In Quest for a Robust Model of the Exchange Rate: A Collective Approach*

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Abstract

This paper assesses the predictive ability of a comprehensive set of empirical models of exchange rates, in addition to a standard technical trading strategy, on monthly exchange-rate returns for four developed and four emerging countries across different horizons. I implement a rolling window approach to the estimation and forecasting of the models, and construct an encompassing forecast. I also assess the economic value of the out-of-sample forecasting power of the empirical models using a simple dynamic allocation strategy, and find three key results: (1) the Taylor rule model consistently outperforms, economically and statistically, the interest rate parity, purchasing power parity, and monetary fundamental models as well as the technical trading strategy. (2) The technical rule has superior predictive power over the random walk benchmark. (3) There appears to be statistical gains from an unrestricted combined forecasting model. These results are robust across countries and horizons.

Keywords: Foreign Exchange; Taylor Rule; Technical Analysis; Forecast Combinations; Emerging Markets.

JEL Classification: F31; F37; G10; G11.

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1 Introduction

A large gap exists between the models used by academics and those adopted by market practitioners. The former tend to employ long run equilibrium equations based on fundamental variables and use standard distribution theory in their modelling approach. In contrast, the majority of market practitioners adopt chartism, which is essentially the use of technical trading rules that lack a theoretical foundation. However, none of these two competing approaches has managed, so far, to provide a model of exchange rate behavior that performs well at different frequencies. The aim of the proposed work is to provide a statistical and economic investigation of a comprehensive menu of fundamental models and a chartists' rule, across different forecast horizons, in an attempt to shed some light on this long-standing debate.

The Fundamental Approach

Academics have tried to address the modelling of exchange rates by employing different approaches and equilibrium relationships. Studies on foreign exchange market efficiency normally entail tests on parity conditions such as the Covered and Uncovered Interest Rate Parity. Also, an important strand of the literature assesses long-run real exchange rate behavior by employing Purchasing Power Parity as a benchmark, a law with important international economic implications. Other theories devoted to the study of the mechanisms of exchange rate determination include tests on standard macroeconomic models, such as the flexible and sticky price monetary model, equilibrium and liquidity models, as well as the portfolio balance model and the more sophisticated new open economy models (Engel, 2002). More recent work carried by Molodtsova and Papell (2008) focuses on variants of the Taylor Rule model, testing the performance of specifications with richer dynamics and providing promising results. Finally, a strand of foreign exchange literature targets microstructural issues of the foreign exchange market in an attempt to rationalize the observed deviations from economic fundamentals. Nevertheless, there has not been a single theory that has managed to provide a fully satisfactory description of exchange rate dynamics, or present robust empirical success across horizons.

The Role of Chartists

Market practitioners tend to believe that exchange rate behavior is, to some extent, predictable with simple rules. Their forecasting methods include technical trading rules, ad hoc techniques and patterns, such as moving average crossovers, oscillators and range breakouts. The majority of academics has long considered these techniques of no value as they lack intuition and objectivity. Interestingly enough, the empirical evidence suggests that technical analysis not only shows no tendency to disappear in the long run but is indeed profitable (Menkhoff and Taylor, 2007). Besides, survey papers report that the vast majority of foreign exchange market participants use chartism at the short-term horizon, while fundamentals are considered more important in the long run, citing the work of Taylor and Allen (1992), Lui and Mole (1998), Cheung and Chinn (2001), and Gehrig and Menkhoff (2004). Given that the purpose of this study is to investigate the dynamics of the foreign exchange market, a market that is highly dominated by market makers (mainly commercial and investment banks), one tends to think that the incorporation of the practitioners' view into the model is a potentially meaningful endeavour.

The Combination of Forecasts

At the same time, it is hard to envisage that one should discard the information contained in fundamentals for exchange rate prediction at short horizons. An extensive literature on forecast combinations (Timmermann, 1995) provides a promising avenue for research towards this direction.

In the present work, I attempt to provide a comprehensive investigation of a large menu of standard models for the exchange rate, including a conventional Moving Average (MA) rule, a rich specification of the Taylor Rule model and a forecast encompassing of all the models, on monthly exchange-rate returns, for four developed and four emerging countries across different horizons. For this purpose, I implement a rolling window approach to the estimation and forecasting of the models, along with a standard, full sample estimation. The performance of the combined startegies, in- and out-of-sample, constitutes one of the main contributions of this paper and offers a novel way to carry out model evaluation both statistically and economically.

I further examine whether the weight given to chartism relative to fundamental analysis decreases with the forecast horizon as it has been well documented by both survey data papers and empirical studies (Menkhoff and Taylor, 2007). I also explore how the relative importance of the MA model evolves over time and investigate whether technical analysis tends to matter more for emerging market currencies, as the documented profitability of volatile currencies potentially indicates that chartism has a greater impact on developing markets relative to developed markets.

Finally, an important contribution is the assessment of the economic value of the in-sample and out-of-sample forecasting power of the empirical models using a simple dynamic allocation strategy, which employs the Sharpe Ratio (SR), a commonly used measure of economic value in the context of mean-variance analysis.

As the main objective of this paper is to provide an empirical investigation of the relative performance of a comprehensive menu of models across forecast horizons, over time and across a panel of developed and emerging countries, a number of questions fall beyond the scope of the present analysis. First, I am not testing the profitability of sophisticated technical trading rules, such as psychological barriers, and support and resistance levels. As a result, I do not build on the evidence documented by De Grauwe and Decupere (1992), Goodhart and Curcio (1992) and Osler (2000, 2003, 2005). Second, my work does not constitute a contribution on the extensive literature of forecast combination techniques. Instead, I focus on implementing a benchmark model of exchange rates. Finally, I do not and cannot make a conclusive statement on the efficiency of the currency market.

To preview my results, I find that the Taylor rule model consistently outperforms, economically and statistically, the interest rate parity, purchasing power parity, and monetary fundamental models as well as the technical trading strategy. This is an important result that adds evidence on the performance of the model beyond the findings of Molodtsova and Papell (2008). I further maintain that the technical rule has superior predictive power over the random walk benchmark and document evidence of statistical gains from a forecast encompassing of the models, findings that justify what practioners do. Most importantly, my results are robust across different countries and horizons.

The remainder of the paper is organized as follows. In Section 2, I present a selective review of the strands of literature that motivate my approach. Section 3 discusses the framework employed in the analysis of exchange rate predictability. Section 4 describes the data set and presents the full sample empirical results. In Section 5, I report the results from the rolling regressions. Section 6 presents the framework for assessing the economic value of exchange rate predictability and the results of the employed dynamic portfolio allocation strategy. Section 7 concludes.

2 Selective Literature Review

2.1 Fundamental Models

2.1.1 The Puzzles in Exchange Rate Economics: UIP, PPP and the Disconnect Puzzle

Throughout the literature it has been difficult to empirically establish the significance of the link between fundamentals and the exchange rate and various anomalies have emerged. The puzzles in exchange rate economics relate to the most prominent fundamental models, namely the Uncovered Interest rate Parity (UIP), Purchasing Power Parity (PPP) and Monetary Fundamentals model (MF).

Empirical work on UIP for a variety of currencies and time horizons generally rejects UIP and the risk-neutral efficient markets hypothesis (Hodrick, 1987; Lewis, 1995; Engel, 1996; Froot and Thaler, 1990). The 'forward bias puzzle', first articulated by Fama (1984), states that the forward market systematically predicts exchange rate movements in the opposite direction than predicted by UIP. Recent developments in this extensive literature suggest that although the forward rate is probably a biased predictor of the future nominal exchange rate, the term structure of forward premia possibly contains some information about future exchange rate movements (Clarida and Taylor, 1997; Sarno and Valente, 2005). Furthermore, there has been a theoretical and empirical motivation for the employment of nonlinearities (Clarida, Sarno, Taylor and Valente, 2003) and, more recently, attempts to understand the forward bias in cross-sectional asset pricing settings (Lustig et al., 2011; Burnside et al., 2011; Menkhoff at al., 2012a).

The 'PPP puzzle' (Rogoff, 1996), relates to the observation that exchange rates do not tend to move together with relative prices, over long periods of time in a world of international goods arbitrage. The academic view on the validity of PPP has changed many times and a large literature has been developed throughout the years. The classic study of Friedman and Schwartz (1963) is a typical illustration of the academic view until the 70's, which assumed the validity of some form of long-run PPP. Although the subsequent rising influence of the monetary approach along with the switch to the floating exchange rate regime seemed to shift opinions towards the validity of continuous PPP, the later poor empirical performance together with the excess volatility of the nominal exchange rate, led to the rejection of PPP in the late 80's. As unit root and cointegration studies could not confirm the validity of the law, a more recent strand of literature addressed the issue either by employing a longer window of data or by the use of panel data. Along with the recent incorporation of nonlinearities (e.g. Taylor, Peel and Sarno, 2001), many researchers have also emphasized the impact of real shocks on the real exchange rate, such as the Harrod-Balassa-Samuelson effect (e.g. Lothian and Taylor, 2008). As the main conclusion remains that PPP could potentially be viewed as a valid long run international condition when applied to bilateral exchange rates between industrialized countries, an explanation of the discrepancy between short and long run exchange rate expectations could indeed be that market participants use different forecasting techniques for different horizons.

On the other hand, numerous studies on the relationship between exchange rates and fundamentals has been focusing on the departure of the nominal exchange rate from its fundamental value: $z_t = f_t - s_t$, where f_t is the long-run equilibrium level of the nominal exchange rate governed by macroeconomic fundamentals and s_t denotes the log-level of the nominal exchange rate (the domestic price of the foreign currency). In these studies, f_t is usually approximated by a set of monetary fundamentals, which include the differential in money supply and the differential in output as in Mark (1995), but can also take different specifications to account e.g. for deviations from equilibria defined by the difference of national price level providing this way a measure for Purchasing Power Parity as in Molodtsova and Papell (2008). The more recent research takes the view that macroeconomic fundamentals co-move with the nominal exchange rate over long periods of time (Groen 2000, 2005; Mark and Sul 2001; Rapach and Wohar 2002; Sarno, Valente, and Wohar 2004; Abhyankar, Sarno and Valente 2005), while the analysis of exchange rate predictability generally relies on long-horizon regressions.

2.1.2 Taylor Rule

A recent strand of literature uses Taylor rules to model exchange rate determination. Engel and West (2005) employ the Taylor rule model as an illustration of present value models where asset prices (exchange rates inclusive) approximate a random walk when the discount factor moves towards the value of one. In their 2006 paper, the authors further build a "model-based" real exchange rate employing the difference between home and foreign output gaps and inflation rates, and report a positive relation between the "model-based" rate and the real exchange rate for the dollar-mark. Mark (2009) indicates that there is a link between the interest rate differential and the Taylor rule differential and suggests that the real dollar-mark exchange rate relates to the Taylor rule fundamentals, while Groen and Matsumoto (2004) and Gali (2008) incorporate Taylor rules in open economy dynamic stochastic general equilibrium models. In this line of reasoning, Molodtsova and Papell (2008) assess the predictability of models that incorporate Taylor rule fundamentals and report evidence of short term predictability for a big panel of countries over the post-Bretton Woods period.

