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# Empirical Evaluation Of Exchange Rate Models

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**Abstract**
In this paper I present an evaluation of forecasts for the exchange rates between the US Dollar and the Australian Dollar, Japanese Yen and the Swiss Franc using different types of models. The literature on exchange rate forecasting includes many papers were the models were not able to outperform the random walk model in forecasting the exchange rate. Using different criteria I find that no single model stands out as the best model for forecasting exchange rates, since the results for the models differ between exchange rates and time periods. Also I find no evidence that economic models systematically outperform the random walk model. It even seems that the random walk model outperforms the other models as seen over the full analysis in this paper. I also implement the exchange rate forecasts obtained from some models to evaluate whether there are possibilities for profitable currency carry trade strategies. Although my data are not completely reliable for this issue the results suggest that profitable currency carry strategies could be possible.

# 1 Introduction

## 1.1 Relevance

Given the daily quantity traded on the foreign exchange market it is not difficult to imagine the importance of an understanding how this market functions. The foreign exchange market had an average daily turnover of around $4.0 trillion in April 2010 according to a report from the Bank of International Settlements, making it the largest market as measured by daily trading volume. The foreign exchange market differs from stock markets in the sense that it never sleeps, due to it's global nature and the different time zones. On the foreign exchange market  it is possible to trade different currencies where the exchange rate stands for the price of one currency expressed in terms of another currency. Many economic actors are interested in exchange rates, first of all currency traders who want to make a profit on exchange rate movements by speculating on them. Successful speculation on exchange rate movements requires an understanding of how the foreign exchange market functions so that they can forecast the exchange rate in the future. Other very important actors on the foreign exchange market are the governments and central banks who try to control their economy. For those governmental organisations the target is keeping their economies stabile. They are also interested in how this market functions because they can only effectively intervene when they have a sound knowledge of which actions to take to get the desired outcome. There are many other economic actors who are directly affected by exchange rate movements in the sense that they do international transactions in different currencies. Exchange rate movements affect economic conditions in a country and in that way everybody is in some way affected by exchange rate movements.

In this paper I will evaluate some models which are used for forecasting exchange rates. For the exchange rates I use monthly averages of three exchange rates against the US Dollar where the exchange rate is stated as the price of one US Dollar denoted in the foreign currency. The models include economic models which are derived from economic theory, as well as pure time series models. For the evaluations I use different criteria which are able to capture different aspects of the forecasts. I Also evaluate whether the forecasts from the models indicate if there are possibly profitable currency carry trades which a zero net investment. Since the data I use are not equal to the exact circumstances a trader faces when deciding on a currency carry trade the evaluations are only indicative for profitable investment strategies. To evaluate the forecasting performance of a model I benchmark it by the random walk model which is the most simple model that can be used for exchange rate forecasting, because it simply states that the exchange rate at time t+h is equal to the exchange rate at time t. A necessary condition for a model to qualify as a good model for exchange rate forecasting is that it is able to beat the random walk model.

## 1.2 Literature review

An influential paper from Meese and Rogoff (1983) that evaluated the forecasts of exchange rates by different models came to the at that time surprising conclusion that these models were not able to outperform the random walk model in the out-of-sample forecasting of exchange rates. Meese and Rogoff (1983) used monthly data of the exchange rate of the US Dollar with three other currencies: the German Mark, Japanese Yen and the British Pound in the period 1973M03-1981M06, where their out-of-sample period began in 1976M12. And they forecasted the exchange rates 1,3,6 and 12 months ahead using rolling regressions. For their economic models they have used information about the fundamentals at time t+h so that it aren't real forecasts but out-of-sample estimates with known explanatory variables. They argued that this gives the models a fair chance, else the bad results could be due to uncertainty about the values of the fundamentals. They evaluated their forecasts with different criteria, including the MAE (Mean Absolute Error), RMSE (Root Mean Squared Error) and the ME (Mean Error). Here the RMSE was taken to be the most important criteria. After trying many models and regression techniques they were not able to systematically beat the random walk model in forecasting the exchange rates. This is similar to the approach I take in this paper where I also use monthly data on three exchange rates and evaluate whether different models are able to outperform the random walk model in forecasting the exchange rate. Diebold and Mariano (1995) derived a test statistic in order to determine whether the RMSE of one model is significantly better than the RMSE of another model, so that I will also be able to determine whether the difference in performance is significant. One of the purposes of this paper is to verify whether the results of Meese and Rogoff (1983) also hold for other exchange rates in other periods over a longer period of time.

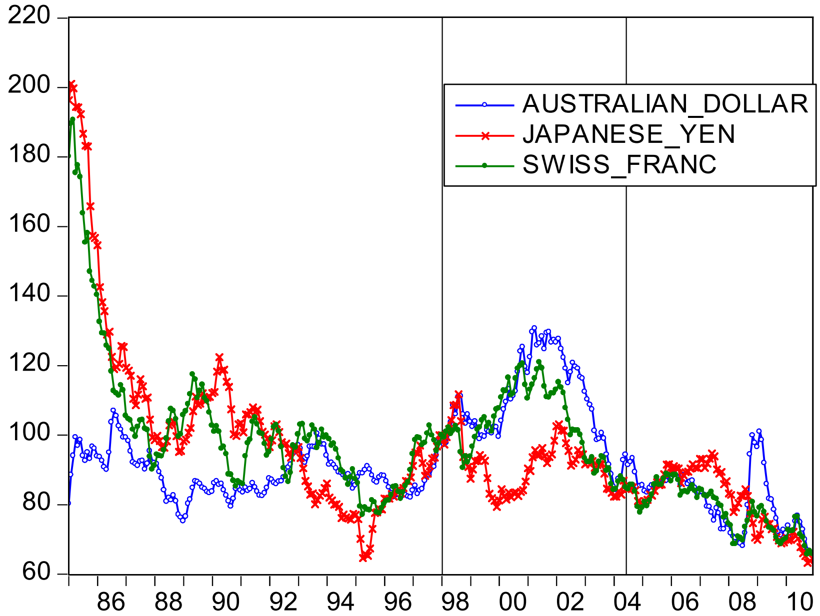
After Meese and Rogoff (1983) there came more papers on forecasting exchange rates. One of the more prominent papers is Mark (1995) where the results suggest that exchange rate models are able to outperform the random walk model in forecasting at longer horizons. Another prominent paper is Cheung et al (2002) where the different models also don't systematically outperform the random walk model. One of the models that is frequently used for forecasting exchange rates is the sticky price monetary model, Neely and Sarno (2002) showed that monetary fundamentals only explain a small portion of the variance in exchange rate movements. Fung et al (2008) used different models, including a combination of them to evaluate their exchange rate forecast for three exchange rates. He found that no model is the best because the performance differs between currencies and forecasting horizons.

Next to the statistical evaluations of the exchange rate forecasts, I also provide an evaluation of the implementation of these forecasts in a zero net investment carry trade strategy. In order to evaluate these results I use methods from Jorda and Taylor (2010a, b) to determine whether strategies based on the exchange rate forecasts give possibilities for profitable strategies.

### 1.3 Exchange rates

For the analysis in this paper I have chosen the bilateral exchange rates between the US Dollar and the Australian Dollar, Japanese Yen and the Swiss Franc. I consider the US as the domestic country and the other as the foreign country. The exchange rates are quoted as the price of one US Dollar in terms of the foreign currency, also called an indirect quotation of the exchange rate where the exchange rate stands for the purchasing power of the US Dollar. If S stands for the exchange rate than if S goes up it means an appreciation of the US Dollar relative to the foreign currency and conversely if S goes down. I selected these three bilateral exchange rates in order to get a sample over a long period of time of freely floating exchange rates. All three are freely floating over the sample period 1985M01-2010M12, where the out-of-sample period starts in 1998M01. Figure 1 shows the exchange rate time series. It can be seen in figure 1 that the US Dollar depreciated sharply against both the Japanese Yen and the Swiss Franc in the years after 1985. For the rest of the period The exchange rates remained more stable. In the out-of-sample period which starts in 1998M01 (first line) the US Dollar depreciated a bit relative to the other currencies with periods where the US Dollar appreciated. The out-of-sample period is also split in two parts as can be seen below.

Figure 1




Empirical exchange rate time series usually contain an unit root. In order to test for stationarity of these series I have applied the augmented Dickey-Fuller test to these series and found that I can't reject the null hypothesis of a unit root. The series of first differences from the exchange rates are stationary, meaning that the three time series of the exchange rates are all I(1).

## 2 Data

In this section I will discuss the data source, the different variables and the transformations that were necessary in order to obtain useful monthly data.

### 2.1 Data source

For the monthly data I have used the International Financial Statistics (IFS) database from the IMF, available on the internet. This is the only source from which the data came that I have used for the analysis presented in this paper. The IFS database is an comprehensive database and contained most of the needed data over the period 1985m01-2010m12. A problem I encountered when searching for the necessary data concerned the interest rate data. In the ideal situation I would be able to obtain interest rates on comparable assets with 1,3,6 and 12 months maturities but such data was not available. Another problem was that the ''smaller'' economies Australia and Switzerland don't publish monthly series for some economic variables.

### 2.2 Economic variables

The table on the next page shows the economic variables I retrieved from the IFS database, together with comments and their symbols for reference.

| Economic variables | | |
|---|---|---|
| *variable* | *comments* | *reference* |
| Exchange rates | Monthly averages of the nominal exchange rates for each country's currency against the US Dollar denoted as the price of one US Dollar in terms of the domestic currency | S |
| Short term interest rates | Treasury bill rates for each of the various country's, except for Australia where the treasury bill rate data were missing for a long period of time, for Australia average interest rates on the money market are used which closely resembles the treasury bill rates | $r_s$ |
| Long term interest rates | Yields on long term government bonds are used | $r_l$ |
| Price levels | CPI from the various country's on a monthly period, only Australia publicizes it on a quarterly basis | P |
| Real income | Industrial production on a monthly basis, for Australia and Switzerland on a quarterly basis (all seasonal adjusted) | IP |
| Money Supply | Non seasonal adjusted monthly data on M1 | M |
| Stock price levels, Raw materials, Foreign exchange | Monthly stock price levels for each of the country's including various measures for the US stocks (NASDAQ and S&P) except for Switzerland were there was some years of missing data. Raw materials include gold and gasoline prices. And foreign exchange the monthly reported amount by the government. | X |

### 2.3 Data transformations

As can be see from the table above not all data on the economic variables was available on a monthly basis. More specifically the price level for Australia and the industrial production for Switzerland and Australia are only available on a quarterly basis. For this reason I have fitted a monthly series for these variables using Matlab's pchip function. For the monthly seasonal unadjusted data on M1 I have used the ARIMA X12 method to obtain a seasonally adjusted series of the M1 variable. For the Raw materials and foreign exchange variables I have transformed the results to dummy variables because the raw series contain many structural breaks and aberrant observation which would effect the forecasts in a wrong way.

