THREE ESSAYS ON THE FOREIGN EXCHANGE MARKETS

by

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ABSTRACT

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The foreign exchange market is full of risk and uncertainty. Researchers are trying many approaches to explain foreign exchange movements and forecast foreign exchange rates. The most quoted methods are forward premium model and vector error correction model (VECM).

The first essay study the explanation power of the macroeconomic news for the foreign exchange fluctuation. We use Kalman filter and maximum likelihood method to extract several dynamic factors from 27 noisy and sparsely observed macroeconomic news deviations. We further input the news factors as independent variables in our VECM analysis. The fitted results show that the news factors' contribution is limited. The out of sample prediction yields the same conclusion.

The uncovered interest rate parity hypothesis has frequently been rejected. This hypothesis, however, has seldom been tested at the very short end of the forecasting horizon where forward rates are measured in days. The second paper reinvestigate the UIRP puzzle in diversified horizons. Using overnight, two-day

and three-day forward rates, we find that the forward premia in these short forward horizons are stationary than the forward premia in longer horizons. This contrasts with recent findings that the forward premia, in longer forward horizons, are fractionally nonstationary. Estimation results indicate that forward premia are essentially unbiased estimates of the future spot returns. Once the interest rate differential is the dominant source of information in the foreign exchange market, the forward premium forecasts the spot returns relatively well.

The last essay we have a empirical study of the VECM prediction power. we use the rolling regression method to generate series of parameters and dynamically predict the next period's foreign exchange rates. We compare the forecast errors from the rolling regression VECM and that of the random walk model. We also set up a trading strategy which longs or shorts the foreign currency based on the forecasts. Our trading simulation shows that this informed trading makes positive return in medium horizon, while the simple buy and hold strategy's return is insignificant.

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Chapter 1

Do Macroeconomic Announcements Affect the Foreign Exchange Markets?

1.1. Introduction

This paper is an empirical study on the effect of macroeconomic news release on foreign exchange markets. It is well known that the macro variables sometimes influence the domestic currency value. But the direction and magnitude of the impacts are quite difficult to tell.

Scholars use various approaches to explain foreign exchange flutuations and predict foreign exchange rates. Most began with the interest rate approach. Clarida and Taylor applied vector error correction model (VECM) to analyze ther term structure of forward exchange premiums in 1997 and 2003. They got satisfactory forecast of spot exchange rates. They worked on a horizon of spot rate longer than 1 month. In contrast, Chaboud and Weight (2003) started with an extremely short horizon. They focused on the intradaily data and found that the UIRP only worked on the scale of several minutes. Some researches have been done on the relationship between spot returns and news surprises. Sen Dong (2006) used two news index and term structure to explain the exchange rate movements. Simpson, Ramchander and Chaudhry (2005) evaluated more news factors and ran a VECM to test their effect on the exchange rates. In this paper we address the question of whether we can get a better forecast for tomorrow's foreign exchange rate by applying a VECM with the organized news surprise factors to analyze the daily exchange rates.

In the United States, the market absorbs several news releases each week, sometimes many surprises in a single day. These news releases have different effects on macroeconomics and drive the domestic currency value in different directions. In order to reduce noise, many researchers only focus on several important variables such as gross domestic product (GDP), consumer price index (CPI) and federal rates. While we agree all the different variables are not equally important, they each contains some information others do not. For example, while both consumer price index (CPI) and consumer price index core (CPI core) measure the retail prices in the urban area, the latter excludes the most fluctuating food and energy prices. Some scholars prefer the CPI core for its stableness. That means they have to give up the price fluctuations from the food and energy categories, which are critical when the crude oil price is highly volatile.

The news announcements can be roughly allocated into two categories. Some are released at higher frequencies but only track certain parts of the economy, such as the durable goods orders, business inventories and initial claims. Some others are released at lower frequencies but give a better picture for the activity of the whole economy, such as the RGDP SAAR, index of leading indicators. The former reveal only part of the economic activities and sometimes provide conflicting information. The later are ideal but their delayed release timing and the redundant information compromise their performance in the foreign exchange analysis.

Besides these inherent information and noise problems, there are some empirical reasons that disallow us from using all the regularly released macroeconomic indicators as independent variables in the model.