2.2 Technical Analysis

The empirical failure of fundamental exchange rate models since the early 1980s has been at least a partial motivation for studies that incorporated chartist techniques along with fundamental analysis. Frankel and Froot (1986) developed an exchange-rate forecasting model where chartists only base their expectations of future changes on the rate's past behavior. Despite the appeal of this approach, there has been a lack of direct empirical evidence, mainly because the relative importance of each technique varies over time and is unobservable.

De Grauwe and Dewachter (1993) extend the model of Frankel and Froot and provide some modifications. De Long et al. (1990a) explain why chartists or 'noise traders' are not driven out of the market by fundamentalists, identified as 'sophisticated traders' using an overlapping generations model. Youssefmir, Huberman and Hogg (1998) further extend the model to continuous time and link the degree of chartism to the frequency of trading, while Vigfusson (1996) estimates a Markov regime-switching model for the exchange rate. This switching model approximates the chartist-and-fundamentalist model in that it has two forecasting equations corresponding to the two elements of the model.

Further developments include the use of bootstrapping (Levich and Thomas 1994; LeBaron 1999; Osler 2000, 2003) and the employment of methods for data-snooping bias testing (Park and Irwin 2005), while a strand of literature studies the link between nonlinearities and technical analysis (Clyde and Osler 1997; Fiess and MacDonald 1999; Kilian and Taylor 2003; De Grauwe and Grimaldi 2006a, 2006b). A number of studies (Curcio et al. 1997; Osler 2000, 2003; Neely and Weller 2003; Kozhan and Salmon 2008) also investigate the profitability of technical analysis on a high-frequency basis, reporting mixed evidence. Finally, Menkhoff et al. (2012b) provide fresh evidence that technical rules are profitable in a large cross-section of 48 currencies.

Overall, the literature on the profitability of technical analysis suggests the existence of significant profits in the foreign exchange market. Menkhoff and Taylor (2007) provide a comprehensive survey on the use of technical analysis in the foreign exchange market. In addition to the analysis of the stylized facts the authors further present the arguments that have been proposed to justify the widespread use of chartism.

2.3 Combining Forecasts

The hypothesis that the information contained in fundamentals is of no value for the forecasting of exchange rates seems rather implausible and it is hard to imagine why market participants would fail to incorporate macroeconomic information in their models. Bacchetta and van Wincoop (2004), in their model of exchange rate determination, embrace the view that foreign exchange practitioners often update the weight they place on different fundamental variables. Their 'scapegoat' theory suggests that market practitioners, in search for a rational explanation of the actual exchange rate movements, may attribute them to a certain macroeconomic fundamental variable that subsequently influences trading strategies. As different observed variables are eligible to become the 'scapegoat', the weights placed on different economic variables are expected to vary over time. Sarno and Valente (2009) suggest that the difficulty of selecting the best predictive model is largely due to frequent shifts in the set of fundamentals driving exchange rates, which they interpret as reflecting swings in market expectations over time (Frankel, 1996), or departures from rationality. They further note that the strength of the link between exchange rates and fundamentals varies across currencies.

I argue that these shifts are further enforced by the nature of the trading activity. While market participants trade continuously, macroeconomic news arrive at discrete intervals for most economic variables. Therefore, it might be that traders are not irrational but need to account somehow for this lack of information between macroeconomic announcements. Following this line of reasoning, one can visualise each model as producing a signal of variable strength at each point in time. This, in turn, motivates the employment of a richer structure that will incorporate a comprehensive set of predictive variables allowing, at the same time, for parameter instability.

Moreover, in a purely econometric context, as Timmermann (1995) notes, several arguments motivate the use of forecast combinations. Bates and Granger (1969) suggest that the forecast combination idea is motivated by a diversification argument. Furthermore, individual forecasts can be affected in a dissimilar way by structural breaks (Figlewski and Urich, 1983; Diebold and Pauly,1987;

Makridakis, 1989; Hendry and Clements, 2004 and Aiolfi and Timmermann, 2004 among others), while individual models might as well suffer from the effects of misspecification bias (Stock and Watson 1998, 2004).

3 The Models

3.1 The Random Walk

The benchmark model is the random walk (RW) model. Since the landmark work of Meese and Rogoff (1983), the RW model represents the prevalent view in international finance literature that exchange rates are not predictable when conditioning on economic fundamentals, particularly at short horizons:

$$\Delta s_{t+1} = \alpha + \varepsilon_{t+1}, \tag{1}$$

where $\Delta s_{t+1} \equiv s_{t+1} - s_t$, s_t denotes the logarithm of the spot exchange rate (domestic price of foreign currency) at time t, and ε_{t+1} is the rational expectations forecast error.

3.2 The Fama Regression

The UIP condition is the fundamental parity condition for foreign exchange market efficiency under risk neutrality, which postulates that the difference in interest rates between two countries should equal the expected change in exchange rates between the countries' currencies:

$$\Delta_h s^e_{t+h} = i_{t,h} - i^*_{t,h}, \tag{2}$$

where $i_{t,h}$ and $i^*_{t,h}$ are the nominal interest rates on domestic and foreign securities with h periods to maturity; $\Delta_h s_{t+h} \equiv s_{t+h} - s_t$; and the superscript e indicates the market expectation based on the information set at time t. UIP is not an arbitrage condition as the expected exchange rate, is unknown at time t. The foreign exchange risk related to future exchange rate movements, therefore, renders the existence of profits uncertain in the event of UIP violation.

Using Covered Interest Parity (CIP), an arbitrage relationship between interest rates and the spot and forward currency values of two countries, and replacing the interest rate differential with the forward premium (or forward discount) $f^h_t - s_t$, UIP has been often tested by estimating the following regression:

$$\Delta_h s_{t+1} = \alpha + \beta(f^h_t - s_t) + \varepsilon_{t+1}. \tag{3}$$

If UIP holds, $\alpha = 0$, $\beta = 1$, and the rational expectations forecast error ε_{t+1} should be uncorrelated with the information set at time t (Fama, 1984). Nevertheless, empirical work carried on the estimation of the UIP equation, for different currencies and time periods, generally rejects UIP (Hodrick, 1987; Lewis, 1995; Engel, 1996). The forward bias puzzle, indeed, refers to the stylized fact that β estimates, for exchange rates against the dollar, are generally closer to minus unity than plus unity (Froot and Thaler, 1990).

I employ the interest rate differential in the following forecasting equation:

$$\Delta_h s^e_{t+h} = \alpha_h + \omega_h (i_{t,h} - i^*_{t,h}) + u_{t+h,t}. \tag{4}$$

3.3 The Purchasing Power Parity

Throughout the PPP literature, the real exchange rate is usually modelled as:

$$q_t \equiv s_t - p_t + p^*_t, \tag{5}$$

where q_t is the logarithm of the real exchange rate, and p_t and p^*_t indicate the logarithms of the domestic and foreign price levels. The null for testing long-run PPP typically suggests that the process generating the real exchange rate series has a unit root, with the alternative being the hypothesis of the series stationarity. As mentioned earlier, throughout the years, the validity of the law has been questioned, led by the fact that numerous studies focusing on the post-Bretton Woods period have failed to reject the unit root null of the real exchange rate, shaping this way the first PPP puzzle. A second PPP puzzle was later formed in view of the 'glacial rate' at which deviations from the parity seem to die out (Rogoff, 1996; Sarno and Taylor 2002).

In the present setting, following Mark (1995) and Molodtsova and Papell (2008), I model the h-period ahead change in the log exchange rate as a function of its current deviation from its fundamental value as follows:

$$\begin{aligned} \Delta_h s_{t+h} &= \alpha_h + \beta_h z_t + u_{t+h,t} \\ z_t &= f_t - s_t, \end{aligned} \tag{6}$$

where f_t is the long-run equilibrium level of the nominal exchange rate determined by macroeconomic fundamentals. At this point, it must be mentioned that when the exchange rate is below its fundamental value it is anticipated to rise, and vice versa. Also, the rate of change, captured by the coefficient β, is expected to increase with the time horizon, as noted by Mark (1995). Under PPP fundamentals:

$$f_{PPP,t} = (p_t - p^*_t). \tag{7}$$

3.4 Monetary Fundamentals

Once again, following Mark (1995) and Molodtsova and Papell (2008), the h-period-ahead change in the log exchange rate can be modelled as a function of its current deviation from its fundamental value, the latter being governed by monetary fundamentals:

$$\Delta_h s_{t+h} = \alpha_h + \beta_h z_t + u_{t+h,t}, \tag{8}$$

where

$$z_t = f_t - s_t$$

and f_t is the long-run equilibrium level of the nominal exchange rate. With respect to the fundamentals, f_t, I select the flexible-price monetary model as representative of the monetary fundamentals:

$$f_{MF,t} = (m - m^*)t - (x - x^*)t, \tag{9}$$

where m_t and x_t denote money supply and an aggregate measure of output, respectively; both variables m_t and x_t are expressed in logs and the asterisk stands for foreign country variables (taking the U.S. as the foreign country).

3.5 Taylor Rule Fundamentals

The Taylor rule states that a central bank adjusts the short-run nominal interest rate in order to respond to inflation and output gap. Postulating Taylor rules for two countries and subtracting one from the other, an equation is derived with the interest rate differential on the left-hand-side and the inflation and output gap on the right-hand-side. Following Taylor (1993), the monetary policy rule is:

$$i_t^T = \pi_t + \phi(\pi_t - \pi^T) + \gamma y_t + q^E, \tag{10}$$

where i_t^T is the target for the short-term nominal interest rate, π_t is the inflation rate, π^T is the target level of inflation, y_t is the output gap, and q^E is the equilibrium level of the real interest rate.

Provided that at least one of the two central banks also targets the PPP level of the exchange rate, the real exchange rate also appears on the right hand side of the equation (Clarida, Gali, and Gertler, 1998). Applying UIP and solving expectations forward, one arrives at the following asymmetric specification:

$$i_t^T = \mu + \lambda\pi_t + \gamma y_t + \delta q_t. \tag{11}$$

If one assumes that the interest rate only partially adjusts to its target within the period, a model with interest rate smoothing should be used and the lagged interest rate differential should now appear on the right hand side of the equation. Following the findings of Molodtsova and Papell (2008), who report that the strongest evidence is provided for asymmetric specifications that incorporate heterogeneous coefficients and interest rate smoothing, I employ a richer specification of the model. Hence, in order to allow for the two central banks to have different response coefficients I employ an heterogeneous model in which the variables (inflation, output gap and lagged interest rates) appear separately. Finally a constant is added to account for the case that the two central banks have different target inflation and equilibrium real interest rates:

$$\Delta_h s_{t+h} = \alpha_h - \omega_{u\pi,h}\pi_t + \omega_{f\pi,h}\pi_t^* - \omega_{uy,h}y_t + \omega_{fy,h}y_t^* + \omega_{q,h}q_t - \omega_{ui,h}i_{t-1} + \omega_{fi,h}i_{t-1}^* + u_{t+h,t}, \quad (12)$$

where the asterisk stands for foreign country variables (taking the U.S. as the foreign country).