## 3 Methods

### 3.1 Models

In order to obtain forecasts for the exchange rates I use different exchange rate models. The first three models are obtained from economic theory as explained before, and I also use models from a time series approach which have little connection to the economic theory about exchange rates.

#### 3.1.1 Uncovered Interest Rate Parity model

The first economic model I use is the Uncovered Interest Rate Parity model which I will refer to as the UIP model. This model states that investing a fixed amount yields the same expected return on comparable assets in the domestic country and abroad. In the best possible situation I would for each month have the yield on the 1,3,6 and 12 month maturity government bonds for each country stated at the same date as the spot exchange rate. However as explained at the data section I use monthly average exchange rates and the required interest rate data wasn't freely available. Nevertheless monthly rates on long term government bonds were available for each country over the whole period, although these data are insufficient to draw conclusions about whether UIP did hold in the given period I am able to make forecasts with the UIP model. In the Ideal situation the model would look like:

$$E_t(\ln s_{t+h} - \ln s_t) = \ln(1 + i_t^*) - \ln(1 + i_t)$$

The actual monthly data on government bond yields show that there can be a persistent wedge between the yields in the different country's without the exchange rate continuously correcting for this wedge. That is why the model below can be an accurate description of the UIP model.

$$\ln s_{t+h} - \ln s_t = \beta_0 + \beta_1(\ln(1 + i_t^*) - \ln(1 + i_t)) + \varepsilon_{t+h}$$

In this model $\beta_0$ can stand for the persistent wedge in the UIP relationship, which can be caused by factors as imperfect capital mobility, risk aversion of investing abroad and imperfect substitutability of the assets. In this situation where the period of the government bonds exceeds the forecasting period h the theoretical coefficient of $\beta_1$ is smaller than 1, but still positive and depending on h.

An advantage of the UIP model over most of the other economic models is that from this model the forecast made are always *ex-ante* meaning that the exchange rate at time t+h can be forecasted with the information set with variables up to time t. Because the information about the spot exchange rate and the interest rates is available in real time the forecasts are also made in real time, making this model very interesting for analysis.

### 3.1.2 Purchasing Power Parity

Another model derived from no arbitrage relationships is the Purchasing Power Parity model which I will call the PPP model from now on. This PPP model is based on the assumption that goods in different country's should have the same price when stated in the same currency. Because else arbitrage would be possible and people would only buy the same product where it is cheapest. Possible reasons for deviations from the PPP relationship are transport times and costs, different products in different country's and incomplete information about the prices abroad. In this study I will use consumer price indices as indicators for the price levels in country's. Using price levels instead of actual prices uses the relative PPP relationship. The data on consumer price indices suggested that they had an upward trend (except for Japan were the price level remained stable for the last 20 years) but that the steepness differed between countries. The PPP relationship is given by:

$$s_t P_t = P_t^*$$

Taking the natural logarithm on both sides of for time t and t+h, rearranging terms and then subtract the equation at time t from that at time t+h gives:

$$\ln s_{t+h} - \ln s_t = \tilde{P}_{t,t+h}^* - \tilde{P}_{t,t+h}$$

Where $\tilde{P}_{t,t+h}$ stands for the growth rate of the price level from period t to period t+h. This relative PPP model states that the increase in the exchange rate from period t to period t+h is equal to the difference of the inflation rates over this period between these two country's. This leads to the following regression model:

$$\ln s_{t+h} - \ln s_t = \beta_0 + \beta_1\left(\tilde{P}^*_{t,t+h} - \tilde{P}_{t,t+h}\right) + \varepsilon_{t+h}$$

The theoretical value of $\beta_0$ is 0, however there seems to be systematic wedges between the inflation rates of the different country's, the constant can correct for this. The theoretical value of $\beta_1$ is 1 when the relative PPP relationship holds exactly. However I use consumer price indices calculated by the statistical centers in each country. Problems arise because the methods to calculate the consumer price indices can differ between country's, this could be due to a different set of goods between country's or different weights assigned to the goods. There is also a distinction between traded and non-traded goods, it is possible that prices of traded goods matter more to the exchange rate then the prices of non-traded goods do.

A problem with this model is that the results can only be obtained after the values of the fundamentals, which are here the consumer price indices, are known. This makes the model not useful for actually forecasting exchange rates.

In order to obtain ex-ante forecasts the relative PPP relationship can also be used to determine whether the exchange rate is above or below the value as predicted by the fundamentals at time t. If the actual value of the exchange rate is either above or below the value predicted by the fundamentals then it is expected that the exchange rate will follow a path to get back in line with the fundamentals. I denote the value of the exchange rate as predicted by the fundamentals at time t as $v_t$. The value of $v_t$ needs to be estimated with the relative PPP model, for the in-sample period this is not a problem, however for the out-sample period the value of $v_t$ should be estimated with the information set known up to time t. The regression model for obtaining the value of $v_t$ is:

$$\ln s_t = \beta_0 + \beta_1(\ln \mathrm{P}^*_\mathrm{t} - \ln \mathrm{P}_\mathrm{t}) + \varepsilon_t$$

After estimating the parameters of this model, the value of $v_t$ can be estimated by:

$$v_t = \widehat{\beta_0} + \widehat{\beta_1}(\ln \mathrm{P}^*_\mathrm{t} - \ln \mathrm{P}_\mathrm{t})$$

After the values $v_t$ have been estimated, forecasts for the exchange rates can be made according to the following regression model, since $v_t$ is already in natural logarithmic form.

$$\ln s_{t+h} - \ln s_t = \beta_0 + \beta_1(v_t - \ln s_t) + \varepsilon_{t+h}$$

It is expected that the value of $\beta_1$ is positive and increases with the forecast horizon h. meaning that the exchange rate is expected to follow a path back to it's fundamentals. However the fundamentals can also change after time t, this effect is summarized in the error term.

With this model it is possible to obtain ex-ante forecasts for the exchange rates, however the forecasts are not made in real time due to the time it takes after period t that the relevant statistics about the fundamentals become known to the public.

### 3.1.3 Sticky Price Monetary model

A bit more complicated but well known model for exchange rates is the sticky price monetary model as developed by Dornbusch (1976) and Frankel (1979), which I will refer to as the SP model. A derivation of the SP model can be found in the international finance literature as I will not derive it here. The specification of this SP model I use is equal to the one Meese and Rogoff (1983) used and stands below.

$$\ln s_t = a_0 + a_1(\ln \mathrm{M}_\mathrm{t}^* - \ln \mathrm{M}_\mathrm{t}) + a_2(\ln \mathrm{y}_\mathrm{t}^* - \ln \mathrm{y}_\mathrm{t}) + a_3\left( \mathrm{r}_{\mathrm{s,t}}^* - \mathrm{r}_{\mathrm{s,t}}\right) + a_4\left( \pi_{\mathrm{e,t}}^* - \pi_{\mathrm{e,t}}\right)$$

The difference between this model and the specification Meese and Rogoff (1983) used is that I use exchange rates quoted as the number of foreign currency that one US Dollar is worth. And they quote the exchange rates as the number of Dollars one unit of foreign currency is worth, this poses no problems. $\ln \mathrm{M}_\mathrm{t}^* - \ln \mathrm{M}_\mathrm{t}$ stands for the foreign money supply relative to the domestic supply at time t, for money supply I use a seasonally adjusted version of M1. The second economic variable $\ln \mathrm{y}_\mathrm{t}^* - \ln \mathrm{y}_\mathrm{t}$ stands for the relative real income between the country's. Normally GDP levels are used which are however publicized only quarterly, for that reason monthly studies on exchange rates use industrial production. The third economic variable in the SP model is $\mathrm{r}_{\mathrm{s,t}}^* - \mathrm{r}_{\mathrm{s,t}}$ stands for the short term interest rate differential between the two country's. And the last economic variable $\pi_{\mathrm{e,t}}^* - \pi_{\mathrm{e,t}}$ resembles the expected long run inflation differential. The proxy I use for this value is obtained from the realized inflation over the last 12 months.

The regression model for obtaining the forecast h months ahead follows from subtracting the above equation for period t from the equation for period t+h. This gives a regression model (not shown) that relates the growth of the exchange rate to the difference in the values of the economic variables and includes a constant. As with the PPP model this approach to forecasting the exchange rates can only be performed ex-post, after the values of the economic variable are known which is after period t+h.

Therefore I also use an ex-ante forecasting model which is quite similar to the one used for the PPP model. The estimated fundamental value of the exchange rate $v_t$ is estimated with information in the in-sample period and for the out-sample period only with information known up to time t. More precisely, $v_t$ is estimated using:

$$\ln s_t = \beta_0 + \beta_1(\ln \mathrm{M}_\mathrm{t}^* - \ln \mathrm{M}_\mathrm{t}) + \beta_2(\ln \mathrm{y}_\mathrm{t}^* - \ln \mathrm{y}_\mathrm{t}) + \beta_3\left( \mathrm{r}_{\mathrm{s,t}}^* - \mathrm{r}_{\mathrm{s,t}}\right) + \beta_4\left( \pi_{\mathrm{e,t}}^* - \pi_{\mathrm{e,t}}\right) + \varepsilon_t$$

With the estimates of $v_t$ ex-ante forecasts can be made n the same way as for the PPP model in ex-ante form.

### 3.1.4 Combination of economic models

The fourth model I use isn't a model on itself but a combination of the forecasts made by the three economic models. Different economic models capture various theoretical relationships in the movement of the exchange rate, which makes it interesting to investigate whether a linear combination of these forecasts outperforms the individual forecasts. The combined forecast is computed by:

$$\hat{f}_{combi,t+h|t} = \sum_{i=1}^{k} \widehat{w}_{i,h,t} \hat{f}_{i,t+h|t}$$

Where $\hat{f}_{i,t+h|t}$ stands for the forecasted exchange rate growth from period t to period t+h from model i. And $\widehat{w}_{i,h,t}$ stands for the weight assigned to the h period ahead forecast at time t from model i. Over all models this weights sum up to 1 because they are constructed by:

$$\widehat{w}_{i,h,t} = \frac{1}{MSE_{i,h,t}} \Big/ \frac{1}{\sum_{i=1}^{k} MSE_{i,h,t}} \qquad (12)$$

Here $MSE_{i,h,t}$ stands for the variance of the regression from model i forecasting h periods ahead up to time t. This means that models with a smaller MSE get a larger weight in constructing the combined forecasts. Forecast combinations will be made for the original economic in which case k is equal to 3 and also for the two ex-ante forecasting models for which k is equal to 2.