Firstly, some pairs of indicators, such as the CPI and CPI core are highly correlated. Secondly, the macroeconomic variables are released at different frequencies. Most indicators are published monthly; others are released quarterly or weekly. It is hard to align these time series. Even in the monthly released data group, some are published in the beginning of month and some are released near the end of the month. It is insufficient to coarsely treat them as providing macroeconomic information for the same month. The way to solve this problem is to align the data in a daily time series. We can clearly identify news release may affect a special day's foreign exchange spot return.

We use the Kalman filter to treat the noise problem. Our procedure is firstly extracting a handful of dynamic factors to represent the 27 macroeconomic announcements. In the second step, we fit the spot rates and forward rates on the extracted factors, to obtain the parameters for the model. Finally, we generate the out-of-sample prediction with the model, and compare the prediction errors from our model with the random walk model.

Because many macroeconomic news releases contain similar information, we classify the news into several categories and use Kalman Filter to extract the useful signal only. Based on UIRP and PPP, we classify the variables into two categories: inflation factor and growth factor. As for the relationship between the extracted news factors and the foreign exchange rates, we try the vector error correction model (VECM) to describe this nonstationary process.

The rest of the paper is organized as the following: section 2 reviews the explanations on the foreign exchange movements, discusses the prior academic literature on the relationship between macroeconomic news and currency market. Section 3 discusses the data. Section 4 describes the methodology we used to extract the dynamic factors, and how to classify the news release. Section 5 tests the fitting ratio of the Kalman filter. Section 6 apply the extracted factors to fit the currency market. Section 7 tries to use our fitted model to forecast the spot rates and compares it with other models. Section 8 use the non overlapped weekly data to do a robust test. Section 9 concludes.

1.2. Previous work

Exchange rate economics is characterized by a bunch of puzzles. The most famous puzzle is the uncovered interest rate parity (UIRP). UIRP argues that if domestic interest rate is higher than the foreign interest rate, the domestic currency will depreciate and the foreign currency will appreciate. As described by the following model:

$$s_{t+1} - s_t = \alpha + \beta(i - i^*) + \varepsilon \tag{1.1}$$

Here, i and i^* denote, respectively, the domestic and foreign interest rate on a one-period zero coupon bond. Ideally, α should be close to 0 and β should be close to 1. However, numerous empirical researches showed that α is indeed close to 0 but β goes to negative. This means that the high-yield currency appreciates rather than depreciates. That is the UIRP called as forward premium puzzle. The forward premium puzzle is now well documented and researchers provided many ways trying to solve it or explain it.

Many economists began from explaining the forward premium puzzle and ended up in out-of-sample forecasting. The most cited method is the vector error correction model (VECM) first incorporated by Clarida and Taylor (1997). They compared their forecast error term with the vector autoregression (VAR) model, random walk model, forward premium regression and forward rate. They found VECM almost beat all the other four methods in root-mean square error (RMSE) and mean absolute error (MAE) measurement.

Another important branch of studies try to analyze the forward premium puzzle in extremely long term or extremely short horizons. Lothian and Wu (2002) tested the uncovered interest rate parity in a period of two centuries. They found that UIRP only worked in the gold standard period. Because the wide application of computers, it is easier to access the intra-day foreign exchange rates and interest rates today. More and more works focus on the extremely short horizons. For example, Chaboud and Weight (2003) studied the exchange rates around a particular point in time (17:00 New York time) and their conclusion is that UIRP works, but just OK for several minutes. Some works try to relate the forward premium (or sometimes just the foreign exchange itself) with the interest rates term structure. These models make some valuable contribution too. For instance, Ahn (2004); Backus, Foresi and Telmer (2001); Backus, Foresi, Mozumdar and Wu (2001); Inci and Lu (2004); Piazzesi (2003).

There are relatively fewer works specializing on the macroeconomics news only. Lu and Wu (2005) used the extended kalman filter to extract two dynamic factors from 17 macroeconomic releases, then related these two factors to the daily term structure of interest rates under the no arbitrage assumption. They found that the inflation factors had large and positive impacts on interest rates. Moreover, the extracted two dynamic factors can explain more than 76% daily variation in LIBOR and swap rates of all maturities.