3.6 The Chartists' function - MA Rules

A moving average rule compares a short- to a long-run moving-average, producing a buy signal when the short-run moving average cuts the long-run moving average from below and vice versa. Apparently, these rules will depend on the time windows chosen for each moving average. I employ the 5-day and the 150-day moving averages following Saacke (2002, p. 464). The 5-150 day combination appears to be the most profitable from the practitioners' point of view, also emerging as the prevailing pair in academic studies. This choice is also consistent with the view that technical analysis might be able to capture a sluggish and then overshooting shorter-term adjustment of exchange rates to fundamental equilibria (Menkhoff and Taylor 2007).

Thus, in the present framework, the h-period ahead change in the log exchange rate is modelled as follows:

$$\Delta_h s_{t+h} = a_h + \omega_5 MA_5 + \omega_{150} MA_{150} + u_{t+h,t}, \quad (13)$$

where MA_5 is the 5-day moving average and MA_{150} is the 150-day moving average.

The MA rule values are computed on a daily basis and the monthly series is subsequently constructed by sampling the data points at the 15th of each month. To verify that no information is lost from the aggregation of the data series, the MA model is estimated separately, on a daily basis. The results—not reported to conserve space but available upon request—suggest that there does not appear to be a significant statistical improvement when the estimation is carried at the daily frequency.

3.7 Combined Regressions

The employment of static, equal weights dominates the forecast combination literature, proving an established benchmark, following the remarkable empirical past performance of equally-weighted forecast combinations (Timmermann, 1995). In the present setting, however, I build a combination of the individual forecasts by estimating the model weights, as follows:

$$\Delta_h s_{t+h} = a_h + \omega_{FR}FR + \omega_{MA}MA + \omega_{PPP}PPP + \omega_{MF}MF + \omega_{TR}TR + u_{t+h,t}, \tag{14}$$

where FR equals the forecast of the Fama regression; MA represents the forecast from the chartists' function; PPP stands for the forecast of the PPP model; MF is given by the forecast of the Monetary Fundamentals model, and TR refers to the forecast provided by the Taylor Rule model.

In essence, I am estimating an encompassing regression with a constant. Following Granger and Ramanathan (1984), I decide not to restrict the weights to sum to unity given that a constrained combination, albeit neat, can be suboptimal.

4 Empirical Results

4.1 Data

The data sample comprises 408 monthly observations ranging from August 1975 to July 2009 for the UK, Japan, Germany and Canada and 241 observations ranging from July 1989 to July 2009 for Singapore, South Africa, Hungary and Taiwan from the IMF's International Financial Statistics (IFS) database. The country choice for the emerging market panel was largely driven by data availability given the number.of macroeconomic variables that had to be obtained for estimation and prediction purposes; the time series.length, hence, constituted the only selection criterion.

I use M1 to approximate money supply for most countries, except for the UK where I employ M0, and Taiwan, for which the data are obtained from the M2 series. I further use the seasonally adjusted industrial production index to account for the countries' national income since GDP data are only available at the quarterly frequency. The price levels are measured by the corresponding consumer price indices. For the output gap, I consider deviations of actual output from a Hodrick-Prescott (1997) trend. I use the Eurodeposit rates as a measure of the 1 month, 3 month, 6 month and 1 year interest rates and the swap rates to account for the 2 year, 3 year, 4 year and 5 year interest rates that the central bank sets every period. Finally, the data sample focuses on eight exchange rates relative to the US Dollar: the UK Pound Sterling (GBP/USD), the Japanese Yen (JPY/USD), the Deutsche Mark/Euro (DEMEURO/USD), the Canadian Dollar (CAD/USD), the Singapore Dollar (SGD/USD), the South African Rand (ZAR/USD), the Hungarian Florint (HUF/USD) and the Taiwanese Dollar (TWD/USD). After the introduction of the Euro in January 1999, the Deutsche

Mark rate is replaced by the Euro for the remaining period (January 1999 to July 2009). All the data are taken from Datastream.

As a preliminary, I test for unit root behavior of each of the time series to be used in the estimation framework of Sections 3 and 4. In more detail, I use the unit root tests proposed by Ng and Perron (2001), for Δs_{t+1} , $(i_t - i_t^*)$, $(MA_5 - MA_{150})$, z_{PPP} , z_{MF} , *and* q_t over the sample. The results—not reported but available upon request—indicate that, for each of the time series examined, the unit root hypothesis is rejected at conventional significance levels.

4.2 Full Sample Results

In total, I estimate six models at eight horizons (1-month, 3-month, 6-month, 1-year, 2-year, 3-year, 4-year and 5-year ahead), for each of the eight countries. To illustrate whether the impact of technical analysis is stronger for emerging market currencies, I present the results for the emerging markets panel (Singapore Dollar, South African Rand, Hungarian Florint and Taiwanese Dollar) separately. The models are estimated by OLS rolling regressions using the Hodrick correction procedure (Hodrick, 1992) for the calculation of the standard errors of the long run regressions. As the data are sampled more finely than the compound return interval, serial correlation of the error term is induced even if the null hypothesis of no.predictability is true (Hansen and Hodrick, 1980). Consequently, the statistical inference in long horizons crucially depends on the choice of the standard errors. The Hodrick correction procedure corrects for heteroskedasticity and eliminates the moving average structure in the error terms, providing a reliable assessment of the statistical significance of the estimated parameters. I, hence, evaluate the models' predictive power by looking at the significance of the estimated coefficients. This constitutes a novel method of model assessment given the robustness of the procedure; essentially, by looking at the statistical significance of the Combined model's coefficients, one is able to evaluate the models across horizons. Subsequently, the models are ranked in terms of the root mean square prediction error (RMSPE).

Overall, three results are apparent. First, the Taylor rule model consistently outperforms the interest rate parity, purchasing power parity, and monetary fundamental models as well as the technical trading strategy. Second, the technical rule has superior predictive power over the random walk benchmark. Third, there appears to be statistical value from a simple, forecast combination of the models. These results are robust across different countries and horizons.

Tables 1, 2, 3 and 4 in Appendix A display the full sample estimated coefficients for the developed markets panel for the 1-month horizon. The Fama regression is, as expected, consistent with carry trade activity, displaying a negative coefficient which is statistically significant for Japan. As far as the MA model is concerned, one can notice that the coefficients are correctly signed though insignificant and moving in opposite directions. The same is true for the PPP model, while the coefficients of the MF appear both inconclusive and insignificant. Finally, the real exchange rate coefficient displays some consistency in the TR model but significance is still not gained at this horizon.

The Combined model results are inconclusive, as different models perform best for different countries. However, an important issue that emerges at this stage is that one can extract statistical value from potentially all the models, at least for particular forecasting horizons. This finding will become more evident during the examination of the rolling estimation results. Inspection of Tables 5, 6, 7 and 8 of Appendix A reveals similar results for the emerging market panel.

Tables 9 and 10 present the relative ranking of the models in terms of RMSPE for the developed and the emerging markets panel respectively. The TR model is overall ranked first for all the countries, and across horizons. Furthermore, there appears to be a horizon effect, in the sense that the forecast gain from employing the TR specification is greater between the 1-year and 3-year horizons.

Another result that emerges from the inspection of the full sample results is that the MA model, as a general rule, beats the RW benchmark (in the cases of Japan, Germany, Canada and Hungary, this result is robust across horizons). The MA rule is overall ranked second in terms of RMSPE. Surprisingly enough, there is not a clear horizon pattern here although it has been well documented in the literature that *"the relative weight given to technical analysis as opposed to fundamental analysis rises as the trading or forecast horizon declines"* (Menkhoff and Taylor, 2007).

When it comes to the standard menu of fundamentals, the picture is mixed. The PPP model displays better statistical performance that the FR and the MF model. However, one is not able to make conclusive statements about the predictability of the parity condition, which outperforms the RW model only for Japan and South Africa (across horizons), and for Germany and Taiwan at horizons greater than two years. Finally, there is little evidence of predictability coming from the FR and MF models, the former showing some good performance for Japan, at short horizons.

5 Predictive Rolling Regressions

The motivation for the rolling estimation method is the hypothesis that the relative participation of fundamentalists and chartists in the market evolves over time. In the same way, the weighting of the macro fundamentals could be dynamic rather than static (Sarno and Valente 2009). Hence, by allowing for parameter instability, I take into account the possibility that agents periodically revise the importance they place on different models. For this purpose, I estimate each model using the first 120 data points for the initial one-period-ahead forecast to be generated. Subsequently, the first data point is discarded while an additional data point at the end of the sample is added and the model is re-estimated. For each of the aforementioned models I construct a one-month-ahead forecast at each step. For the developed markets panel, the data from February 1975 to January 1984 are employed for estimation and the rest are saved for out-of-sample forecasting. Likewise, my estimation window for the emerging markets panel ranges from July 1989 until June 1998. The RMSPE results are presented in Figures 5-10 of the Appendix and are indicative of the time-varying forecasting performance of the models across windows, countries and horizons. The plots of the models' coefficients, which clearly display evidence of parameter instability, further justify the implementation of rolling windows estimation (i.e. Figures 1-4).

5.1 Developed Markets Panel: Rolling Regressions Results

The full sample estimation results hold true for the rolling out-of-sample exercise. The Taylor rule model once again outperforms the FR, MA, PPP as well as the MF model. The technical rule comes third, still maintaining its superior predictive power over the random walk benchmark. The RMSPEs become larger with longer horizons with the exception of the 5-year forecast horizon where the pattern is sometimes reversed.

The FR model is indicative of carry trade activity, as expected, displaying a negative coefficient for horizons shorter than two years. The coefficient subsequently becomes positive and statistical significance is gained at longer horizons. On the other hand, the coefficients of the MA model, are correctly signed and move in opposite directions; however, they only become significant after the 2-year forecasting horizon. Along these lines, the PPP model exhibits a coefficient which is correctly signed and increasing in size and significance after the one year horizon. The results for the MF model are rather inconclusive, displaying horizon patterns. For the TR model, the effect of inflation appears to be captured by the real exchange rate coefficient which becomes statistically significant from the one year horizon onwards and is negatively signed. The remaining coefficients do not often display significance but are generally signed in accordance to the findings of Molodtsova and Papell (2008).

5.2 Emerging Markets Panel: Rolling Regressions Results

The rolling out-of-sample exercise displays similar results for the emerging markets panel with the model ranking for the two best models (TR and MA) maintained. However, the FR model is consistently the worst performer in the emerging markets panel.