### 3.1.5 ARMA model

The last two models I use for creating the forecasts are based on linear time series methods. Since the time series for the exchange rates are all I(1) the exchange rates are in first differences. For the ARMA(p,q) model there must be decided which AR and MA lags are included. The autocorrelations of the exchange rate returns show that the autocorrelations decline to almost zero after one lag for the forecasting period equal to 1. For the longer forecasting periods, the autocorrelations are less informative because the returns are by construction auto correlated up to h-1 periods. I have decided to set p and q both equal to 1 for all forecast horizons. However because the forecasts for period t+h should be made with information about the exchange rates up to time t the AR and MA term are both h months back.

### 3.1.6 ARMA(X) model

The ARMA(X) model is an extension of the above mentioned ARMA model by including other variables, with the ARMA framework of the model the same as above. I use the following variables:

- The sign of the exchange rate return over the last h-months period ending at time t
- The natural logarithm of the value of the exchange rate at time t
- The relative increase in stock prices in the US as compared to the foreign country from period t to period t+h
- The sign of the change of the gasoline price over the same period
- The sign of the change of the gold price over the same period
- The sign of the relative change of the foreign exchange reserves between the US and the foreign country

Note that I include variables which are unknown become known at or after period t+h. This ARMA(X) model is therefore not an appropriate model for forecasting the exchange rates. However it is useful for determining whether exchange rates can be estimated when other relevant variables are known.

## 3.2 Estimation methods

I will discuss the used in-sample and out-sample periods, the method to obtain parameter estimates of the various models, the moving window used and the forecasting periods.

### 3.2.1 Sample periods

The data I have used in this study are monthly data from the period starting in the first month of 1985 denoted as 1985m01 and ending in the last month of the year 2010, 2010m12 in total 312 observations. The period for which the exchange rate will be forecasted is fixed and starts at 1998m01. This leaves 156 observations for estimating the parameters of the various models, ensuring there remain enough degrees of freedom. However, since the out-sample period and the start of the in-sample period are fixed the moving window has to adjust because it has to forecast the exchange rates at time t+h using information known about the exchange rate up to time t. I will also do the forecast evaluations for each half of the out-sample period. So splitting the out-sample period in two sub periods of 1998m01-2004m06 and 2004m07-2010m12 which both contain 78 months.

### 3.2.2 Parameter estimation

In order to obtain the parameter estimates of the different models I use rolling regressions, also called moving windows for the estimation period. An advantage of using moving windows over expanding windows is that for exchange rate models the observations in the past could become less relevant as time passes due to changes in the economical environment of country's, and also that each forecast is obtained from a regression with an equal amount of degrees of freedom. Since I use monthly data over a long period of time there are enough degrees of freedom, without needing additional observations. For the actual estimation of the parameters of the models I rely on OLS estimates. Although OLS might not be the most efficient unbiased estimator because such time series are expected to contain heteroskedasticity and autocorrelation, but the large sample properties of OLS estimates make this estimates still reliable. An expected problem is that the regressors could be endogenous, which means correlated with the error term through omitted variables. This leaves a bias in the estimates of the partial effects of the model variables. Due to this problem I will focus solely on forecast performance of the various models.

### 3.2.3 Forecasting

The forecast lengths I will use are 1,3,6 and 12 months ahead, where the forecast length is denoted as h months. I don't forecast the actual exchange rates at time t+h from time t, but the returns $\ln s_{t+h} - \ln s_t$ from time t to t+h. In this way I indirectly estimate the exchange rates at time t+h because the returns contain all the information to calculate the forecasted exchange rate at time t+h. The returns $\ln s_{t+h} - \ln s_t$ are approximately in percentage terms when the difference is relatively small. In order to obtain the forecasts the parameters of the models are estimated with information about the exchange rate up to h months before the out-sample period begins. The forecasts $\hat{f}_{t+h|t}$ can be computed as the expected value of the return with information about the exchange rate up to time t. Depending on the model specification whether the explaining variables are up to time t or t+h. Due to these forecasting methods the different forecasts are by construction not independent for periods of h-1 months.

## 3.3 Evaluating forecasts

In order to evaluate the forecasting performance of the competing models I use several different measures of forecast accuracy, capturing different aspects of the forecast performance. Most importantly I use as a benchmark the random walk model which is the most simple model that can be used to make forecasts for the exchange rates.

### 3.3.1 Benchmark

In order to determine the forecast quality of the competing models I benchmark them by a simple random walk model. The random walk model for the exchange rates is simply an AR(1) model with the AR parameter $\emptyset_1$ fixed at the value 1. The random walk for the exchange rate time series is:

$$\ln s_{t+h} = \ln s_t + \varepsilon_{t+h}$$

Where $\varepsilon_t$ is a white noise time series. The random walk implies that the only factors influencing the growth of the exchange rate from time t to t+h are the idiosyncratic factors $\varepsilon_{t+h}$ which are unknown up tot time t+h. The optimal forecast for $\ln s_{t+h}$ is the exchange rate as observed at time t, from which it follows that the return forecasts are all equal to zero. For an exchange rate model to qualify as an appropriate model for the studied sample a necessary condition is that it beats the random walk model.

### 3.3.2 Unbiased forecasts

One of the important features of good forecasts is that they are unbiased. This means that the forecasted exchange rate returns from period t to period t+h aren't systematically lower or higher then the actual exchange rate returns. In order to determine whether this is the case T-statistics will be computed, testing the null hypothesis of unbiased forecasts. These T-statistics are based on the forecast errors:

$$e_{t+h|t} = f_{t+h,t} - \hat{f}_{t+h|t}$$

This means testing whether the mean forecast errors differ significantly from zero by dividing the mean forecast error by it's sample standard deviation. This statistic follows under the null hypothesis of unbiased forecast a T-distribution with 155 (or 77 for the sub periods) degrees of freedom and is approximately normal distributed. For good quality forecasts small absolute values of this T-statistic are desired.

### 3.3.3 Mean absolute error

Another measure to evaluate the forecasts obtained from the competing models is by calculating their mean absolute error (MAE) as defined by:

$$MAE = \frac{1}{P}\sum \left|e_{t+h|t}\right|$$

To determine whether the value of the MAE indicates good quality forecasts it is benchmarked by dividing it by the MAE of the random walk model. The MAE of the random walk model is equal to the mean of the absolute actual returns of the exchange rate since the random walk model predicts no change. Lower values of the MAE indicate better forecast meaning that values below 1 indicate that the model outperforms the random walk model.

### 3.3.4 Mean squared error

The models are all estimated with a least squares method, meaning that the sum of squared errors are minimized. That is why the most important criterion for evaluating forecast performance evaluates the squared forecast errors. The mean squared error (MSE) is calculated with:

$$MSE = \frac{1}{P}\sum e_{t+h|t}^2$$

In the same way as with the MAE the results are presented relative to the benchmark by dividing the MSE for the forecasts obtained by the models by the MSE of the random walk. Values below 1 are indicative that the models outperforms the random walk. However it cannot be determined from this statistic whether the models perform significantly better then the random walk model, for this purpose I also report Diebold-Mariano statistics from which it can be determined whether a model performs significantly better then another model on the MSE criterion.

### 3.3.5 Diebold-Mariano test

In order to determine whether a models forecast accuracy significantly outperforms another models forecast accuracy Diebold and Mariano (1995) derived a test for this purpose. The test is based on the loss differential:

$$\mathrm{d_t} \equiv e_{1,t|t-h}^{2} - e_{2,t|t-h}^{2}$$

Where $e_{i,t|t-h}^{2}$ stands for the squared forecast error for period t-h to period t from model i. I choose for model 1 one of the competing models and for model 2 always the random walk model. The Diebold Mariano Statistic is calculated by:

$$\mathrm{DM} = \frac{\overline{\mathrm{d_t}}}{\sqrt{\frac{1}{\mathrm{P}}\widehat{\mathrm{var}(\mathrm{d_t})}}}$$

With $\overline{\mathrm{d_t}}$ the sample mean loss differential and $\widehat{\mathrm{var}(\mathrm{d_t})}$ the sample variance of the loss differential. For forecasting periods h longer then 1 month the forecast errors are not independent. For this reason the sample variance of the loss differential needs to be computed by:

$$\widehat{\mathrm{var}(\mathrm{d_t})} = \gamma_0 + 2\sum_{\mathrm{i=1}}^{\mathrm{h-1}} \gamma_\mathrm{i}$$

Where $\gamma_\mathrm{i}$ stands for the *i*-th order sample covariance. Asymptotically the DM statistic follows a standard normal distribution under the null hypothesis of equal forecast accuracy. Significant negative values of the DM statistic indicate that a model outperforms the random walk model.

### 3.3.6 Direction of Change statistics

Another widely applied criterion for evaluating exchange rate forecasts in the international finance literature is the direction of change statistic, also called the DoC statistics. This statistic gives the proportion of the forecasts for which the sign of the exchange rate is correctly forecasted. A useful benchmark is that half of the signs are correctly forecasted.

## 3.4 Evaluating carry trading strategies

Possible implementations of exchange rate forecasting are in currency carry trade strategies. In a currency carry trade a trader goes short in one currency where he pays the interest rate and uses that sum to go long in another currency where he earns an interest rate and when the period ends the trader converts this sum back into the original currency. Since these strategies don't require an investment from the trader it shouldn't be possible to be a profitable strategy for a long time.

