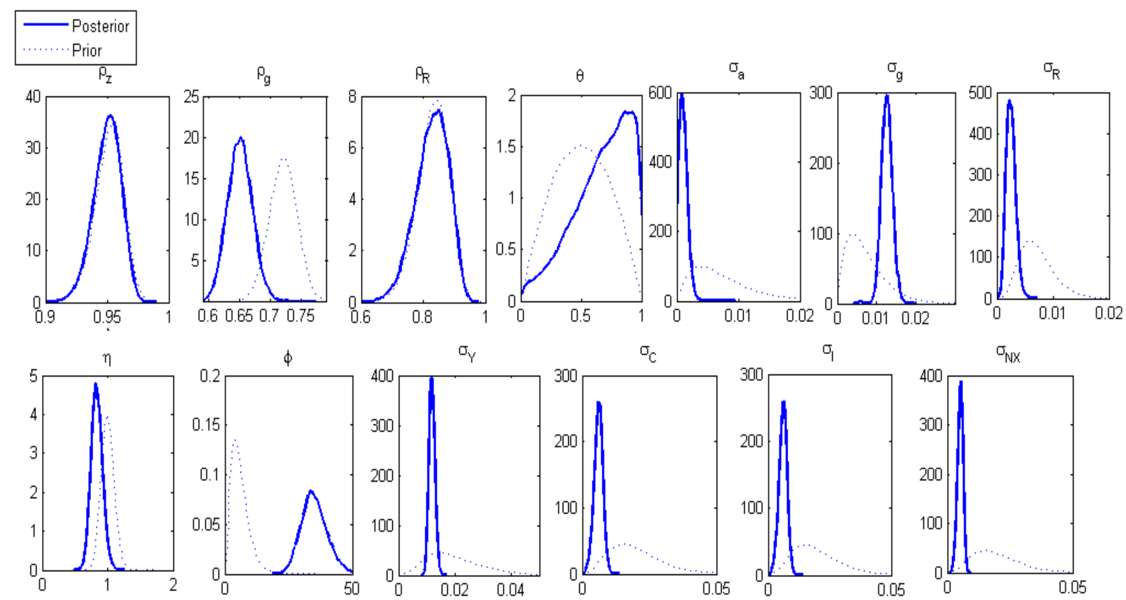
Sources: The Bank of Korea and author's calculations

Figure 22: Priors and Posteriors: Stochastic trend model



Notes:
1. The plots in this figure draw the prior and posterior distributions of the parameters in the stochastic trend model.

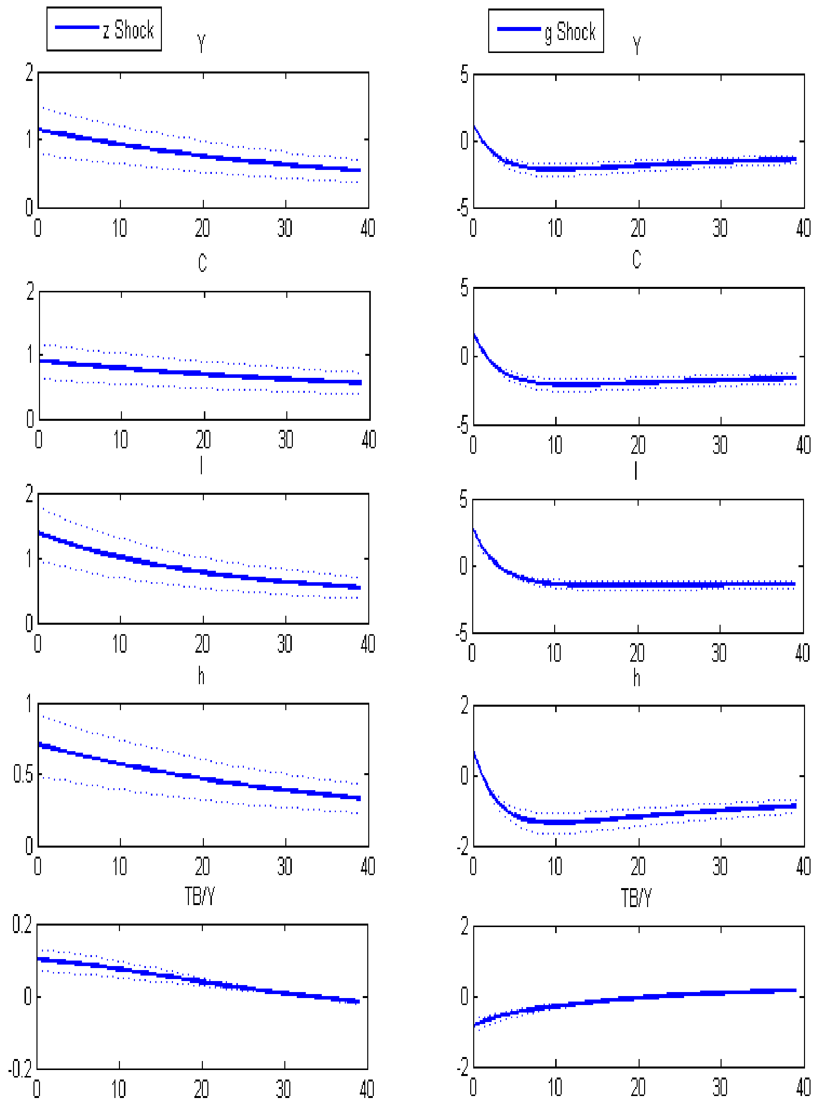
Figure 23: Priors and Posteriors: Encompassing model