The FR results are again suggestive of carry trade activity, displaying a statistically significant interest rate coefficient after the 1-year horizon. The MA coefficients now show some significance for the South African Rand and the Hungarian Florint (at 1-year and 2-year horizons), as well as for the Taiwanese Dollar (at the 2-year horizon). In general, one can notice a slight improvement in the MA model behavior moving to the emerging markets panel. The PPP model displays significance and economically meaningful coefficients for a big part of the sample as one moves to forecast horizons that are greater than one year, across countries. The generally negative coefficient of the MF model does extremely well in terms of significance for the Hungarian Florint across horizons, while it appears to add some value in the case of the Singaporean Dollar (after the 3-month horizon) as well as for the South African Rand (at the 2-year horizon), but it does not perform well for the Taiwanese Dollar. Coming to the TR model, the real exchange rate coefficient is once more statistically significant and correctly signed at medium and longer term horizons. However, more coefficients are now statistically significant for different parts of the sample and for different countries.

5.3 Forecast Combination: Rolling Regressions Results

An inspection of the out-of-sample results of the forecast encompassing regression reveals an evident time variation in both the coefficients and their statistical significance. The encompassing regression offers a new perspective to the model selection procedure. In essence, to the extent that one employs the correct t-statistics (Hodrick-corrected statistics are applied for the purposes of this exercise), it is possible to assess the contribution of each model in a statistical significance metric, over time and across horizons. The results for the 1-month horizon appear on Figures 11 and.12 The picture is rather mixed; the p-values of the models' coefficients display an evident time variation; in general one can see that different models are statistically significant over time, providing further evidence to the hypothesis that market agents periodically revise the importance they assign to each model. As expected, as one moves to longer horizons the coefficients tend to become more significant.

Finally, the RMSPE of the encompassing regression appears lower than the RMSPE of the RW model, suggesting the existence of statistical gains from the combination of the models. When it comes to the robustness of this result, I refer to the recently developed inference procedure by Clark and West (2006, 2007) for testing the null of equal predictive ability of two nested models. This procedure takes into account the fact that under the null the RMSPE of the alternative model is expected to be greater than that of the RW benchmark. This is because the alternative model introduces noise into the forecasting process by estimating a parameter vector that is not helpful in prediction.

5.4 Is Technical Analysis a method of information processing?

The covariation between the MA and fundamental models' coefficients for different countries and horizons naturally leads to the question whether technical analysis could be interpreted as a method of information processing (Menkhoff and Taylor 2007), providing an explanation to the long debate around the mechanism through which fundamental news are conveyed to market prices. From the long articulated statement that "learning takes time" to the theory that foreign exchange professionals reveal bandwagon expectations (Froot and Ito 1989; Frankel and Froot 1990a, 1990b; Ito 1990), this is not an unfamiliar concept. The present work, in line with Molodtsova and Papell (2008), contradicts the statement that exchange rates converge toward fundamental values only over longer horizons (Mark, 1995; Lothian and Taylor, 1996), as the TR model is found to display predictability even at 1-month ahead forecasts. Nevertheless, it is also true that there are often statistical gains from the combination of forecasts. It is, therefore, possible that these gains originate from chartism, since the TR specification already incorporates a comprehensive set of fundamentals.

Figures 5-10 report the RMSPE results. The comovement of the MA and PPP RMSPEs is still evident; nevertheless, the presence of the RW model offers a new perspective. The three models move together across countries and horizons with the MA model providing an improvement over the individual predictions of the RW and PPP, the latter representing by construction a mean reversion to a fundamental equilibrium. The definition of long-short MA itself, also embraces a similar error correction concept with the long MA element standing for the "fundamental" value as determined by the market. However, the inspection of the rolling regression plots of the MA model (Figure 1) rather complicates the picture. Although the coefficients are consistently correctly signed and moving in opposite directions, statistical significance is gained only after the 2-year forecast horizon. The most striking result is, however, that this rarely happens when the long and short regression coefficients cross, i.e. at the most informative points; in fact, significance appears to be stronger when the coefficient values diverge. In addition, as previously mentioned, the MA model does not fall in the RMSPE rankings at longer forecast horizons.

For these reasons, one tends to conclude that technical analysis might as well represent non-fundamental elements of exchange rate determination such as self-fulfilling expectations or market psychology (Taylor and Allen, 1992). The evidence, however, is far from systematic.

6 Economic Value

6.1 The Framework

This section describes the framework employed for the economic evaluation of different exchange rate (FX) strategies based on the models examined above. The exercise is conducted by analyzing the performance of a dynamically rebalanced portfolio following these strategies relative to a random walk benchmark. The economic evaluation is again conducted both in sample and out of sample. The in-sample period ranges from August 1975 to July 1984 and the out-of-sample period moves forward by successively updating the parameter estimates of the predictive regression on a monthly basis using a 10-year rolling window.

For the purposes of the exercise, I consider a US investor who builds a portfolio by allocating her wealth among eight assets that are identical in all respects except the currency of denomination (GBP, JPY, EUR, CAD, SGD, ZAR, HUF and TWD). The main objective of the analysis is, thus, to determine whether there is economic value in predicting FX returns using each FX model separately as well as their forecast combination. Throughout this analysis, I maintain the hypothesis that the risky assets constitute a zero-cost investment, and hence the investor's net balances accumulate interest at the domestic riskless rate. This implies that the return from investing in each of the risky assets is equal to the domestic riskless rate plus the currency return ($i_t + \Delta_1 s_{t+1}$). The return from domestic riskless investing is proxied by the 1-month US Eurodeposit rate.

The investor rebalances her portfolio on a monthly basis by taking a long position on the three currencies that she predicts to appreciate the most, simultaneously shorting the three currencies that she projects to depreciate the most, over a horizon of one month. This way, she always drops two currencies from her portfolio allocation[1]. Each month she takes two steps. First, she uses the respective model to forecast the cumulative long-short portfolio return. Second, conditional on the forecast, she dynamically rebalances her portfolio following the long-short strategy described above.

In order to measure the economic value of each strategy, I rely on the Sharpe Ratio (SR), which is a commonly used measure of economic value in the context of mean-variance analysis. By employing this approach, I do not make use of volatility and correlation forecasts. Also, in assessing the profitability of the dynamic strategies, the effect of transaction costs is not taken into consideration.

6.2 Empirical Results on Economic Value

Table 11 reports the full sample results of the economic value exercise. The ranking of the models persists, with TR forecasts being the best, yielding a SR of 0.82, the only positive value among all models' SRs. The MA comes second with a SR of -0.20. The MA specification again manages to beat the RW benchmark. Finally, the MF and FR models come last, both yielding very low SR values. This is explained by the collapse of the carry trade strategy during the crisis, which constitutes a big part of the sample period used for the economic value exercise.

The out of sample predictions refer to the period between June 2003 and July 2009. The rolling window for the Sharpe Ratio calculation comprises 3 years of monthly data. The results show that there is high economic value associated with the TR model, which outperforms the RW model 73% of the time. More importantly, the SR calculated for the TR strategy is most of the time positive and displays the lowest variance.

The rolling windows results are displayed in Figure 9, where one can study the out-of-sample

[1] This is a standard practice to market participants which is generally associated with hedge funds and is further documented in the literature (Alexander and Dimitriu, 2002; Barra RogersCasey Research, 2000).

portfolio performance for each of the six models. The Combined model, MA rule, the PPP and the MF models, which are all found to outperform the RW model, displays higher economic value than the TR specification in the first part of the sample but yields negative SR values between 2007 and 2009. The volatility of all the models except for the TR is high.

I finally construct a combination strategy allowing the investor to reassess her model choice on a monthly basis. Every period, she selects the best model in terms of statistical significance (the one that displays the minimum average p-value across the eight currency pairs)[2]. The out of sample SRs for the combined model now refer to the period between April 2005 and July 2009 while the rolling window for the SR calculation, as before, comprises 3 years of monthly data.

The results show that although the TR model is still ranked first, the Combined Model is ranked second beating the RW benchmark and displaying low volatility (Figure 13). Nevertheless, it must be noted that due to data scarsity, the presented window is limited to four years and mainly covers the crisis period, something that could potentially distort the real picture.

7 Conclusion

Exchange rate forecasting has been a non-trivial endeavour throughout the literature as it has been difficult to empirically establish a link between fundamentals and exchange rate movements. Recent work in this field has employed Taylor rules to model exchange rate determination reporting promising results, as well as evidence of short term predictability. Furthermore, numerous studies have examined the profitability of chartist techniques suggesting the existence of significant profits in the foreign exchange market.

In the present work, having assessed the forecasting ability of a comprehensive set of models for exchange rate determination, including a standard menu of fundamentals, a rich Taylor Rule specification and a simple technical trading strategy along with a model motivated by the literature on forecast combinations, I document three results. First, the Taylor rule model emerges as the best model, economically and statistically, at different horizons, displaying good performance across different countries. To my knowledge, this is the first time that the performance of this model has been assessed across different horizons, with a further emphasis put on the economic value of its predictions. The striking success of the Taylor rule model is a very strong result that appears to be robust both in the developed markets and the emerging markets under examination.

A second finding of this study, is that the technical rule displays superior predictive power over

[2] Along these lines, it would be interesting to build a combination strategy that would rank the candidate models in terms of RMSPE rather than statistical significance. However, this would not yield a new insight as the TR is consistently the best model in terms of RMSPE through the whole out-of-sample period, across countries. The combined model in that case would correspond to the TR model and would rank first in terms of SR, displaying minimum volatility.

the random walk benchmark at the monthly frequency. The contribution of this result lies on the estimation frequency and the simplicity of the model employed. Although the literature on the profitability of technical analysis suggests the existence of profits, the majority of these studies targets the implementation of these techniques at high frequency, or employs more sophisticated models. However, my evidence suggests that there does not appear to be a horizon pattern in the performance of technical analysis. The finding that traditional MA rules do not appear to be very profitable in the 1990s is in line with the documented result that profits from technical analysis are declining over time (Logue and Sweeney, 1977; Cornell and Dietrich, 1978; Dooley and Shafer, 1983; Sweeney, 1986).

A final contribution is that there appears to be statistical gains from a simple forecast combination of the individual models. As this result is robust across different countries and horizons, further research should be carried out in the direction of identifying a more powerful forecast combination strategy, which will allow for time varying weights according to underlying market conditions and the level of fundamental variables. In this line of reasoning, understanding the mechanism of interaction of different types of market participants also remains a big challenge in this research agenda.

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9 Appendix

Table 1: Full Sample Results for the Developed Markets Panel: Regression Coefficients for the FR, PPP and MF Model

	FR	
	Constant	**Interest Rate Differential**
UK	0.002753	-0.0991
Japan	-0.008016*	-0.1453*
Germany	-0.002481	-0.0633
Canada	0.000598	-0.0473
	PPP	
	Constant	**ZPPP**
UK	-0.007964	0.019022
Japan	0.076053	0.016861
Germany	0.005295	0.014344
Canada	0.002598	0.011987
	MF	
	Constant	**ZMF**
UK	0.001809	-0.000005
Japan	-0.004664	0.000005
Germany	-0.001870	0.000001
Canada	0.003574	-0.000012

The table reports the estimated coefficients for the FR, PPP and MF specifications with a constant at 1 month horizon. The asterisk denotes significance.