Another important research was done by Simpson, Ramchander and Chaudhry (2005). They evaluated 23 news releases and classified the news releases in more detailed categories. To my knowledge, they first used inflation, growth, domestic demand and interest categories to classify the news announcements. They applied VECM with all 23 news variables to build their model. They found that the exchange rates failed to respond to the economy growth indicators.

Sen Dong (2006) applied CPI, industrial production index and term structure to explain the exchange rate movements and found "that the correlation between the model-implied exchange rate changes and the data is over 60%."[1]

1.3. Data description and the measurement of deviations

1.3.1. Data description: news surprise

We collect the consensus estimates of 27 macroeconomic announcements provided by Money Market Services (MMS). All of these 27 variables have a time spread of more than 10 years. The starting dates of these variables vary from Jan. 1980 to Sep. 1991. The ending dates from Nov. 2004 to Mar. 2005. Unfortunately, we have no macroeconomic news data from foreign countries. We choose the common sample from Nov. 2nd, 1993 to Jun. 1st, 2004 to extract the dynamic unobserved variables, and leave the last 5 months from Jun. 2nd, 2004 to Nov. 17th, 2004 for out of sample test.

As we know, the announcement itself doesn't make any difference if it has been fully anticipated already. In other words, surprises or deviations are more

[1] Sen Dong, 2006, "Macro Variables Do Drive Exchange Rate Movements: Evidence from a No-Arbitrage Model", P31

important for our model building. How to measure the diversities then? We followed the measurement used by most economists. We define the *surprise* as the standardized difference between the announced and the expected indicators, represented by:

$$Surprise_i = (Actual_i - survey_i)/\sigma_i \tag{1.2}$$

Here both $Actual_i$ and $survey_i$ come from MMS. The former is the announcement itself; the latter is produced by MMS. The MMS surveys are obtained from estimates of approximately 40 academics and practitioners. They are interviewed 1 week before the news release, and the median value of the estimates are taken as the survey. They are believed to be unbiased estimates of the forthcoming announcements. σ_i is the standard deviation of the whole *ith* announcement's differences between the actual and the forecast. We call this measurement as *surprise*. It describes the pure surprise away from the market's expectation.

Because the announcements have different release schedule and different frequency, as I noted in the introduction part, we aligned them in a daily time series. To fulfill this purpose, we generate a date series which includes all the business date from Nov. 2nd, 1993 to Nov. 17th, 2004, and insert all the macroeconomic announcements into their corresponding dates. All the other dates without news release have value 0 indicating that there are no surprises or no deviations on these days.

Out of the 27 announcements, 23 variables are released monthly. GDP and GDP price index are released quarterly[2]. Initial claims are announced weekly. Federal Open Market Committee (FOMC) has a regular meeting every 6 weeks, so the target fed funds rate is releases every 6 weeks[3]. Table 1.1 and Table 1.2 lists the summary statistics of all the 27 macroeconomic announcement $surprise$. We can find that all 27 $surprise$ variables have mean insignificant different to 0. That means the analysts' estimates are unbiased.

1.3.2. Data description: foreign exchange spot rates and forward rates

For the foreign exchange rates part, the spot rates and overnight forward rates in daily frequency are obtained from the Bloomberg system, which were collected by Bloomberg as the average of the inter-bank quotes during the New York trading hours. We choose United States Dollar (USD) as the domestic currency, and study 4 important foreign currencies as my objects: Australia Dollar (AUD), Canada

[2]Both GDP and GDP price index have three scheduled releases in each quarter: preliminary, revised and final reading. Actually, these two announcements have monthly releases and I include them all. Most news announced in the morning

[3]I include all the special cases such as fed had 3 continuous meeting from Oct. to the end of 2001.

Dollar (CAD), British Bound (GBP) and Japanese Yen (JPY). We didn't include the very important European currencies such as the Deutsche Mark (DEM) and French Franc (FRF), because after entering the euro currency system, their behavior is somewhat inconsistent. Similar to the news data treatment, we have the in sample data from Nov. 2nd, 1993 to Jun. 1st, 2004, and leave Jun. 2nd, 2004 to Nov. 17th, 2004 for the out of sample test.