### 3.4.1 designing the carry trade

I will evaluate the strategy of a trader who each month invests the same amount in the carry trade, the trader only needs to select the direction of the carry trade. This means he has to decide in which currency he goes short. Jorda and Taylor (2010a, b) described this situation which I will summarize here, further details can be found in their papers. Let $x_{t+1}$ denote the ex-post, monthly excess return given by:

$$x_{t+1} = \Delta s_{t+1} + (i_t - i_t^*) \qquad (21)$$

Here $x_{t+1}$ stands for the realized return when a trader goes short abroad, invests in the US and after

1 month pays the loan back abroad. The interest rate $i_t$ stands for the short term rate calculated to a monthly term. And $i_t^*$ for the short term interest rate abroad. If $x_{t+1} < 0$ then the trader has to reverse the direction of the trade. What a trader needs to do is not forecast the exact exchange rate at time t+1 but instead the carry trade direction. Because the interest rates are known to the trader he uses the forecast from his model to get an estimate of $x_{t+1}$ from which he only reads the sign. The return a trader realizes from this strategy is equal to $\widehat{u_{t+1}}$ defined by (22).

$$\widehat{u_{t+1}} = sign(\widehat{x_{t+1}})x_{t+1} \qquad (22)$$

For this strategy to be profitable the traders models must be able to forecast the correct sign of the carry trade which could be different from the sign of the exchange rate movement if there is a gap between the interest rates. Especially when $x_{t+1}$ has a large absolute value a correct estimation of the direction is profitable, so the models don't need to estimate a large proportion of the trade direction correctly, but just a reasonable proportion for which $x_{t+1}$ is relatively large. The models a trader uses are always ex-ante models. I use the following models to evaluate the carry trade strategy:

- Random Walk: No exchange rate movement, also used as benchmark
- UIP: Estimated with long term interest rates
- PPP: in its ex-ante form
- SP: In its ex-ante form
- ARMA(1,1)
- Combination of UIP, PPP, SP and ARMA(1,1)

### 3.4.2 Evaluating the carry trade

In order to evaluate the carry trade with different models I report the average monthly return, its standard deviation and the proportion of carry trade directions it forecasted correctly. Beside these criteria I also use the random walk model as the benchmark against which to compare the returns. For this purpose I use the Giacomini and White (2006) test statistic:

$$\mathrm{GW} = \frac{\Delta\bar{\mathrm{L}}}{\sqrt{\frac{\hat{\sigma}_{\mathrm{L}}^2}{\mathrm{P}}}} \to N(0,1)$$

With $\hat{\sigma}_{\mathrm{L}}^2$ the estimated variance of $\Delta\mathrm{L}_{t+1}$. For $\Delta\mathrm{L}_{t+1}$ I consider the following three investment-performance measures which capture different aspects of the performance of the carry trade.

*Return:*

$$\Delta\mathrm{L}_{t+1} = \hat{u}_{t+1}^1 - \hat{u}_{t+1}^0$$

*Sharpe Ratio:*

$$\Delta\mathrm{L}_{t+1} = \frac{\hat{u}_{t+1}^1}{\hat{\sigma}_1} - \frac{\hat{u}_{t+1}^0}{\hat{\sigma}_0}$$

*Skewness:*

$$\Delta\mathrm{L}_{t+1} = \left(\frac{\hat{u}_{t+1}^1}{\hat{\sigma}_1}\right)^3 - \left(\frac{\hat{u}_{t+1}^0}{\hat{\sigma}_0}\right)^3$$

Where model 1 is one of the ex-ante models and model 0 is the random walk model. The variance of each of the models was obtained from the moving window and for the random walk it is the variance of the returns for the last 155 periods (length of moving window for h=1).

## 4 Results

Here I will discuss the evaluation of each of the exchange rate forecasts I made, the results for the full sample are presented in the text and the results for the two subsamples can be found in the appendix. Tables in the appendix are in chronological order according to the order in this section. If a test statistic is significant it is marked by either +(-) or ++(--) indicating a significantly positive (negative) value at the 5% (1%) level.

### 4.1 US Dollar-Japanese Yen exchange rate

On the next page the results of the forecast evaluations are presented for the US Dollar-Japanese Yen exchange rate. The mean forecast errors seem to indicate that there was a positive bias in the forecasts for the full sample. This means that the forecasts made overvalued the US Dollar relative to the Japanese Yen. The bias for each of the models and forecasting periods differ across the two subsamples indicating that the forecast quality differs over time.

The MAE criteria seems to indicate that the forecasts made by the various competing models do not perform better then the forecasts from the random walk model. Most of the values are near 1, indicating an equal quality of the forecasts. Some are a bit below 1 and most are above 1 indicating that the forecast quality of the random walk model seems to be better then of the competing models. The ex-ante forecast seem to be outperformed by the random walk model. This could indicate that exchange rates do not return to fundamental values on a relatively short term.

The most important criteria I have used, the MSE suggests that the models seem to have an almost equal forecast quality as the random walk on short horizons. But they seem to perform worse then the random walk on long horizons of 12 months. The MSE indicates that the forecasts obtained from the ex-ante models are less accurate than those from the random walk model. This result holds not only for the full out-sample period but also for the two subsamples. The MSE ratios are indicative for whether the MSE of the models are better than those for the random walk model. With the Diebold-Mariano test it can be determined whether the MSE of a model is significantly below or above that of the random walk model. Those DM statistics indicate that for the full out-sample period most of these MSE ratios don't differ significantly from the random walk model. Only the sticky price monetary model performs significantly worse at the 12 month horizon. This is not what would to be expected because this model is the most advanced of the three economic models. This result is also seen for the two subsamples, where the combination of the ex-ante models also performs worse than the random walk model for a 12 month horizon.

The last criterion used is the DoC statistic, indicating whether the model was successful in determining whether the exchange rate would move up or down. The economic models seem to have DoC ratios a bit over 0,5. However the ex-ante models have DoC ratios under 0,5 indicating that they are not capable of forecasting whether the exchange rate appreciates or depreciates. The DoC ratios are better for the first than for the second subsample.

| Evaluation of the US Dollar-Japanese Yen exchange rate forecasts 1998M01-2010M12 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Economic models | | | | Ex ante models | | |
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,65$^{+}$ | 0,88 | 0,19 | 0,91 | 0,77 | 0,81 | 0,79 |
| **3 months** | 2,55$^{++}$ | 1,39 | 0,68 | 1,56 | 1,18 | 1,48 | 1,36 |
| **6 months** | 3,20$^{++}$ | 1,26 | 1,80$^{+}$ | 2,28$^{+}$ | 1,24 | 1,94$^{+}$ | 1,72$^{+}$ |
| **12 months** | 4,46$^{++}$ | 0,94 | 4,02$^{++}$ | 4,42$^{++}$ | 1,30 | 2,43$^{++}$ | 2,08$^{+}$ |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,006 | 0,997 | 1,007 | 0,988 | 1,011 | 1,028 | 1,018 |
| **3 months** | 1,032 | 0,997 | 1,110 | 1,013 | 1,067 | 1,070 | 1,054 |
| **6 months** | 1,025 | 1,005 | 1,024 | 0,970 | 1,096 | 1,094 | 1,064 |
| **12 months** | 1,041 | 1,067 | 1,391 | 1,073 | 1,205 | 1,141 | 1,151 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,024 | 0,977 | 1,005 | 0,978 | 1,017 | 1,026 | 1,018 |
| **3 months** | 1,088 | 0,940 | 1,184 | 1,010 | 1,116 | 1,078 | 1,077 |
| **6 months** | 1,097 | 0,995 | 1,211 | 0,993 | 1,269 | 1,093 | 1,117 |
| **12 months** | 1,211 | 1,220 | 2,103 | 1,246 | 1,682 | 1,145 | 1,269 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,18 | -1,15 | 0,09 | -1,01 | 0,98 | 0,72 | 0,69 |
| **3 months** | 1,42 | -0,80 | 1,43 | 0,18 | 1,37 | 0,74 | 0,87 |
| **6 months** | 0,96 | -0,06 | 1,03 | -0,07 | 1,18 | 0,60 | 0,80 |
| **12 months** | 0,80 | 1,19 | 2,08$^{+}$ | 1,14 | 1,31 | 0,61 | 1,20 |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,532 | 0,481 | 0,532 | 0,519 | 0,468 | 0,449 | 0,462 |
| **3 months** | 0,462 | 0,564 | 0,494 | 0,526 | 0,487 | 0,442 | 0,436 |
| **6 months** | 0,506 | 0,513 | 0,564 | 0,526 | 0,494 | 0,513 | 0,423 |
| **12 months** | 0,468 | 0,494 | 0,583 | 0,526 | 0,449 | 0,468 | 0,391 |

### 4.2 US Dollar-Australian Dollar exchange rate

In the same way as for the US Dollar-Japanese Yen exchange rate forecasts, I present here the forecast evaluations for the US Dollar-Australian Dollar exchange rates. The T-statistics for the null of unbiased forecast indicate that most forecasts overestimate the value of the US Dollar relative to the Australian Dollar. However over the whole period the T-statistics show that most of these biases are not significant. For the two subsamples the results are different, especially at a 12 month horizon there seems to be a significant positive bias in the first period for some of the models.

The MAE of the models measured relative to the MAE of the random walk model seems to indicate that on a short horizon the forecast from the competing models are a bit better, but however at longer forecast horizons the models except the SP model are outperformed by the random walk model. The ex-ante models seem to perform worse than the models in first differences. This is what would be expected because of the information advantage in constructing the economic models over the ex-ante models. For the two subsamples the results are nearly the same based on the MAE criterion.

The MSE criterion shows similar results as the MAE criterion, with some more extreme values. Again it seems that the models are not able to systematically beat the random walk model. It even seems that the random walk model usually outperforms the other models. Overall the SP model seems to perform best, both for the whole sample as also for the two subsamples.
The Diebold Mariano statistics show almost no significant differences in the MSE ratios for the economic models and the random walk model. For most forecasts the DM statistic is positive however. For the ex-ante models the PPP model has a significantly higher MSE than the random walk model for the first three forecasting periods.

| Evaluation of the US dollar-Australian Dollar exchange rate forecasts 1998m01-2010m12 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Economic models | | | | Ex ante models | | |
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,01 | 1,38 | 0,61 | 1,00 | 1,02 | -0,07 | 0,48 |
| **3 months** | 1,45 | $1{,}69^{+}$ | 0,88 | 1,33 | 1,05 | -0,20 | 0,43 |
| **6 months** | 1,64 | $1{,}86^{+}$ | 0,60 | 1,30 | 1,24 | -0,48 | 0,40 |
| **12 months** | $1{,}73^{+}$ | $2{,}32^{+}$ | -1,01 | 0,67 | 1,52 | -0,20 | 0,77 |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,986 | 0,995 | 0,971 | 0,971 | 1,010 | 0,991 | 0,995 |
| **3 months** | 1,017 | 1,020 | 1,022 | 0,979 | 1,066 | 1,010 | 1,021 |
| **6 months** | 1,071 | 1,056 | 1,008 | 1,015 | 1,106 | 1,028 | 1,043 |
| **12 months** | 1,112 | 1,084 | 0,879 | 0,931 | 1,224 | 1,105 | 1,138 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,021 | 0,979 | 0,994 | 0,979 | 1,031 | 0,991 | 1,002 |
| **3 months** | 1,106 | 1,016 | 1,034 | 1,010 | 1,095 | 1,042 | 1,053 |
| **6 months** | 1,255 | 1,060 | 1,075 | 1,073 | 1,151 | 1,094 | 1,096 |
| **12 months** | 1,333 | 1,123 | 0,851 | 0,957 | 1,201 | 1,207 | 1,144 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,73 | -0,84 | -0,14 | -0,89 | $2{,}53^{++}$ | -0,41 | 0,18 |
| **3 months** | 0,93 | 0,61 | 0,40 | 0,19 | $2{,}44^{++}$ | 0,70 | 1,31 |
| **6 months** | 1,17 | $1{,}73^{+}$ | 0,71 | 0,77 | $2{,}72^{++}$ | 1,08 | $1{,}68^{+}$ |
| **12 months** | 1,29 | 1,50 | -1,09 | -0,45 | 1,33 | 1,47 | $1{,}66^{+}$ |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,551 | 0,551 | 0,622 | 0,615 | 0,455 | 0,532 | 0,513 |
| **3 months** | 0,474 | 0,487 | 0,647 | 0,596 | 0,372 | 0,545 | 0,442 |
| **6 months** | 0,449 | 0,430 | 0,603 | 0,526 | 0,359 | 0,462 | 0,430 |
| **12 months** | 0,487 | 0,423 | 0,705 | 0,590 | 0,449 | 0,423 | 0,365 |

As the final criterion, the DoC statistic indicates that only the SP model had a good accuracy in forecasting the sign of the change in the exchange rate returns. Some of the ex-ante forecasts had little accuracy in forecasting the signs, this could indicate that the exchange rates did not follow a path to get in line with the estimated fundamental values.