Notes:

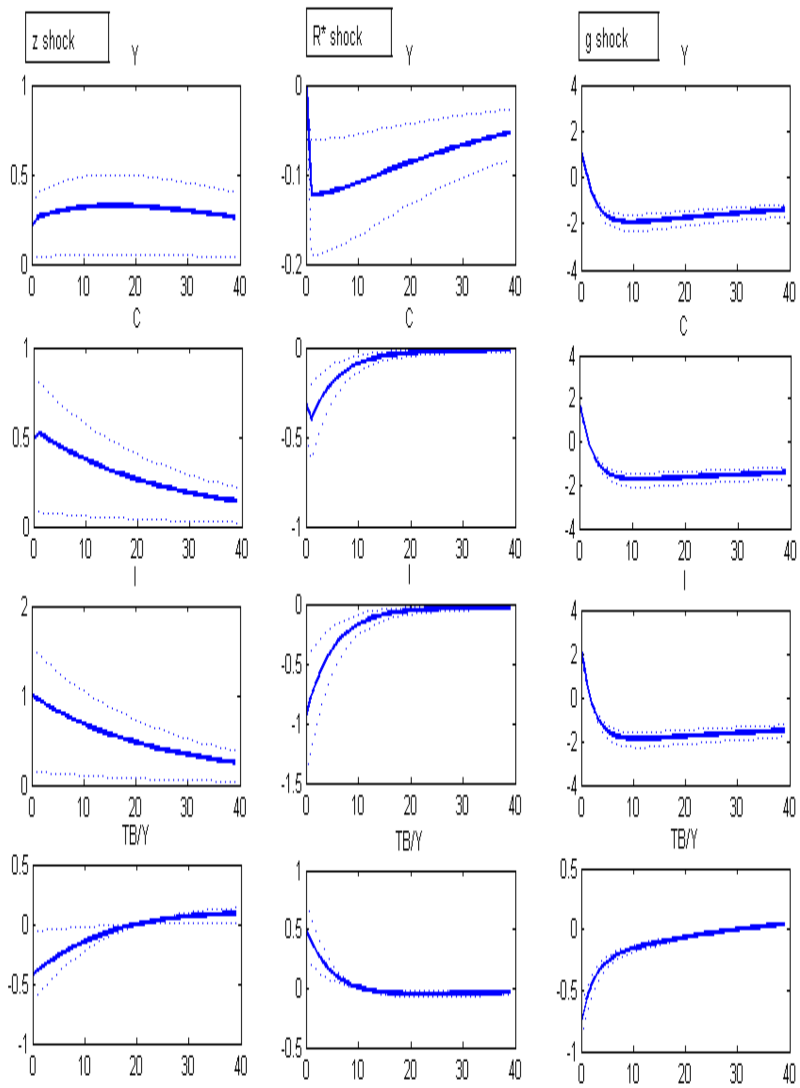
1. The plots in this figure draw the prior and posterior distributions of the parameters in the encompassing model.

Figure 24: Impulse Response functions: Stochastic trend model



Notes:
1. Each column depicts the repones of output(Y), consumption(C), investment(I), employment(h) and trade balance scaled by output (TB/Y) as deviations form steady state, after an estimated 1 S.D. shock to transitory technology process (z shock) and permanent technology process (g shock). Dash lines depict 90 percent interval based on the posterior distribution.

Figure 25: Impulse response functions: Encompassing model



Notes:

1. Each column depicts the repones of output(Y), consumption(C), investment(I) and trade balance scaled by output (TB/Y) as deviations form steady state, after an estimated 1 S.D. shock to transitory technology process (z shock), the foreign interest rate process (R^*) and permanent technology process (g shock). Dash lines depict 90 percent interval based on the posterior distribution.

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