Table 2: Full Sample Results for the Developed Markets Panel: Regression Coefficients for the MA Model

	MA		
	Constant	**MA5**	**MA150**
UK	-0.017637*	0.039045	-0.07338
Japan	0.037552	0.00526	-0.01332
Germany	0.007464	0.025638	-0.03978
Canada	0.003297	0.054901	-0.06854

The table reports the estimated coefficients for the MA specification with a constant at 1 month horizon. The asterisk denotes significance.

Table 3: Full Sample Results for the Developed Markets Panel: Regression Coefficients for the TR Model

Taylor Rule								
	Constant	**p**	**p***	**y**	**y***	**q**	**i**	**i***
UK	-0.039802	-0.045681	0.051856	-0.003045*	0.002375	-0.025016	-0.000523	0.000685
Japan	0.391160	-0.092982	0.043369	0.000167	-0.002628	-0.036628*	-0.001341	0.002896*
Germany	-0.129352	0.044612	-0.016111	-0.000895	0.000711	-0.020848	0.000547	0.001367
Canada	0.020294	0.006317	-0.010212	0.000027	0.001164	-0.010042	-0.000623	0.000393

The table reports the estimated coefficients for the TR specification with a constant at 1 month horizon. The asterisk denotes significance.

Table 4: Full Sample Results for the Developed Markets Panel: Regression Coefficients for the Combined Model

Combined Model						
	Constant	**FR**	**MA**	**PPP**	**MF**	**TR**
UK	-0.000082	-1.658465*	0.264569	-0.002191	-0.473578	0.023336
Japan	0.484045	-0.145764	0.724338	0.151052	0.151052	-1.682664
Germany	0.331359	-0.001126	-0.777185*	-0.259003	0.000147	0.697276*
Canada	-1.196255	-0.964475*	-0.195935	-0.461072	-0.402442	-0.174180

The table reports the estimated coefficients for the Combined specification with a constant at 1 month horizon. The asterisk denotes significance.

Table 5: Full Sample Results for the Emerging Markets Panel: Regression Coefficients for the FR, PPP and MF Model

FR		
	Constant	**Interest Rate Differential**
Singapore	-0.003512	-0.1567
South Africa	0.005115*	-0.0219
Hungary	0.005239*	-0.0098
Taiwan	0.000954	-0.0251
PPP		
	Constant	**ZPP**
Singapore	0.004074	0.015415
South Africa	0.031720	0.017076
Hungary	-0.022302	-0.005191
Taiwan	0.027454	0.008023
MF		
	Constant	**ZMF**
Singapore	-0.001906	0.000002
South Africa	0.006207	-0.000006
Hungary	0.012432*	-0.000003
Taiwan	0.002175	0.000000

The table reports the estimated coefficients for the FR, PPP and MF specifications with a constant at 1 month horizon. The asterisk denotes significance.

Table 6: Full Sample Results for the Emerging Markets Panel: Regression Coefficients for the MA Model

MA			
	Constant	**MA5**	**MA150**
Singapore	0.011016	-0.027794	0.002482
South Africa	0.015859	0.037096	-0.044406
Hungary	0.053845*	0.032864	-0.042705
Taiwan	0.052113	0.039274	-0.054316

The table reports the estimated coefficients for the MA specification with a constant at 1 month horizon. The asterisk denotes significance.

Table 7: Full Sample Results for the Emerging Markets Panel: Regression Coefficients for the TR Model

	TR							
	Constant	**p**	**p***	**y**	**y***	**q**	**i**	**i***
Singapore	-0.224338	0.094582	-0.047495	-0.000056	-0.000187	-0.002285	-0.001896	0.001502
South Africa	-0.073294	0.013788	0.012909	0.001661	-0.001679	-0.037257	0.000416	0.003226
Hungary	1.159206*	0.024430	-0.205808	-0.000191	-0.000972	-0.068495*	0.000061	0.003186
Taiwan	-0.064798	0.015067	0.020099	0.000276	-0.000747	-0.028863	-0.000068	0.000631

The table reports the estimated coefficients for the TR specification with a constant at 1 month horizon. The asterisk denotes significance.

Table 8: Full Sample Results for the Emerging Markets Panel: Regression Coefficients for the Combined Model

	Combined Model					
	Constant	**FR**	**MA**	**PPP**	**MF**	**TR**
Singapore	-0.002562	0.749451	0.804480	-0.021708	-0.851484	2.9392091*
South Africa	2.123094*	0.80614138*	1.579366	-0.996874	1.2467491*	2.6705427*
Hungary	-0.058931	-0.002622	0.325215	2.5918868*	-0.004568	-1.045729
Taiwan	2.3316166*	-2.490704	1.0625556*	0.387007	0.941339	1.0770411*

The table reports the estimated coefficients for the Combined specification with a constant at 1 month horizon. The asterisk denotes significance.

Table 9: Full Sample Results for the Developed Markets Panel: Model Ranking across Horizons

UK								
Model Ranking	**1M**	**3M**	**6M**	**1 Year**	**2 Year**	**3 Year**	**4 Year**	**5 Year**
1	TR	TR	TR	TR	TR	TR	TR	TR
2	MA	MA	MA	MA	MA	MA	RW	RW
3	RW	RW	RW	RW	RW	RW	MA	MA
4	FR	PPP	PPP	PPP	PPP	PPP	PPP	PPP
5	PPP	FR	FR	MF	MF	MF	MF	FR
6	MF	MF	MF	FR	FR	FR	FR	MF
Japan								
Model Ranking	**1M**	**3M**	**6M**	**1 Year**	**2 Year**	**3 Year**	**4 Year**	**5 Year**
1	TR	TR	TR	TR	TR	TR	TR	TR
2	FR	PPP	PPP	PPP	PPP	PPP	PPP	PPP
3	PPP	FR	FR	MA	MA	MA	MA	FR
4	MA	MA	MA	RW	RW	RW	RW	MA
5	RW	RW	RW	FR	MF	FR	MF	RW
6	MF	MF	MF	MF	FR	MF	FR	MF
Germany								
Model Ranking	**1M**	**3M**	**6M**	**1 Year**	**2 Year**	**3 Year**	**4 Year**	**5 Year**
1	TR	TR	TR	TR	TR	TR	TR	TR
2	MA	FR	MA	MA	PPP	PPP	PPP	PPP
3	RW	MA	RW	RW	MA	MA	MA	MA
4	PPP	RW	PPP	PPP	RW	RW	RW	RW
5	FR	PPP	FR	FR	FR	MF	FR	MF
6	MF	MF	MF	MF	MF	FR	MF	FR
Canada								
Model Ranking	**1M**	**3M**	**6M**	**1 Year**	**2 Year**	**3 Year**	**4 Year**	**5 Year**
1	TR	TR	TR	TR	TR	TR	TR	TR
2	MA	MA	MA	MA	MA	MA	MA	MA
3	MF	RW	RW	RW	MF	RW	RW	RW
4	RW	PPP	PPP	PPP	RW	PPP	PPP	PPP
5	PPP	MF	MF	MF	PPP	MF	MF	MF
6	FR	FR	FR	FR	FR	FR	FR	FR

Ranking based on RMSPE calculations; sample period ranges from February 1975 to July 2009.

Table 10: Full Sample Results for the Emerging Markets Panel: Model Ranking across Horizons

Singapore								
Model Ranking	**1M**	**3M**	**6M**	**1 Year**	**2 Year**	**3 Year**	**4 Year**	**5 Year**
1	TR	TR	TR	TR	TR	TR	TR	TR
2	FR	FR	MA	MA	MA	MA	MA	MA
3	RW	RW	RW	RW	RW	RW	RW	RW
4	MA	MA	PPP	FR	PPP	PPP	PPP	PPP
5	PPP	PPP	FR	PPP	FR	FR	FR	FR
6	MF	MF	MF	MF	MF	MF	MF	MF
South Africa								
Model Ranking	**1M**	**3M**	**6M**	**1 Year**	**2 Year**	**3 Year**	**4 Year**	**5 Year**
1	TR	TR	TR	TR	TR	TR	TR	TR
2	MA	PPP	PPP	PPP	PPP	PPP	PPP	PPP
3	PPP	MA	MA	MA	MA	RW	RW	RW
4	RW	RW	RW	RW	RW	MA	MA	MA
5	FR	FR	FR	FR	FR	MF	MF	MF
6	MF	MF	MF	MF	MF	FR	FR	FR
Hungary								
Model Ranking	**1M**	**3M**	**6M**	**1 Year**	**2 Year**	**3 Year**	**4 Year**	**5 Year**
1	TR	TR	TR	TR	TR	TR	TR	TR
2	MF	MA	MA	MA	MF	MA	MA	MA
3	MA	MF	RW	MF	MA	MF	RW	RW
4	RW	RW	MF	RW	RW	RW	MF	MF
5	PPP	PPP	PPP	FR	FR	FR	FR	FR
6	FR	FR	FR	PPP	PPP	PPP	PPP	PPP
Taiwan								
Model Ranking	**1M**	**3M**	**6M**	**1 Year**	**2 Year**	**3 Year**	**4 Year**	**5 Year**
1	TR	TR	TR	TR	TR	TR	TR	TR
2	MA	MA	MA	MA	PPP	PPP	PPP	PPP
3	RW	RW	RW	RW	MA	RW	RW	MA
4	PPP	PPP	PPP	PPP	RW	MA	MA	RW
5	MF	MF	MF	FR	FR	FR	FR	FR
6	FR	FR	FR	MF	MF	MF	MF	MF

Ranking based on RMSPE calculations; sample period ranges from July 1989 to July 2009.

Table 11: Full Sample Results: Economic Value

Sharpe Ratios						
FR	**MA**	**PPP**	**MF**	**COMBINED**	**TR**	**RW**
-0.91	-0.20	-0.43	-0.75		0.82	-0.53
Sharpe Ratios, Min P-val Strategy						
FR	**MA**	**PPP**	**MF**	**COMBINED**	**TR**	**RW**
-0.84	-0.91	-0.74	-1.15	-0.08	0.81	-2.06

Ranking based on Sharpe Ratio calculations; sample period ranges from July 1989 to July 2009.