### 4.3 US Dollar-Swiss Franc exchange rate

For the third bilateral exchange rate, the same forecast evaluations have been calculated. Starting with the measure of bias, the T-statistics for the null of unbiased forecast indicate that the forecasts over the whole period seem to overestimate the value of the US Dollar relative to that of the Swiss Franc. Significant values indicating biased forecasts are obtained at the longer horizons. The ex-ante SP models seems to have a highly significant bias in the forecasts at longer horizons. The results differ for the two subsamples here in the second subsample there is a strong positive bias.

**Evaluation of the US dollar-Swiss Franc exchange rate forecasts 1998m01-2010m12**

| | Economic models | | | | Ex ante models | | |
|---|---|---|---|---|---|---|---|
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,00 | 0,82 | 0,55 | 0,45 | 0,21 | 1,30 | 0,77 |
| **3 months** | 0,29 | 1,13 | 1,06 | 0,83 | 0,29 | $2{,}36^{++}$ | 1,42 |
| **6 months** | 0,62 | 1,62 | $1{,}79^{+}$ | 1,40 | -0,26 | $2{,}68^{++}$ | 1,45 |
| **12 months** | 0,52 | $2{,}94^{++}$ | $2{,}09^{+}$ | $1{,}90^{+}$ | -1,59 | $3{,}52^{++}$ | 1,46 |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,006 | 1,001 | 0,989 | 0,983 | 1,023 | 1,027 | 1,021 |
| **3 months** | 1,022 | 1,046 | 1,030 | 1,014 | 1,097 | 1,097 | 1,090 |
| **6 months** | 1,024 | 1,076 | 1,124 | 1,044 | 1,143 | 1,210 | 1,162 |
| **12 months** | 1,102 | 1,102 | 1,391 | 1,188 | 1,497 | 1,393 | 1,380 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,006 | 1,007 | 0,993 | 0,981 | 1,030 | 1,046 | 1,030 |
| **3 months** | 1,046 | 1,065 | 1,058 | 1,020 | 1,143 | 1,212 | 1,142 |
| **6 months** | 1,129 | 1,140 | 1,246 | 1,119 | 1,328 | 1,415 | 1,290 |
| **12 months** | 1,263 | 1,186 | 1,930 | 1,402 | 2,250 | 2,044 | 1,822 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,20 | 0,33 | -0,19 | -0,89 | 1,45 | $1{,}76^{+}$ | $1{,}65^{+}$ |
| **3 months** | 0,50 | 1,55 | 0,69 | 0,34 | 1,62 | $1{,}81^{+}$ | $1{,}85^{+}$ |
| **6 months** | 0,67 | 1,28 | $1{,}84^{+}$ | 0,90 | $1{,}69^{+}$ | $1{,}66^{+}$ | $1{,}94^{+}$ |
| **12 months** | $1{,}73^{+}$ | $1{,}79^{+}$ | $2{,}80^{++}$ | $3{,}06^{++}$ | 1,60 | 1,42 | $2{,}07^{+}$ |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,519 | 0,539 | 0,564 | 0,558 | 0,449 | 0,506 | 0,494 |
| **3 months** | 0,455 | 0,449 | 0,532 | 0,481 | 0,468 | 0,532 | 0,506 |
| **6 months** | 0,487 | 0,513 | 0,430 | 0,468 | 0,506 | 0,500 | 0,494 |
| **12 months** | 0,500 | 0,436 | 0,359 | 0,397 | 0,378 | 0,423 | 0,404 |

The MAE as a measure to compare the forecast accuracy of the models with the random walk model indicates better forecast accuracy for the random walk model. This result holds also for the two subsamples. Again the forecasts obtained with the actual values of the fundamentals seem to be better than those of the ex-ante models.

The MSE criterion tells almost the same story, the forecasts of the various competing models are systematically outperformed by those of the random walk model. And the ex-ante models have a lower forecast accuracy than the economic models. These results are also obtained from the two subsamples. The DM statistic shows that although the random walk model usually obtains lower values on the MSE criterion, these values are mostly not significantly lower than those of the various competing models. At the longer horizon the DM statistic is sometimes significantly positive. This indicates that the forecast made from the various competing models and the random walk model are not very different in forecasting accuracy.

The DoC statistics indicate that the models are not very well able to forecast the sign of the exchange rate returns. Most values are around 0,5 which is what would be expected when randomly forecasting the signs. This result is mostly due to the low values of the DoC statistic in the first subsample.

### 4.2 Evaluating time series models

The table below reports the evaluation criteria for the time series models. For the full sample the results seem to be unbiased, except at the longer horizons for the US Dollar-Japanese Yen exchange rate and the ARMA(X) model for the exchange rate with the Swiss Franc, a reason for this could be that the exogenous variables experienced a structural break.  The results for the two subsamples show that in the first subsample many forecasts are negatively biased while for the second subsample many forecast are positively biased.

Comparing the forecasts of the models with the random walk model based on the MAE criterion shows that for the full sample the time series models perform better than the random walk on short horizons and that for longer horizons the random walk model performs better. These results are also obtained from both sub periods where also the time series models get outperformed by the random walk model at the 12 month horizon.

The MSE statistics show the same results as the MAE statistics in that for longer horizons the models get outperformed by the random walk model. Whether these difference are significant can be checked by the DM statistic where some forecasts significantly outperform the random walk model at short horizons, while the DM statistic takes positive values for longer horizons indicating a better performance of the random walk model. These results also hold for the two subsamples.

The DoC statistics indicate that ARMA(X) models are accurate in forecasting the sign of the exchange rate movements at short horizons. Where the DoC statistics seem to decline when the forecast horizon gets longer. Also the ARMA models have a lower DoC statistic than the ARMA(X) models.

| Evaluation of ARMA and ARMA(X) forecasts 1998m01-2010m12 | | | | | | |
|---|---|---|---|---|---|---|
| | Australia | | Japan | | Switzerland | |
| **ME** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 1,02 | 0,40 | 0,63 | 1,24 | 0,72 | -0,08 |
| **3 months** | 1,00 | -0,29 | 1,98$^{+}$ | 0,43 | 1,28 | -2,45$^{--}$ |
| **6 months** | 0,63 | -1,19 | 2,43$^{++}$ | 1,49 | 0,58 | -3,40$^{--}$ |
| **12 months** | 0,68 | 1,02 | 3,55$^{++}$ | 2,88$^{++}$ | -1,14 | -2,55$^{--}$ |
| | | | | | | |
| **MAE** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,926 | 0,865 | 1,013 | 0,983 | 0,975 | 0,884 |
| **3 months** | 1,012 | 0,964 | 1,050 | 1,033 | 1,041 | 0,891 |
| **6 months** | 1,099 | 0,942 | 1,022 | 1,229 | 1,088 | 1,042 |
| **12 months** | 1,084 | 1,255 | 1,215 | 1,229 | 1,420 | 1,309 |
| | | | | | | |
| **MSE** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,848 | 0,721 | 0,972 | 0,937 | 0,986 | 0,809 |
| **3 months** | 1,051 | 0,929 | 1,064 | 1,033 | 1,064 | 0,868 |
| **6 months** | 1,262 | 0,835 | 1,070 | 1,502 | 1,187 | 1,293 |
| **12 months** | 1,169 | 1,337 | 1,45 | 1,54 | 1,890 | 1,833 |
| | | | | | | |
| **DM** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | -2,30$^{-}$ | -2,46$^{--}$ | -0,42 | -0,86 | -0,25 | -2,55$^{--}$ |
| **3 months** | 1,03 | -1,10 | 1,50 | 0,24 | 1,32 | -0,70 |
| **6 months** | 1,66$^{+}$ | -1,07 | 0,77 | 1,69$^{+}$ | 1,55 | 0,84 |
| **12 months** | 0,72 | 0,95 | 2,139$^{+}$ | 1,328 | 2,78$^{++}$ | 1,22 |
| | | | | | | |
| **DoC** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,596 | 0,667 | 0,539 | 0,654 | 0,590 | 0,654 |
| **3 months** | 0,539 | 0,641 | 0,423 | 0,667 | 0,474 | 0,692 |
| **6 months** | 0,506 | 0,647 | 0,487 | 0,506 | 0,430 | 0,641 |
| **12 months** | 0,442 | 0,468 | 0,391 | 0,577 | 0,423 | 0,596 |

### 4.3 Evaluating carry trade strategies

The following tables show the evaluations of the carry trade where the exchange rate is forecasted with different ex-ante models and also a combination of them.