Table 1.3 lists summary of these 4 currencies. Because we take USD as domestic currency, we invert the original GBP and AUD data. We not only report the statistic summary of spot rates and forward rates[4], but also the summary of spot returns and forward premium[5].

1.4. Model to extract systematic factors

1.4.1. Using dynamic Kalman filter to extract the news factor

There are so many macroeconomic announcements every month. The foreign exchange market always expects something everyday, domestic or foreign. Every macroeconomic variable has its special effects and some common factors with other published announcements. If we can combine these indicators by some

[4]Spot rates and forward rates are in logarithms.

[5]Spot return is defined by S(t+1) - S(t), and forward premium is f(t) - S(t). All in logarithms too. To increase the readability, we multiply the spot returns and forward premiums by 1000.

reasonable model, we can draw a clearer picture of the economy and analyze the foreign exchange movement in a more robust way.

In this part, we extract the dynamic factors with Kalman filter and maximum likelihood, following the method used by Lu and Wu (2005).

The state equation is

$$dX_t = -\alpha X_t dt + dW_t \tag{1.3}$$

Here $X \in \mathbb{R}^n$ denotes the n dimensional state vector, they represent the systematic state of the economy. For example, if we want to extract 2 factors such as inflation and growth effect of the economy, X is a 2 dimensional state vector. To simplify the question, we assume that the state vector X follows a $VAR(1)$ dynamics

$$X_t = e^{-\kappa \triangle t} X_{t-1} + \sqrt{I \triangle t}\varepsilon_t \tag{1.4}$$

Here ε_t denotes an $(n \times 1)$ independent and identically distributed standard normal random vector. $\triangle t$ denotes the discrete time interval. Because we use daily data, $\triangle t = 1/252$. I is an $(n \times n)$ identity matrix. κ is an $(n \times n)$ unknown matrix.

The measurement equation is

$$M_t = HX_t + e_t \tag{1.5}$$

Here $M \in \mathbb{R}^N$ denotes a N dimensional measurement vector. It represents N series of macroeconomic news deviations such as *surprises* of CPI, GDP or federal rate, etc. H is a $(N \times n)$ matrix of factor loading coefficients. e_t is a $(N \times 1)$ vector of measurement noises of the macroeconomic data series. The covariance matrix of the measurement errors is $R^M = E(e_t e_t^T)$. Following the prior works, we assume that the measurement errors are independent to the error terms in the state equation (6). And the measurement errors themselves are mutually independent. In other words, $R_{ii}^M = \sigma_i^2$, $i = 1,2,3,...,N$ and $R_{ij}^M = 0$, if $i \neq j$.

Because X denotes the hidden state being estimated, I use $\overline{X_t}$ to represent the ex ante forecast value at time $(t-1)$, and $\widehat{X_t}$ is the ex post update. Similarly, because V is the covariance matrix of the hidden state, we define $\overline{V_t}$ the ex ante forecast of time t value calculated at time $(t-1)$, and $\widehat{V_t}$ is the ex post update. A is the covariance matrix of macroeconomic measurement series M. In summary, all the ex ante forecast are,

$$\overline{X_t} = e^{-\kappa \triangle t} \widehat{X_{t-1}}; \tag{1.6}$$

$$\overline{V_t} = e^{-\kappa \triangle t} \widehat{V_{t-1}} (e^{-\kappa \triangle t})^T + I \triangle t; \tag{1.7}$$

$$\overline{M_t} = H \overline{X}_t; \tag{1.8}$$

$$\overline{A_t} = H \overline{V_t} H^T + R^M; \tag{1.9}$$

The ex post filtering updates are,

$$\widehat{X_{t+1}} = \overline{X_{t+1}} + K_{t+1}(M_{t+1} - \overline{M_{t+1}}); \tag{1.10}$$

$$\widehat{V_{t+1}} = \overline{V_{t+1}} - K_{t+1} \overline{A_{t+1}} K_{t+1}^T; \tag{1.11}$$

While the Kalman gain is K_t,

$$K_t = \overline{V_t} H^T (\overline{A_t})^{-1}; \tag{1.12}$$

By combining the ex ante and ex post, we can use a recursive program to estimate the model. There are 5 unknown parameters: $\Theta \equiv \{\kappa, H, R^M, X_{0,} V_0\}$.