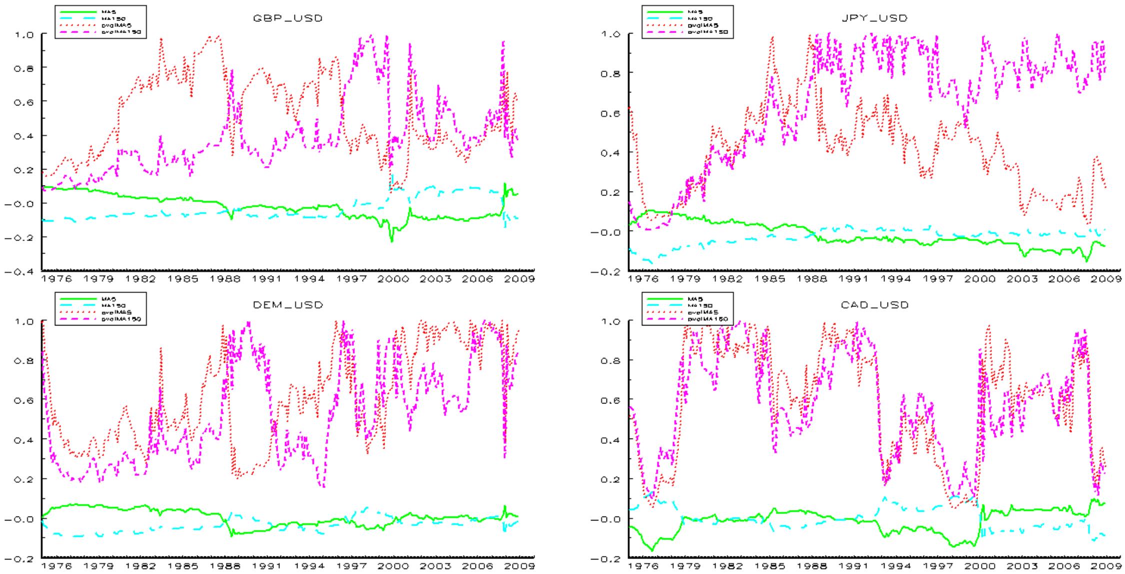

Figure 1: Developed Markets panel: Coefficients and p-values for the MA model at the 1-month horizon.

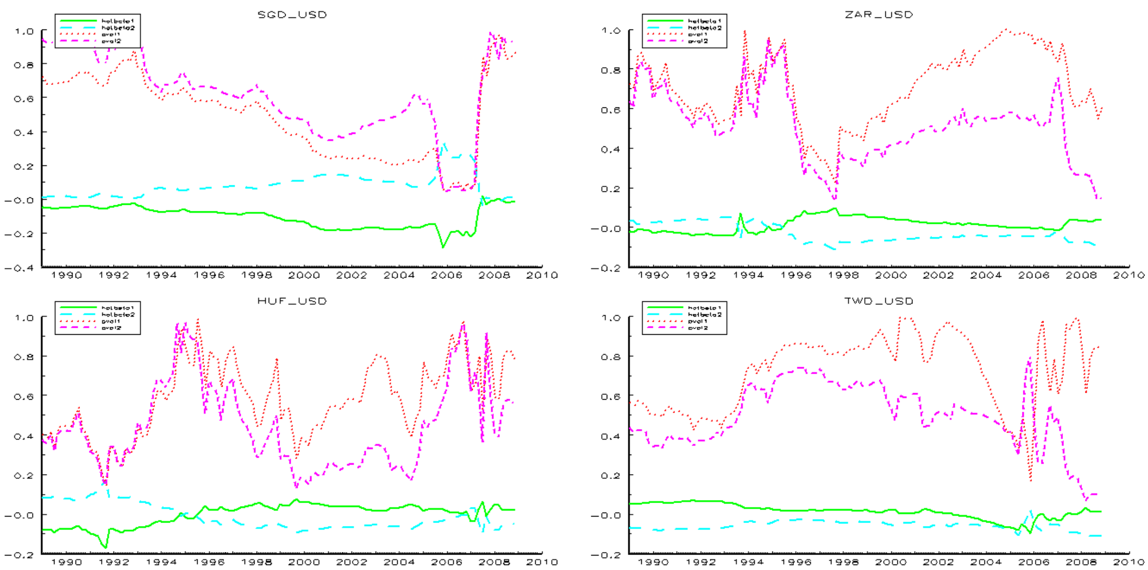

Figure 2: Emerging Markets panel: Coefficients and p-values for the MA model at the 1-month horizon.

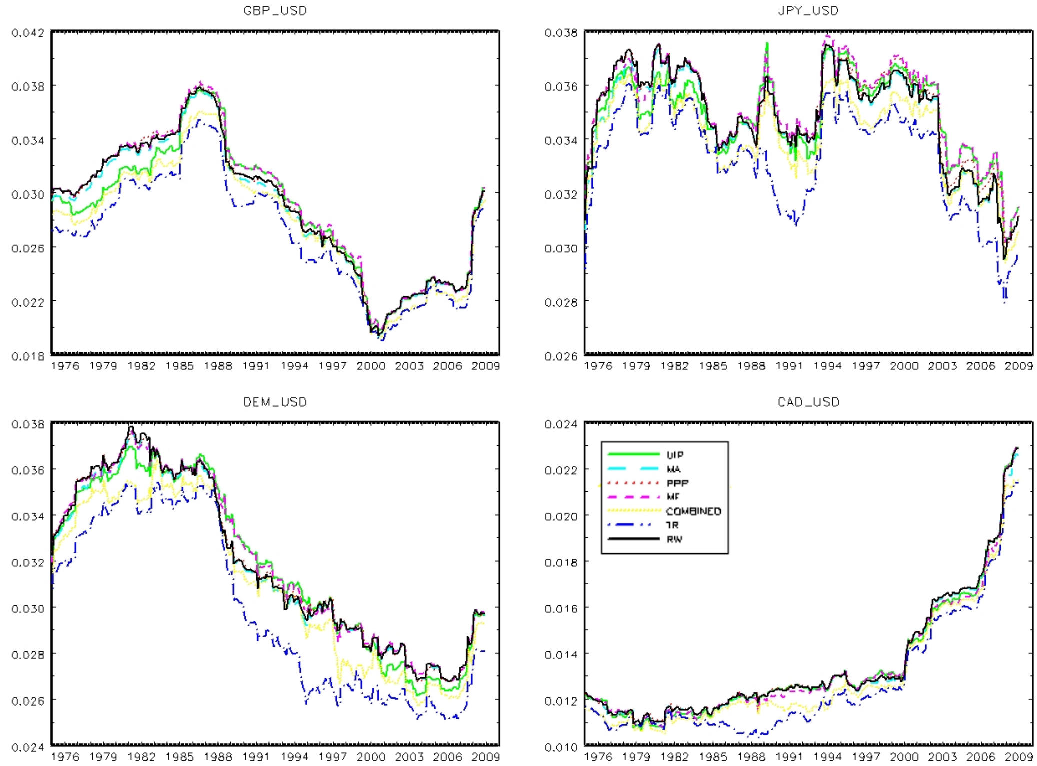

Figure 3: Rolling Regression Results for the Developed Markets panel: RMSPEs at the 1-month horizon.

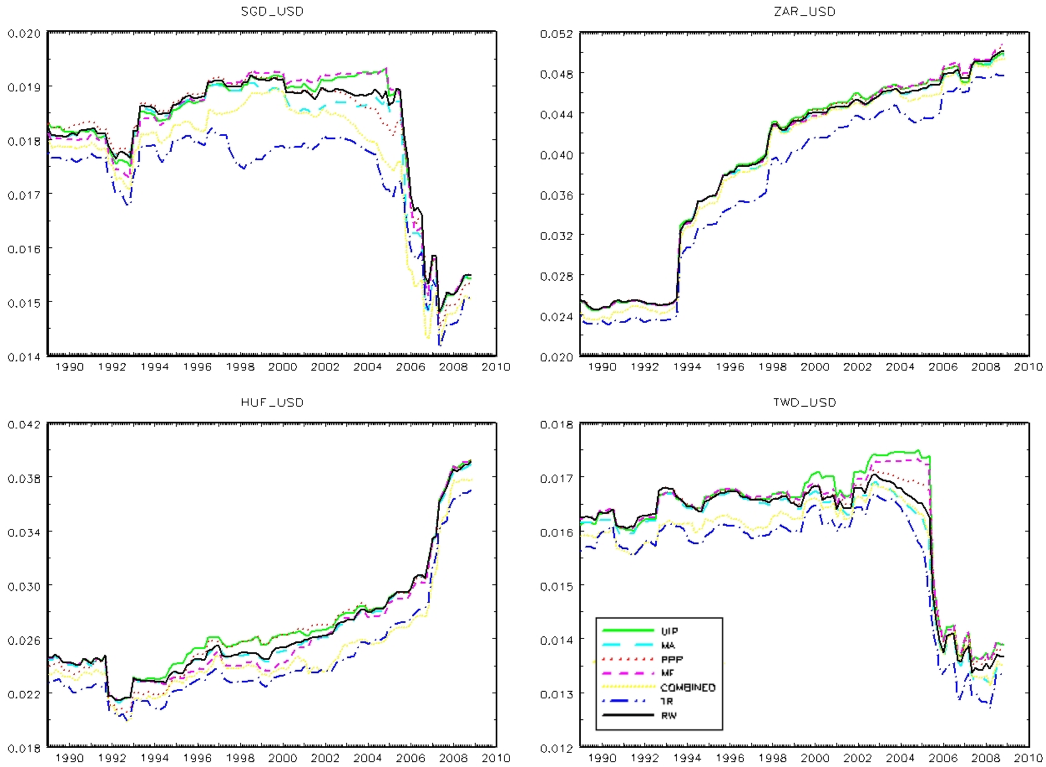

Figure 4: Rolling Regression Results for the Emerging Markets panel: RMSPEs at the 1-month horizon.

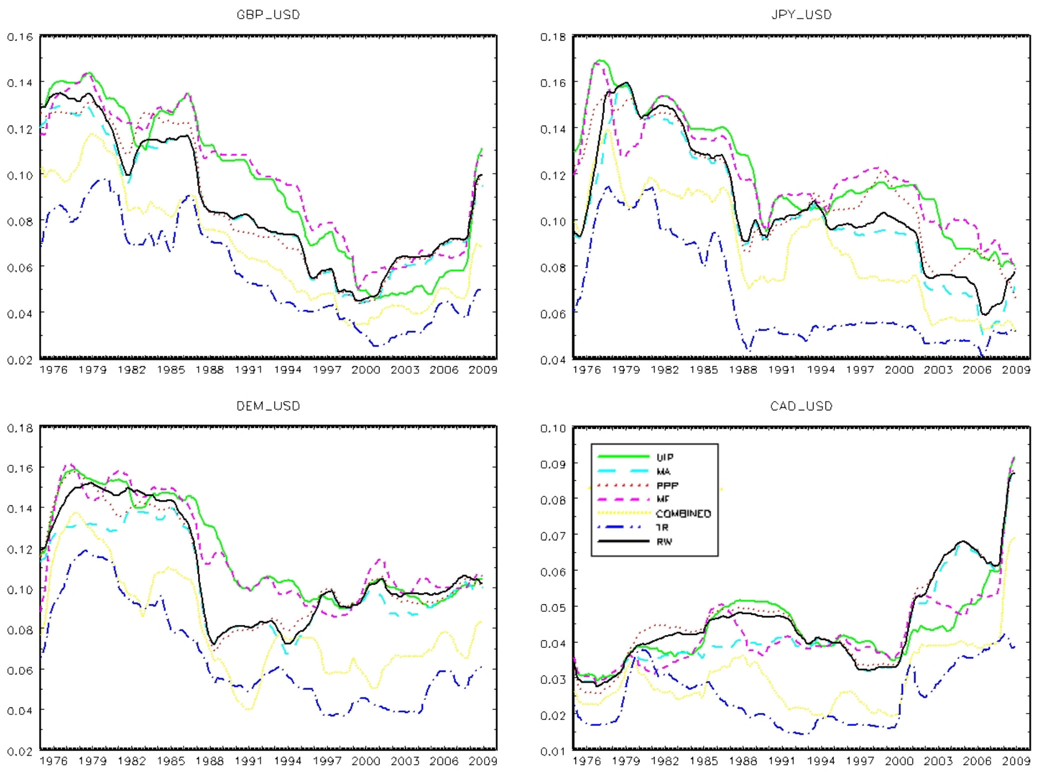

Figure 5: Rolling regression Results for the Developed Markets panel: RMSPEs at the 1-year horizon.