#### 4.3.1 US Dollar-Japanese Yen carry trade

The random walk seems have a negative average return over the full sample with a relatively high standard deviation. The variance of the returns is quite similar across the different models, however the average returns differ. It seems that the PPP and SP models when estimated in an ex-ante form don't perform well. And the ARMA model seems to perform best, this is an interesting result because the ARMA model is easy to estimate and can also be estimated in real time. Similar results also hold for the two sub periods. Only the ARMA model seems to significantly outperform the random walk model at a significance level of 5%. Also the ARMA model has the highest proportion of correctly estimated carry trade directions.

| Evaluation of US Dollar-Japanese Yen carry trade 1998m01-2010m12 | | | | | | |
|---|---|---|---|---|---|---|
| | RW | UIP | PPP | SP | ARMA | Combi |
| **Avg return** | -0,033 | 0,027 | -0,154 | -0,178 | 0,421 | 0,200 |
| **Std.dev** | 0,208 | 0,208 | 0,207 | 0,207 | 0,205 | 0,207 |
| **GW Return** | - | 0,40 | -0,66 | -0,56 | 1,63 | - |
| **GW Sharpe** | - | 0,41 | -0,67 | -0,59 | 1,71$^{+}$ | - |
| **GW Skew** | - | -0,02 | -0,24 | 0,62 | 1,75$^{+}$ | - |
| **Direction** | 0,545 | 0,545 | 0,519 | 0,506 | 0,558 | 0,539 |

### 4.3.2 US Dollar-Australian Dollar carry trade

For this exchange rate the random walk has a positive average monthly return, just as the SP model. Again it seems that the ARMA model outperforms the other models although because of the good performance of the random walk model for this exchange rate the difference is not significant. Comparing the results for the full sample with those for the two sub samples shows that there is a difference between the two subsamples. However the ARMA model seems to perform best for every period.

| Evaluation of US Dollar-Australian Dollar carry trade 1998m01-2010m12 | | | | | | |
|---|---|---|---|---|---|---|
| | RW | UIP | PPP | SP | ARMA | Combi |
| **Avg return** | 0,407 | 0,213 | -0,244 | 0,278 | 0,931 | 0,616 |
| **Std.dev** | 0,257 | 0,258 | 0,258 | 0,258 | 0,248 | 0,254 |
| **GW Return** | - | -0,66 | -2,41$^{--}$ | -0,58 | 1,49 | - |
| **GW Sharpe** | - | -0,60 | -2,24$^{-}$ | -0,65 | 1,58 | - |
| **GW Skew** | - | -0,26 | -1,48 | 0,37 | 1,40 | - |
| **Direction** | 0,590 | 0,558 | 0,551 | 0,558 | 0,635 | 0,603 |

### 4.3.3 US Dollar-Swiss Franc carry trade

Here the random walk has a negative average return for the full period and for both sub periods. Also the ex-ante models have negative average returns for the full period. Same as with the other exchange rates the ARMA model again outperforms the other models and seems to be able support profitable carry trade strategies. However in this analysis I have not accounted for factors like transaction costs, actual interest rates and I have used monthly average nominal exchange rates while a trader faces nominal spot exchange rates. This results for the ARMA model suggest that it might be interesting for further research.

| Evaluation of US Dollar-Swiss Franc carry trade 1998m01-2010m12 | | | | | | |
|---|---|---|---|---|---|---|
| | RW | UIP | PPP | SP | ARMA | Combi |
| **Avg return** | -0,112 | 0,299 | -0,151 | -0,212 | 0,630 | 0,284 |
| **Std.dev** | 0,204 | 0,203 | 0,204 | 0,204 | 0,198 | 0,203 |
| **GW Return** | - | 1,28 | -0,13 | -0,44 | 2,52$^{++}$ | - |
| **GW Sharpe** | - | 1,35 | -0,03 | -0,44 | 2,59$^{++}$ | - |
| **GW Skew** | - | 1,78$^{+}$ | 1,04 | 0,08 | 1,98$^{+}$ | - |
| **Direction** | 0,526 | 0,558 | 0,513 | 0,468 | 0,635 | 0,577 |

## 5 Conclusion

This paper presented an evaluation of exchange rate forecasts obtained from different models. The literature suggested that it was not to be expected that the obtained forecast would systematically beat the random walk. And after evaluating the forecast with a wide range of evaluation criteria I must conclude that the forecast I obtained were not systematically better than those from the random walk model were the forecast of the exchange rate is simply equal to the current exchange rate. For the exchange rates I have used a relatively large period so that both the in sample as well as the out sample periods are relatively long. As the evaluations show, no single model stands out as the best and the results differ over time and between different exchange rates.

The models I used can be classified according to the information set required to use it for forecasting. The ex-ante models are systematically outperformed by the random walk model while the forecasting performance of other models doesn't differ much from that of the random walk model.  Combinations of forecasts don't seem to perform better than the individual models and also not better than the random walk model. The Diebold Mariano statistic shows that only a few forecasts are significantly better than those from the random walk model. The results I found show even worse performance of the economic models in forecasting the exchange rate as compared to the results in most other papers.

Not only have I evaluated the forecasts based on statistical criteria, I have also implemented the forecast of some models in trading strategies. From the evaluation of these trading strategies I conclude that it could be that profitable strategies are possible based on these exchange rate forecasts were the ARMA model stands out as the best model. However since the data I have used are not the actual circumstances a trader faces I cannot draw a final conclusion on this topic.

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## Appendix

**Evaluation of the US Dollar-Japanese Yen exchange rate forecasts 1998M01-2004M06**

| | Economic models | | | | Ex ante models | | |
|---|---|---|---|---|---|---|---|
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,38 | 0,22 | 0,21 | 0,60 | -0,09 | 0,25 | 0,07 |
| **3 months** | 1,76$^{+}$ | 0,32 | 1,15 | 1,14 | -0,79 | 0,52 | -0,11 |
| **6 months** | 2,49$^{++}$ | -0,24 | 2,90$^{++}$ | 1,97$^{+}$ | -1,35 | 0,58 | -0,31 |
| **12 months** | 4,13$^{++}$ | -1,19 | 7,29$^{++}$ | 5,30$^{++}$ | -2,37$^{--}$ | -0,28 | -1,37 |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,012 | 1,005 | 0,987 | 0,987 | 1,021 | 1,047 | 1,033 |
| **3 months** | 1,029 | 1,005 | 1,061 | 0,989 | 1,094 | 1,107 | 1,077 |
| **6 months** | 1,041 | 1,059 | 0,877 | 0,915 | 1,124 | 1,159 | 1,099 |
| **12 months** | 1,132 | 1,108 | 1,102 | 0,990 | 1,205 | 1,030 | 1,083 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,034 | 0,984 | 1,005 | 0,986 | 1,019 | 1,035 | 1,021 |
| **3 months** | 1,097 | 0,968 | 1,110 | 1,003 | 1,126 | 1,112 | 1,090 |
| **6 months** | 1,145 | 1,073 | 0,969 | 0,936 | 1,318 | 1,133 | 1,137 |
| **12 months** | 1,373 | 1,264 | 1,409 | 1,043 | 1,806 | 1,019 | 1,214 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,08 | -0,69 | 0,08 | -0,54 | 0,69 | 0,57 | 0,49 |
| **3 months** | 1,00 | -0,54 | 0,64 | 0,04 | 0,95 | 0,64 | 0,62 |
| **6 months** | 0,98 | 0,81 | -0,14 | -0,47 | 0,89 | 0,53 | 0,58 |
| **12 months** | 0,96 | 0,95 | 1,11 | 0,18 | 1,00 | 0,06 | 0,62 |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,53 | 0,45 | 0,54 | 0,50 | 0,487 | 0,436 | 0,423 |
| **3 months** | 0,51 | 0,62 | 0,58 | 0,55 | 0,474 | 0,449 | 0,449 |
| **6 months** | 0,53 | 0,49 | 0,64 | 0,60 | 0,513 | 0,487 | 0,462 |
| **12 months** | 0,46 | 0,55 | 0,63 | 0,60 | 0,551 | 0,551 | 0,513 |

| Evaluation of the US Dollar-Japanese Yen exchange rate forecasts 2004M07-2010M12 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Economic models | | | | Ex ante models | | |
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,92 | 1,11 | 0,05 | 0,68 | 1,31 | 0,97 | 1,14 |
| **3 months** | 1,86$^{+}$ | 1,85$^{+}$ | -0,26 | 1,06 | 2,95$^{++}$ | 1,73$^{+}$ | 2,34$^{++}$ |
| **6 months** | 2,00$^{+}$ | 2,61$^{++}$ | -0,22 | 1,21 | 4,25$^{++}$ | 2,50$^{++}$ | 3,41$^{++}$ |
| **12 months** | 1,98$^{+}$ | 3,35$^{++}$ | 0,26 | 1,29 | 6,93$^{++}$ | 4,30$^{++}$ | 5,78$^{++}$ |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,997 | 0,987 | 1,032 | 0,989 | 0,999 | 1,005 | 1,002 |
| **3 months** | 1,036 | 0,988 | 1,166 | 1,041 | 1,035 | 1,027 | 1,027 |
| **6 months** | 1,004 | 0,939 | 1,206 | 1,037 | 1,063 | 1,014 | 1,020 |
| **12 months** | 0,917 | 1,012 | 1,782 | 1,184 | 1,205 | 1,289 | 1,243 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,011 | 0,968 | 1,004 | 0,966 | 1,015 | 1,014 | 1,013 |
| **3 months** | 1,074 | 0,898 | 1,292 | 1,020 | 1,100 | 1,030 | 1,057 |
| **6 months** | 1,019 | 0,872 | 1,597 | 1,084 | 1,189 | 1,030 | 1,086 |
| **12 months** | 0,949 | 1,149 | 3,227 | 1,574 | 1,480 | 1,350 | 1,359 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,47 | -0,93 | 0,05 | -0,88 | 0,83 | 0,95 | 0,92 |
| **3 months** | 1,40 | -0,62 | 1,53 | 0,25 | 1,41 | 0,69 | 1,40 |
| **6 months** | 0,21 | -0,84 | 1,69$^{+}$ | 0,68 | 1,39 | 0,50 | 1,57 |
| **12 months** | -0,38 | 0,88 | 2,10$^{+}$ | 1,60 | 1,35 | 1,65$^{+}$ | 2,32$^{+}$ |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,539 | 0,410 | 0,526 | 0,539 | 0,449 | 0,462 | 0,500 |
| **3 months** | 0,410 | 0,513 | 0,410 | 0,500 | 0,500 | 0,436 | 0,423 |
| **6 months** | 0,487 | 0,539 | 0,487 | 0,449 | 0,474 | 0,539 | 0,385 |
| **12 months** | 0,474 | 0,436 | 0,539 | 0,449 | 0,346 | 0,385 | 0,269 |