Then we use maximize likelihood method to estimate these 5 parameters. The daily log likelihood function is:

$$L_t(\Theta) = -0.5\log|\overline{A_t}| - 0.5[(M_t - \overline{M_t})^T(\overline{A_t})^{-1}(M_t - \overline{M_t})]; \tag{1.13}$$

We sum all the daily log likelihood functions and maximize the result to estimate the unknown parameters.

$$\Theta = \arg\max_{\Theta} \sum_{t=0}^{T} L_t(\Theta); \tag{1.14}$$

1.4.2. Extract the invisible dynamic factors

As described in section 1, most macroeconomic variables include more than one systematic factors. Different classification can determine different measurement equations and then extract different dynamic factors. Basically, all the macroeconomic data series can be classified into two factors: real GDP growth factor and inflation factor. We allocate the 27 macroeconomic announcements into 4 kinds of indicators, then analyze these 4 indicators' effect to the growth factor and inflation factor respectively.

Table 1.4 shows our loading method. We analyze all the news in detail and use $+$ to represent the positive effect to the spot returns; $-$ represents negative effect.

0 represents no effect to the spot return. h1 represents the extracted growth factor and h2 is the inflation factor.

All the announcements are classified as the following groups: domestic consumer demand group, economic growth group, domestic inflation and domestic interest rate group.

Seven of the 27 announcements are considered to disclose the domestic consumer demand changing: business inventory, capacity utilization, consumer confidence, trade balance, personal consumption expenditures (PCE), personal income, retail sales except auto and retail sales. These indicators only have influence to the inflation factor except the retail indicators. More demand means higher price, so that capacity, confidence, PCE, trade balance and income push the pice higher, while inventory reduces the demand so does the price. Larger retail index pulls the price too, and it is a positive indicator to the economic growth. We think retail sales and retails except auto sales have positive effect both on growth and inflation factors.

The economic growth group have eight announcements. They are initial claims, RGDP, construction spending, durable goods orders, housing starts, industrial production, index of leading indicators and new home sales. These indicators have direct influence on our growth factor. For example, more initial claims suggest that economy is slowing down while the others send positive signals.

There are another eight announcements can be allocated as domestic inflation group: GDPPI, CPI, CPI core, hourly earnings, nonfarm payroll, PPI, PPI core and unemployment rate. Five of them are price index, which of course have positive effect to the inflation factor. Hourly earnings and nonfarm payroll are positive related to domestic demand and so pull up the price. While the unemployment is negative indicator to both the price level and the growth rate.

The last three announcements belong to interest rate group. Fed's main purpose is to keep a acceptable inflation rate; that is the reason we take it as a positive indicator to inflation factor. Larger amount of consumer credit will push the interest rate up and so to the price level. Treasury budget goes higher, the long term treasury bonds yield tends to lower, so does the price level.

We need to recognize that this loading is just an approximation. The economy is a very complex process. In other words, we cannot assume this allocation is perfect. For example, the fed funds rate is primarily an inflation indicator, the positive surprise in fed funds rate shall indicate a higher inflation risk. Therefore we assign a positive loading in its h2 loading and a 0 in its h1 loading. However, in many cases the higher fed rate increases the investment cost and is a bad news to real GDP growth. Here we only focus on the main and immediate influence.

1.5. Extracting systematic factors from macroeconomic releases

Table 1.5 lists the estimation of the factor loading matrix H. h1 represents the loading on growth and h2 on the inflation effects. rr_i is the variance of the estimation error for each macroeconomic variable. We report its value in the *error* column.

$$rr_i = var(M_i - H_i \times X) \tag{1.15}$$

Here M_i represents the ith announced macro announcement. $(H_i \times X)$ is the estimation from the dynamic Kalman filter method.

FV is the forecasted percentage variance. We define it as

$$FV = 1 - \frac{rr_i}{rm_i} \tag{1.16}$$

rm here is the variance to the ith vector of $surprises$, and its value is reported in the *var* column. FV indicates the quality of the forecast: the closer to 1, the better.