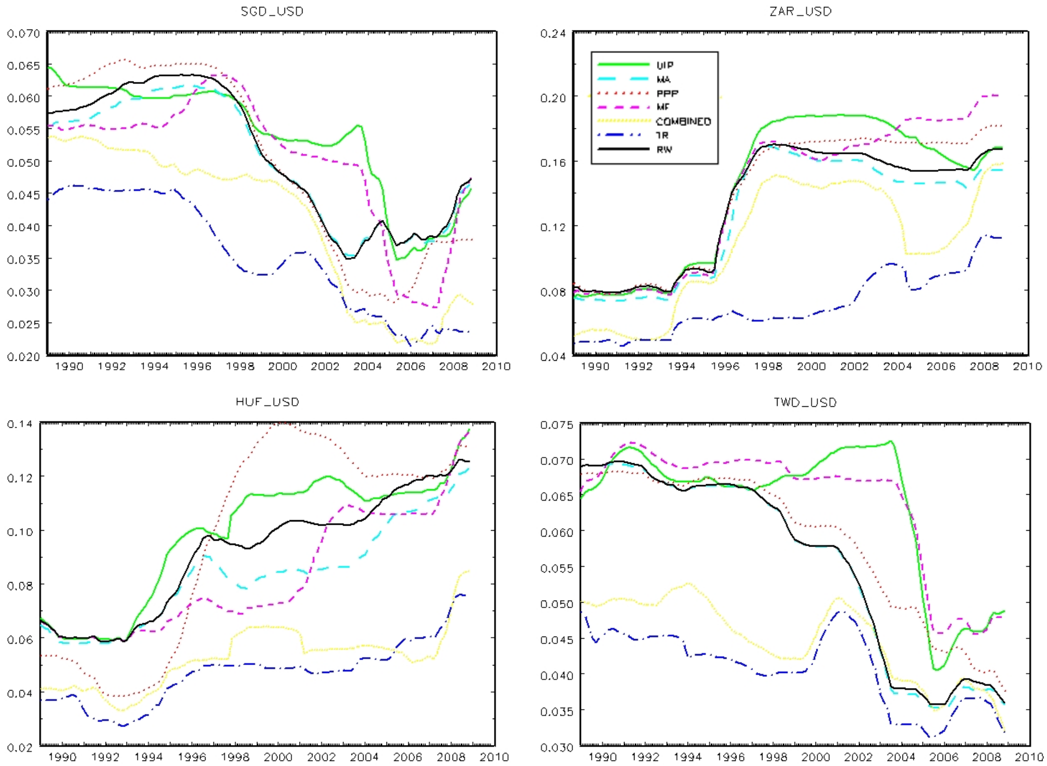

Figure 6: Rolling Regression Results for the Emerging Markets panel: RMSPEs at the 1-year horizon.

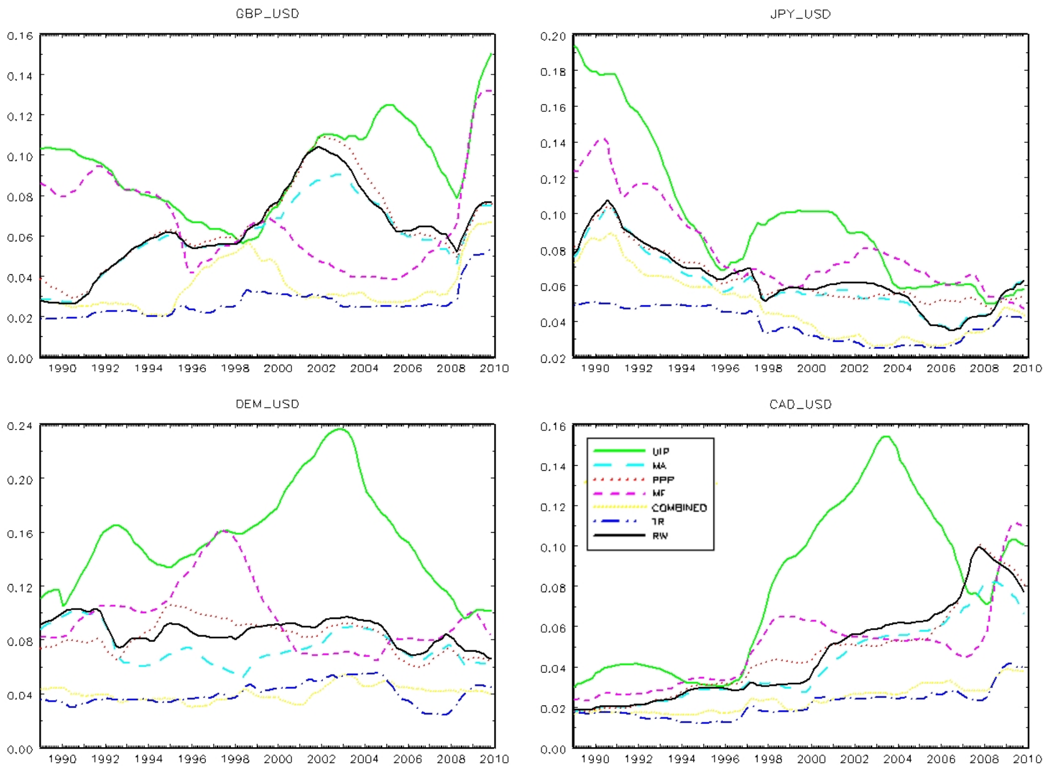

Figure 7: Rolling Regression Results for the Developed Markets panel: RMSPEs at the 5-year horizon.

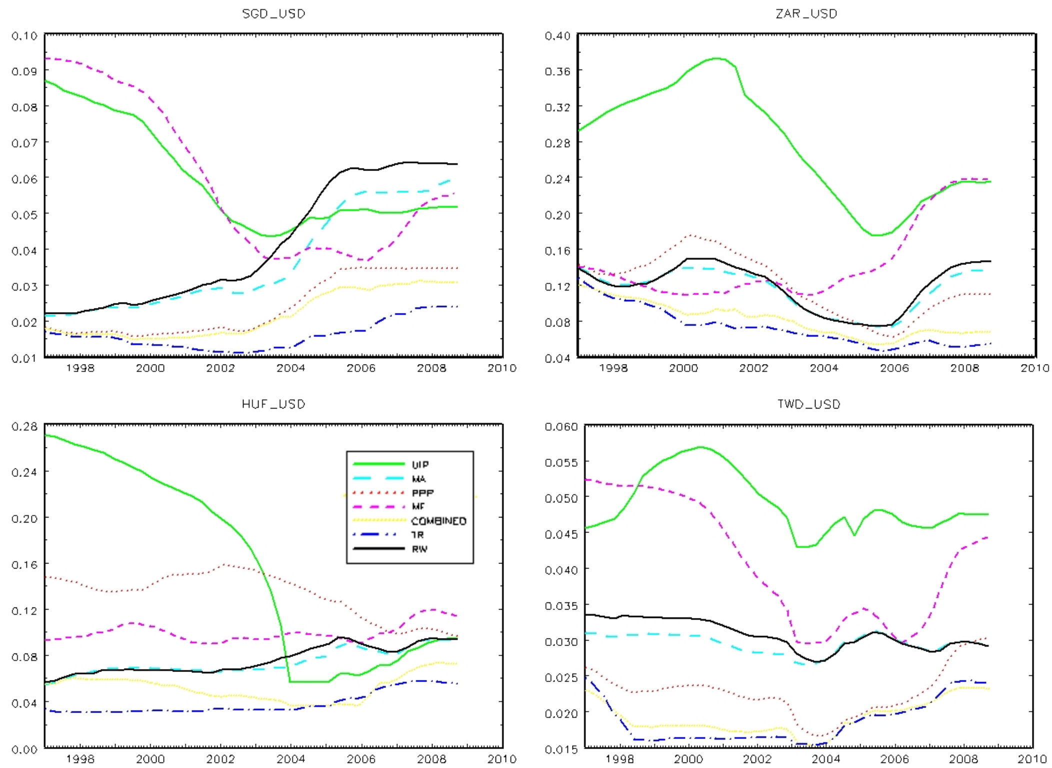

Figure 8: Rolling Regression Results for the Emerging Markets panel: RMSPEs at the 5-year horizon.

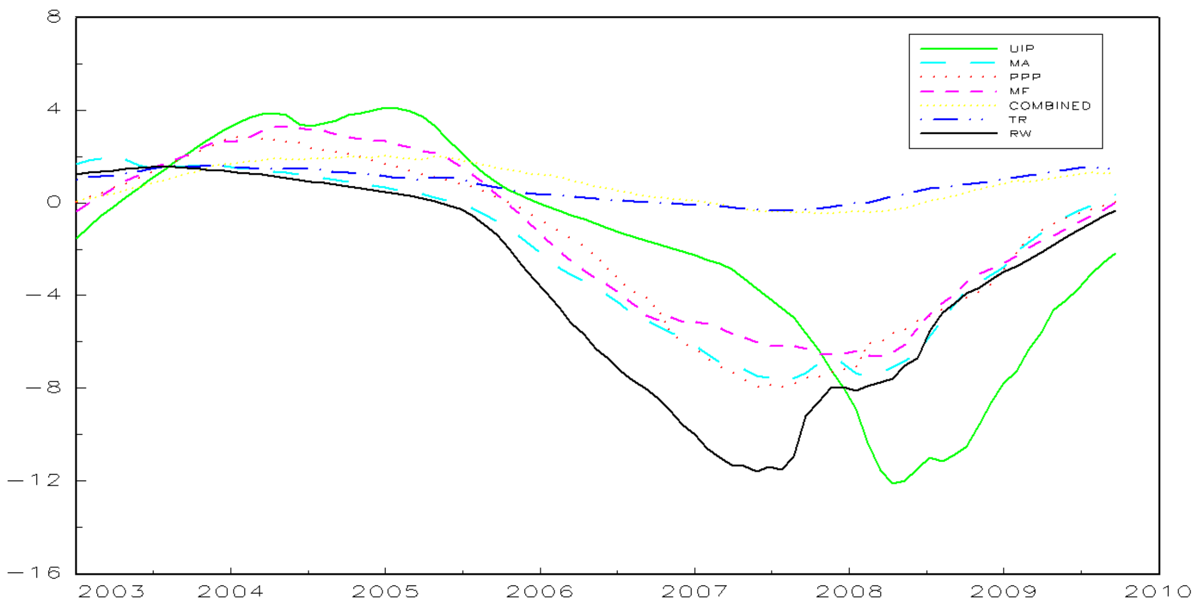

Figure 9: Rolling Regression Results for the Economic Value exercise: The evolution of Sharpe ratios for the different Strategies.