**Evaluation of the US dollar-Australian Dollar exchange rate forecasts 1998m01-2004m06**

| | Economic models | | | | Ex ante models | | |
|---|---|---|---|---|---|---|---|
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,39 | 0,70 | 0,55 | 0,88 | -0,09 | 0,08 | 0,00 |
| **3 months** | 2,06$^{+}$ | 0,95 | 1,20 | 1,40 | -1,04 | -0,34 | -0,69 |
| **6 months** | 2,77$^{++}$ | 1,23 | 1,84$^{+}$ | 1,92$^{+}$ | -1,42 | -0,27 | -0,86 |
| **12 months** | 2,24$^{+}$ | 0,68 | 0,12 | 0,95 | -3,65$^{--}$ | -0,98 | -2,25$^{-}$ |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,002 | 1,015 | 0,970 | 0,991 | 1,012 | 1,012 | 1,012 |
| **3 months** | 1,031 | 1,049 | 1,002 | 1,008 | 1,066 | 1,084 | 1,070 |
| **6 months** | 1,074 | 1,113 | 0,954 | 1,038 | 1,142 | 1,127 | 1,120 |
| **12 months** | 1,066 | 1,121 | 0,845 | 0,987 | 1,164 | 1,233 | 1,190 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,017 | 1,037 | 0,973 | 0,994 | 1,050 | 1,039 | 1,039 |
| **3 months** | 1,033 | 1,088 | 0,956 | 0,994 | 1,154 | 1,181 | 1,156 |
| **6 months** | 1,095 | 1,195 | 0,863 | 1,011 | 1,321 | 1,305 | 1,300 |
| **12 months** | 1,151 | 1,251 | 0,816 | 0,996 | 1,211 | 1,462 | 1,294 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,47 | 1,99$^{+}$ | -0,47 | -0,20 | 1,72$^{+}$ | 1,35 | 1,76$^{+}$ |
| **3 months** | 0,45 | 2,37$^{++}$ | -0,32 | -0,08 | 1,44 | 2,17$^{+}$ | 1,90$^{+}$ |
| **6 months** | 0,63 | 2,68$^{++}$ | -0,91 | 0,11 | 1,91$^{+}$ | 2,39$^{++}$ | 2,17$^{+}$ |
| **12 months** | 0,70 | 1,85$^{+}$ | -0,91 | -0,04 | 1,19 | 2,62$^{++}$ | 5,23$^{++}$ |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,487 | 0,500 | 0,615 | 0,564 | 0,474 | 0,449 | 0,423 |
| **3 months** | 0,474 | 0,436 | 0,654 | 0,551 | 0,410 | 0,410 | 0,321 |
| **6 months** | 0,487 | 0,359 | 0,654 | 0,526 | 0,333 | 0,308 | 0,244 |
| **12 months** | 0,526 | 0,269 | 0,731 | 0,564 | 0,500 | 0,269 | 0,295 |

| Evaluation of the US dollar-Australian Dollar exchange rate forecasts 2004m07-2010m12 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Economic models | | | | Ex ante models | | |
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,22 | 1,20 | 0,35 | 0,58 | 1,37 | -0,15 | 0,61 |
| **3 months** | 0,41 | 1,39 | 0,28 | 0,67 | 2,07$^{+}$ | 0,01 | 1,05 |
| **6 months** | 0,33 | 1,40 | -0,32 | 0,35 | 2,62$^{++}$ | -0,40 | 1,12 |
| **12 months** | 0,43 | 2,69$^{++}$ | -1,47 | 0,02 | 6,43$^{++}$ | 0,80 | 3,66$^{++}$ |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,972 | 0,976 | 0,972 | 0,953 | 1,008 | 0,971 | 0,981 |
| **3 months** | 1,006 | 0,995 | 1,038 | 0,954 | 1,066 | 0,947 | 0,980 |
| **6 months** | 1,068 | 1,013 | 1,049 | 0,997 | 1,079 | 0,951 | 0,984 |
| **12 months** | 1,160 | 1,045 | 0,913 | 0,874 | 1,287 | 0,974 | 1,085 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,024 | 0,946 | 1,006 | 0,971 | 1,019 | 0,963 | 0,981 |
| **3 months** | 1,139 | 0,983 | 1,069 | 1,018 | 1,068 | 0,978 | 1,006 |
| **6 months** | 1,321 | 1,004 | 1,163 | 1,099 | 1,081 | 1,007 | 1,012 |
| **12 months** | 1,487 | 1,014 | 0,882 | 0,925 | 1,194 | 0,990 | 1,016 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,58 | -1,46 | 0,10 | -0,89 | 2,13$^{+}$ | -1,19 | -1,22 |
| **3 months** | 0,86 | -0,54 | 0,67 | 0,24 | 2,44$^{++}$ | -0,29 | 0,13 |
| **6 months** | 1,10 | 0,12 | 1,32 | 0,79 | 2,41$^{++}$ | 0,06 | 0,24 |
| **12 months** | 1,17 | 0,25 | -0,63 | -0,49 | 0,81 | -0,08 | 0,14 |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,615 | 0,603 | 0,628 | 0,667 | 0,436 | 0,615 | 0,603 |
| **3 months** | 0,474 | 0,539 | 0,641 | 0,641 | 0,333 | 0,680 | 0,564 |
| **6 months** | 0,410 | 0,500 | 0,551 | 0,526 | 0,385 | 0,615 | 0,615 |
| **12 months** | 0,449 | 0,577 | 0,680 | 0,615 | 0,397 | 0,577 | 0,436 |

| Evaluation of the US dollar-Swiss Franc exchange rate forecasts 1998m01-2004m06 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Economic models | | | | Ex ante models | | |
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,02 | 0,34 | 0,76 | 0,38 | -0,11 | 0,86 | 0,40 |
| **3 months** | 0,36 | 0,37 | 1,03 | 0,60 | -0,58 | 1,43 | 0,55 |
| **6 months** | 1,03 | 1,00 | 1,77$^{+}$ | 1,33 | -1,15 | 1,67 | 0,57 |
| **12 months** | 0,78 | 1,29 | 1,88$^{+}$ | 1,44 | -2,82$^{--}$ | 1,12 | -0,45 |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,019 | 1,011 | 1,029 | 1,015 | 1,043 | 1,056 | 1,043 |
| **3 months** | 1,032 | 1,053 | 1,020 | 1,027 | 1,172 | 1,177 | 1,164 |
| **6 months** | 1,013 | 1,005 | 1,123 | 1,033 | 1,280 | 1,397 | 1,316 |
| **12 months** | 1,059 | 1,082 | 1,386 | 1,177 | 1,898 | 1,527 | 1,598 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,009 | 1,029 | 1,058 | 1,022 | 1,057 | 1,093 | 1,061 |
| **3 months** | 1,031 | 1,064 | 1,059 | 1,032 | 1,265 | 1,384 | 1,261 |
| **6 months** | 1,029 | 0,994 | 1,283 | 1,081 | 1,663 | 1,852 | 1,591 |
| **12 months** | 1,110 | 1,148 | 2,067 | 1,405 | 3,064 | 2,229 | 2,131 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,49 | 1,08 | 1,37 | 1,15 | 1,56 | 1,80$^{+}$ | 1,77$^{+}$ |
| **3 months** | 1,05 | 0,97 | 0,90 | 1,09 | 1,65$^{+}$ | 1,79$^{+}$ | 1,87$^{+}$ |
| **6 months** | 0,69 | -0,14 | 2,13$^{+}$ | 1,82$^{+}$ | 1,71$^{+}$ | 1,70$^{+}$ | 2,03$^{+}$ |
| **12 months** | 1,80$^{+}$ | 1,38 | 1,94$^{+}$ | 1,99$^{+}$ | 1,74$^{+}$ | 1,47 | 2,44$^{++}$ |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,436 | 0,513 | 0,487 | 0,487 | 0,359 | 0,462 | 0,462 |
| **3 months** | 0,372 | 0,436 | 0,500 | 0,436 | 0,372 | 0,474 | 0,462 |
| **6 months** | 0,462 | 0,564 | 0,423 | 0,410 | 0,397 | 0,474 | 0,436 |
| **12 months** | 0,487 | 0,372 | 0,256 | 0,308 | 0,244 | 0,372 | 0,346 |

| Evaluation of the US dollar-Swiss Franc exchange rate forecasts 2004m07-2010m12 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Economic models | | | | Ex ante models | | |
| **ME** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | -0,03 | 0,82 | 0,00 | 0,26 | 0,41 | 0,98 | 0,69 |
| **3 months** | 0,04 | 1,24 | 0,45 | 0,57 | 1,12 | $1{,}96^{+}$ | 1,54 |
| **6 months** | -0,05 | 1,27 | 0,79 | 0,69 | 0,93 | $2{,}18^{+}$ | 1,55 |
| **12 months** | -0,06 | $3{,}03^{--}$ | 0,99 | 1,23 | $1{,}78^{+}$ | $4{,}62^{++}$ | $3{,}42^{++}$ |
| | | | | | | | |
| **MAE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,992 | 0,990 | 0,948 | 0,949 | 1,002 | 0,997 | 0,999 |
| **3 months** | 1,010 | 1,037 | 1,042 | 1,000 | 1,016 | 1,010 | 1,009 |
| **6 months** | 1,034 | 1,142 | 1,125 | 1,054 | 1,016 | 1,036 | 1,019 |
| **12 months** | 1,151 | 1,125 | 1,397 | 1,200 | 1,034 | 1,239 | 1,129 |
| | | | | | | | |
| **MSE** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 1,003 | 0,984 | 0,928 | 0,939 | 1,004 | 1,000 | 1,000 |
| **3 months** | 1,062 | 1,065 | 1,056 | 1,007 | 1,012 | 1,028 | 1,016 |
| **6 months** | 1,213 | 1,263 | 1,214 | 1,151 | 1,047 | 1,046 | 1,037 |
| **12 months** | 1,472 | 1,238 | 1,743 | 1,399 | 1,138 | 1,793 | 1,401 |
| | | | | | | | |
| **DM** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,06 | -0,53 | -1,22 | -1,58 | 0,18 | -0,04 | 0,01 |
| **3 months** | 0,33 | 1,30 | 0,35 | 0,06 | 0,29 | 0,73 | 0,50 |
| **6 months** | 0,61 | 1,44 | 0,98 | 0,63 | 0,56 | 0,88 | 0,74 |
| **12 months** | 1,54 | 1,22 | $3{,}25^{++}$ | $2{,}88^{++}$ | 1,37 | 1,01 | 1,09 |
| | | | | | | | |
| **DoC** | UIP | PPP | SP | Combi | PPP | SP | Combi |
| **1 month** | 0,603 | 0,564 | 0,641 | 0,628 | 0,539 | 0,551 | 0,526 |
| **3 months** | 0,539 | 0,462 | 0,564 | 0,526 | 0,564 | 0,590 | 0,551 |
| **6 months** | 0,513 | 0,462 | 0,436 | 0,526 | 0,615 | 0,526 | 0,551 |
| **12 months** | 0,513 | 0,500 | 0,462 | 0,487 | 0,513 | 0,474 | 0,462 |