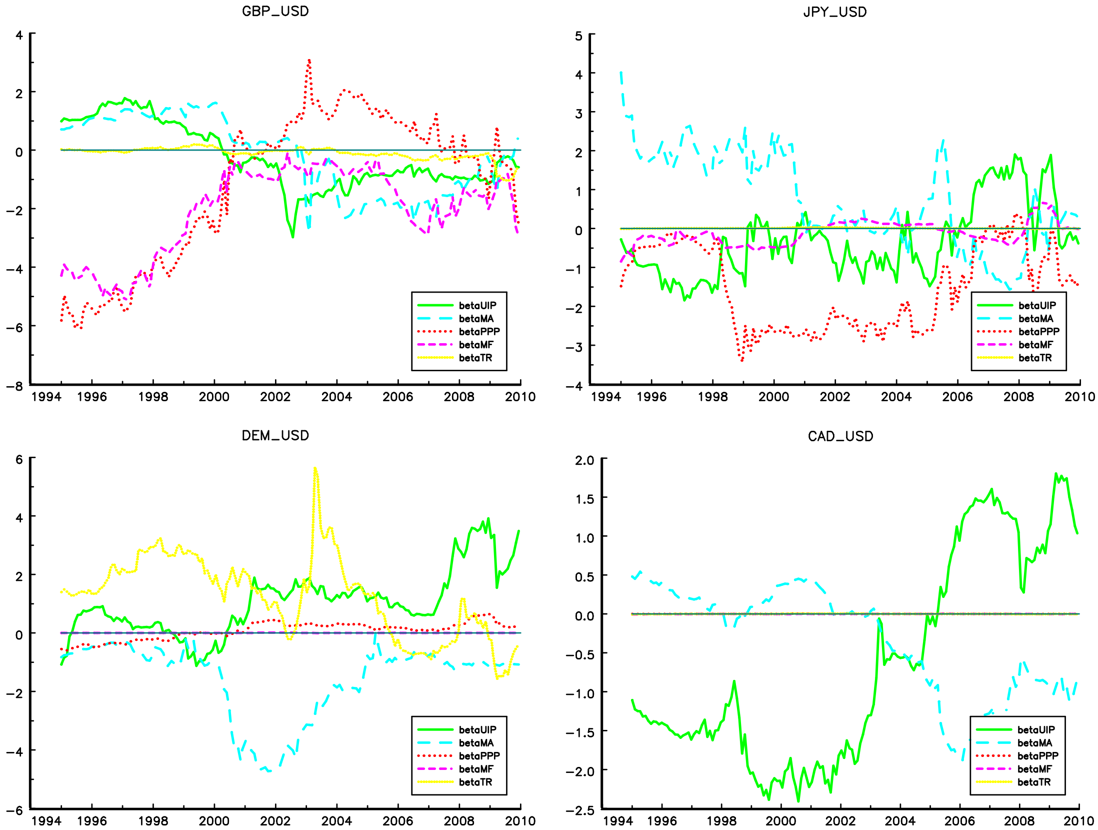

Figure 10: Developed Markets panel: Coefficients for the Combined model at the 1-month

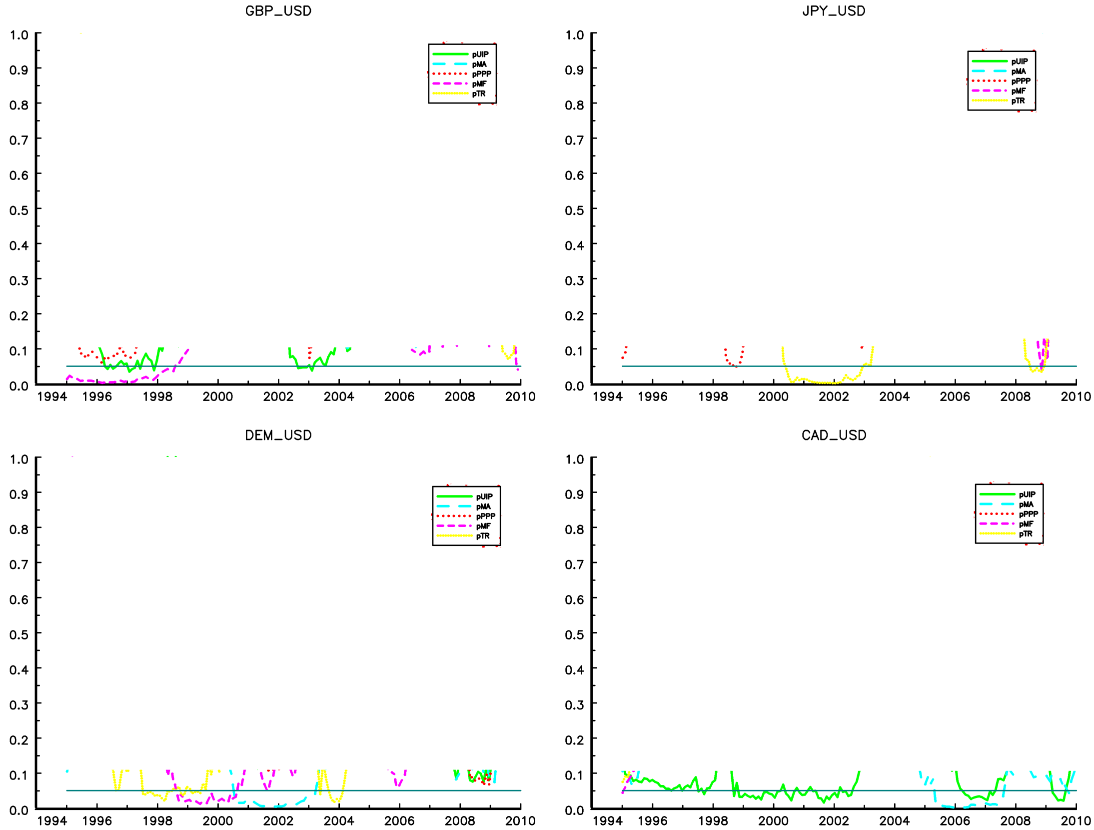

Figure 11: Developed Markets panel: P-values for the Combined model at the 1-month

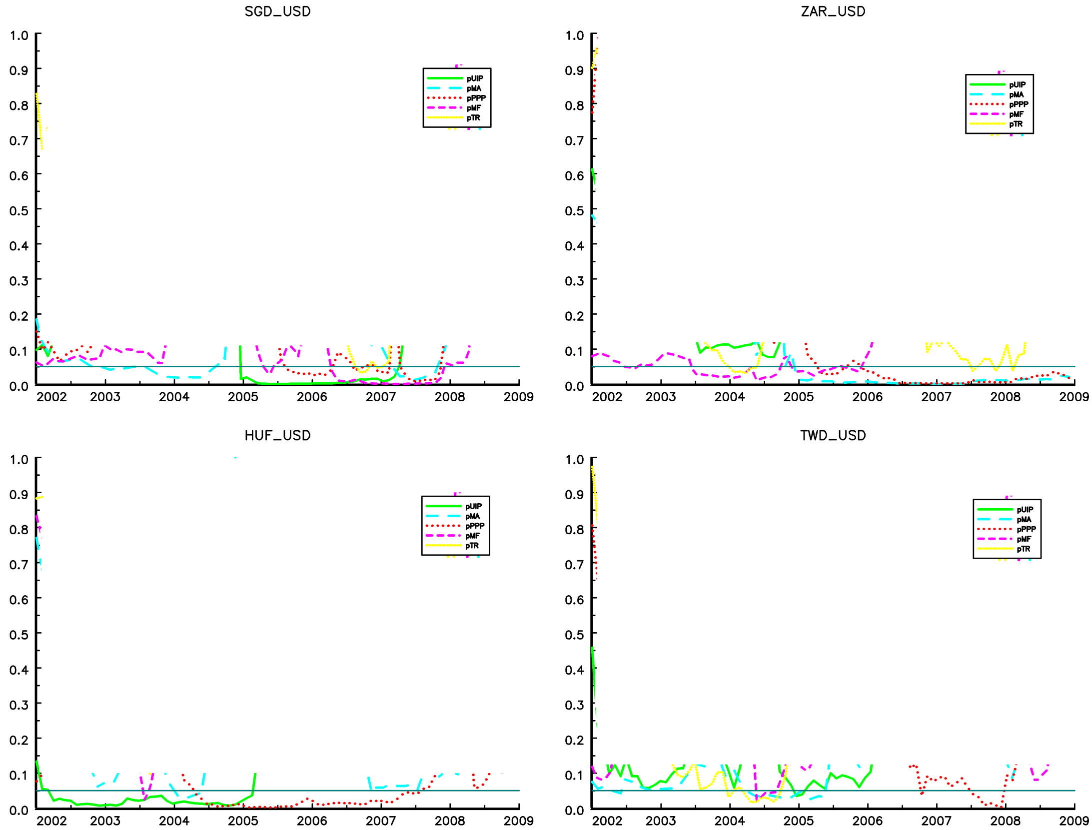

Figure 12: Emerging Markets panel: P-values for the Combined model at the 1-month

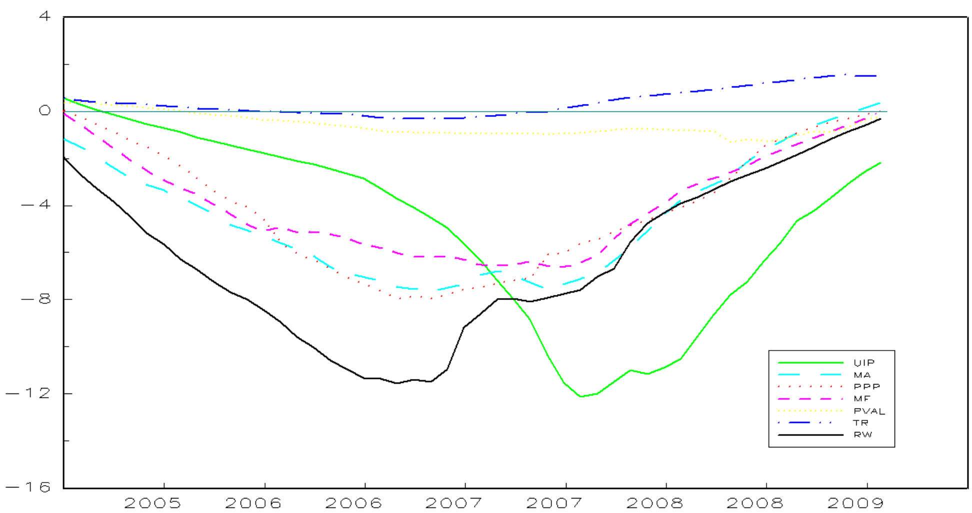

Figure 13: Rolling Regression Results for the Economic Value exercise: The evolution of Sharpe ratios for the P-value Strategy.