| Evaluation of ARMA and ARMA(X) forecasts 1998m01-2004m06 | | | | | | |
|---|---|---|---|---|---|---|
| | Australia | | Japan | | Switzerland | |
| **ME** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,62 | -0,45 | 0,13 | 0,24 | 0,42 | -0,43 |
| **3 months** | 0,40 | -1,01 | 0,19 | -1,16 | 0,58 | -2,66$^{--}$ |
| **6 months** | -0,10 | -2,53$^{--}$ | -0,32 | -3,08$^{--}$ | -0,06 | -4,70$^{--}$ |
| **12 months** | -0,38 | -2,07$^{-}$ | -0,44 | -2,81$^{--}$ | -2,77$^{--}$ | -6,96$^{--}$ |
| | | | | | | |
| **MAE** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,956 | 0,903 | 1,007 | 1,032 | 0,968 | 0,930 |
| **3 months** | 1,030 | 1,032 | 1,037 | 1,031 | 1,094 | 0,797 |
| **6 months** | 1,027 | 1,008 | 1,058 | 1,055 | 1,184 | 1,081 |
| **12 months** | 1,146 | 1,396 | 1,209 | 1,009 | 1,546 | 1,495 |
| | | | | | | |
| **MSE** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,953 | 0,878 | 0,965 | 0,983 | 1,001 | 0,854 |
| **3 months** | 1,070 | 1,042 | 1,014 | 1,005 | 1,148 | 0,680 |
| **6 months** | 1,068 | 1,037 | 1,077 | 1,123 | 1,378 | 1,367 |
| **12 months** | 1,369 | 1,686 | 1,490 | 1,007 | 2,124 | 2,263 |
| | | | | | | |
| **DM** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | -0,62 | -1,26 | -0,32 | -0,17 | 0,01 | -1,24 |
| **3 months** | 0,74 | 0,32 | 0,29 | 0,03 | 1,82$^{+}$ | -1,45 |
| **6 months** | 0,45 | 0,14 | 0,64 | 0,41 | 1,87$^{+}$ | 0,65 |
| **12 months** | 1,54 | 3,02$^{++}$ | 1,84$^{+}$ | 0,02 | 2,70$^{++}$ | 1,18 |
| | | | | | | |
| **DoC** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,577 | 0,680 | 0,539 | 0,615 | 0,603 | 0,603 |
| **3 months** | 0,487 | 0,551 | 0,397 | 0,667 | 0,410 | 0,718 |
| **6 months** | 0,462 | 0,615 | 0,474 | 0,603 | 0,410 | 0,667 |
| **12 months** | 0,359 | 0,333 | 0,321 | 0,654 | 0,410 | 0,577 |

**Evaluation of ARMA and ARMA(X) forecasts 2004m07-2010m12**

| | Australia | | Japan | | Switzerland | |
|---|---|---|---|---|---|---|
| **ME** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,80 | 0,95 | 0,82 | $1{,}70^{+}$ | 0,60 | 0,34 |
| **3 months** | 0,93 | 0,39 | $2{,}88^{++}$ | $2{,}06^{+}$ | 1,27 | -1,01 |
| **6 months** | 0,78 | 0,36 | $4{,}86^{++}$ | $5{,}54^{++}$ | 0,91 | -0,55 |
| **12 months** | 1,43 | 4,39 | $8{,}76^{++}$ | $7{,}79^{++}$ | $1{,}70^{+}$ | $4{,}40^{--}$ |
| | | | | | | |
| **MAE** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,898 | 0,831 | 1,020 | 0,926 | 0,982 | 0,836 |
| **3 months** | 0,997 | 0,906 | 1,065 | 1,036 | 0,984 | 0,993 |
| **6 months** | 1,155 | 0,891 | 0,977 | 1,446 | 0,999 | 1,006 |
| **12 months** | 1,019 | 1,109 | 1,223 | 1,526 | 1,274 | 1,096 |
| | | | | | | |
| **MSE** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,786 | 0,630 | 0,981 | 0,874 | 0,971 | 0,765 |
| **3 months** | 1,043 | 0,876 | 1,136 | 1,072 | 0,975 | 1,068 |
| **6 months** | 1,343 | 0,752 | 1,057 | 2,109 | 1,025 | 1,231 |
| **12 months** | 0,999 | 1,039 | 1,394 | 2,406 | 1,571 | 1,248 |
| | | | | | | |
| **DM** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | $-2{,}27^{-}$ | $-2{,}19^{-}$ | -0,35 | -1,26 | -0,60 | $-2{,}52^{--}$ |
| **3 months** | 0,76 | $-1{,}82^{-}$ | $1{,}82^{+}$ | 0,41 | -0,62 | 0,23 |
| **6 months** | $1{,}71^{+}$ | -1,44 | 0,44 | $1{,}99^{+}$ | 0,21 | 0,53 |
| **12 months** | 0,00 | 0,07 | 1,20 | $1{,}67^{+}$ | $1{,}74^{+}$ | 0,77 |
| | | | | | | |
| **DoC** | ARMA | ARMA(X) | ARMA | ARMA(X) | ARMA | ARMA(X) |
| **1 month** | 0,615 | 0,654 | 0,539 | 0,692 | 0,577 | 0,705 |
| **3 months** | 0,590 | 0,731 | 0,449 | 0,667 | 0,539 | 0,667 |
| **6 months** | 0,551 | 0,680 | 0,500 | 0,410 | 0,449 | 0,615 |
| **12 months** | 0,526 | 0,603 | 0,462 | 0,500 | 0,436 | 0,615 |

**Evaluation of US Dollar-Japanese Yen carry trade 1998m01-2004m06**

| | RW | UIP | PPP | SP | ARMA | Combi |
|---|---|---|---|---|---|---|
| **Avg return** | 0,076 | 0,076 | -0,095 | 0,041 | 0,255 | 0,319 |
| **Std.dev** | 0,318 | 0,318 | 0,318 | 0,318 | 0,316 | 0,416 |
| **GW Return** | - | *** | -0,56 | -0,08 | 0,42 | - |
| **GW Sharpe** | - | -0,16 | -0,57 | -0,10 | 0,42 | - |
| **GW Skew** | - | -1,07 | 0,50 | 0,98 | 0,92 | - |
| **Direction** | 0,539 | 0,539 | 0,487 | 0,487 | 0,539 | 0,539 |

**Evaluation of US Dollar-Japanese Yen carry trade 2004m07-2010m12**

| | RW | UIP | PPP | SP | ARMA | Combi |
|---|---|---|---|---|---|---|
| **Avg return** | -0,141 | -0,022 | -0,213 | -0,398 | 0,586 | 0,081 |
| **Std.dev** | 0,269 | 0,270 | 0,269 | 0,266 | 0,262 | 0,270 |
| **GW Return** | - | 0,40 | -0,35 | -0,94 | 2,03$^{+}$ | - |
| **GW Sharpe** | - | 0,41 | -0,35 | -0,90 | 2,08$^{+}$ | - |
| **GW Skew** | - | 0,06 | -0,86 | -1,11 | 2,18$^{+}$ | - |
| **Direction** | 0,551 | 0,551 | 0,551 | 0,526 | 0,577 | 0,539 |

**Evaluation of US Dollar-Australian Dollar carry trade 1998m01-2004m06**

| | RW | UIP | PPP | SP | ARMA | Combi |
|---|---|---|---|---|---|---|
| **Avg return** | 0,235 | -0,028 | -0,048 | -0,105 | 0,477 | 0,268 |
| **Std.dev** | 0,313 | 0,314 | 0,314 | 0,314 | 0,310 | 0,313 |
| **GW Return** | - | -0,47 | -0,72 | -0,82 | 0,61 | - |
| **GW Sharpe** | - | -0,42 | -0,75 | -0,82 | 0,65 | - |
| **GW Skew** | - | -0,01 | -0,38 | 0,24 | 1,02 | - |
| **Direction** | 0,526 | 0,487 | 0,551 | 0,462 | 0,590 | 0,564 |

**Evaluation of US Dollar-Australian Dollar carry trade 2004m07-2010m12**

| | RW | UIP | PPP | SP | ARMA | Combi |
|---|---|---|---|---|---|---|
| **Avg return** | 0,578 | 0,453 | -0,440 | 0,662 | 1,385 | 0,963 |
| **Std.dev** | 0,408 | 0,410 | 0,410 | 0,407 | 0,382 | 0,399 |
| **GW Return** | - | -0,71 | -2,77$^{--}$ | 0,55 | 1,38 | - |
| **GW Sharpe** | - | -0,70 | -2,65$^{--}$ | 0,57 | 1,51 | - |
| **GW Skew** | - | -1,50 | -2,64$^{--}$ | 0,68 | 1,30 | - |
| **Direction** | 0,654 | 0,628 | 0,551 | 0,654 | 0,680 | 0,641 |

| Evaluation of US Dollar-Swiss Franc carry trade 1998m01-2004m06 | | | | | | |
|---|---|---|---|---|---|---|
| | RW | UIP | PPP | SP | ARMA | Combi |
| **Avg return** | -0,028 | -0,060 | -0,340 | -0,108 | 0,591 | 0,142 |
| **Std.dev** | 0,290 | 0,290 | 0,288 | 0,290 | 0,282 | 0,290 |
| **GW Return** | - | -0,08 | -0,99 | -0,22 | 1,56 | - |
| **GW Sharpe** | - | -0,04 | -0,97 | -0,17 | $1,65^{+}$ | - |
| **GW Skew** | - | $1,69^{+}$ | 0,63 | 1,18 | $1,82^{+}$ | - |
| **Direction** | 0,590 | 0,474 | 0,500 | 0,474 | 0,628 | 0,551 |

| Evaluation of US Dollar-Swiss Franc carry trade 2004m07-2010m12 | | | | | | |
|---|---|---|---|---|---|---|
| | RW | UIP | PPP | SP | ARMA | Combi |
| **Avg return** | -0,197 | 0,657 | 0,039 | -0,317 | 0,669 | 0,426 |
| **Std.dev** | 0,289 | 0,280 | 0,290 | 0,288 | 0,280 | 0,286 |
| **GW Return** | - | $1,77^{+}$ | 0,46 | -0,45 | $1,99^{+}$ | - |
| **GW Sharpe** | - | $1,72^{+}$ | 0,46 | -0,48 | $1,98^{+}$ | - |
| **GW Skew** | - | 1,31 | 0,92 | -0,98 | 1,46 | - |
| **Direction** | 0,462 | 0,641 | 0,526 | 0,462 | 0,641 | 0,603 |