Table 1.5 shows that our estimate is satisfactory. Most parameters in h1 and h2 are significant. The estimate error variance is smaller than the original variance. Most FVs are in the range between 0.9 and 1, except for the capacity utilization, consumer confidence and CPI. The best fitting comes from business inventory, whose FV is 99.48%. And the worst fitting comes from capacity utilization, whose FV is 69.54%. The result shows that our loading matrix is reliable. Moreover, the generated growth and inflation factors can represent those 27 macroeconomic announcements.

1.6. VECM with extracted news input

The dynamic Kalman Filter method generates not only the loading matrix H, but also the extracted dynamic factors Xs. X has a dimension of $n \times 2$. n is the observations number.

There are many models describe the relationship between foreign exchange rates and forward rates. We make use of the classical vector error correction model (VECM) which was first introduced by Richard Clarida and Mark Taylor in 1997. VECM is an ideal model to help better understand the nature for any nonstationary process. It also improves the forecasting ability in a longer time horizon.

Many articles observe that the spot exchange rate possesses a unit root and can be write as:

$$s_t = w_t + \varepsilon_t \tag{1.17}$$

Where s_t is the logarithm of the spot exchange rate, and ε_t is a stationary process with mean 0. w_t represents a unit root process which is assumed as a first order process:

$$w_t = w_{t-1} + e_t + \theta \tag{1.18}$$

Here θ is a constant and e_t is a stationary process. Compiling the formula together we get

$$s_t - s_{t-1} = \theta + e_t + \varepsilon_t - \varepsilon_{t-1} \tag{1.19}$$

Since θ is a constant and the later three items are stationary, we have shown that first difference of the logarithm of the spot exchange rate is stationary.

Then we build a vector y_t which includes the logarithm of both the spot exchange rates and the overnight forward rates:

$$y_t = [s_t, f_{t,1d}]' \tag{1.20}$$

Moreover, y_t is a 2 dimension co-integrated vector. There exists an $2 \times r$ matrix α such that

$$z_t = \alpha' y_t \tag{1.21}$$

r is the number of co-intergrating relations, which we get from Johansen's trace test at 95% level.

Now the VECM form becomes:

$$\Delta y_t = \beta x_t + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \ldots + \Gamma_k \Delta y_{t-k} + \gamma z_{t-1} + \varepsilon_t \tag{1.22}$$

Where Δ is the first difference operator, γ is a coefficients matrix which has dimension $2 \times r$. x_t is the extracted dynamic factors representing the effect of the macroeconomic deviations originating from the 27 macroeconomic variables.

1.6.1. Lag checks for the later work

The number of lags to pick is critical in time series analysis. We need it to decide the k value for the co-integrated VAR model. Moreover, VECM requires Δy_t to be stationary, so we need to do a unit root test in addition to cointergration test. Both of these tests require the lag as an input.

We use the Akaike's Information Criterion (AIC) to measure the goodness of different autoregression model with lags from 1 to 8 and report the result in table 1.6. From the AIC value we obtain the smallest return for each currency. We found k=5 for AUD and GBP, while k=6 for CAD and JPY.

Because the lag check is very important to the following process, we use likelihood ratio (LR ratio) to double check this problem. The LR ratio tests are exhibited in Table 1.7. Under 5% critia level, we find that AUD and GBP rejected lag 4 in favor of lag 5 as optimal lag length. While CAD and JPY rejected lag 5 in favor of lag 6 as their optimal lag length.

1.6.2. Unit root test

Many literature suggested that s_t and f_t have unit roots. We employ the augmented Dickey - Fuller (ADF) test on the forward and spot rates for the unit root test.

Table 1.8 reports the results of the unit root test. The critical value of ADF test in 1% level, 5% level and 10% level are –3.458, –2.871 and –2.594 respectively. We used two ways to run the ADF test: one with constant only, the other with both constant and a deterministic trend together. We run the ADF test to the currencies as well as to the extracted factors.

In the currencies part, we find that the unit root hypothesis can not be rejected in both the spot exchange rate levels and the forward rate levels. This result is consistent with the existing literature and confirms that both the spot and the forward exchange rates are nonstationary. The ADF test for the first differences of both spot and forward rates shows that the first differences are stationary. That is consistent with our proof in equation (19).

For the extracted dynamic news factors, growth and inflation factors strongly reject the unit root hypothesis and suggest these series are stationary. Since all the dynamic factors are stationary we do not need to check their stationarity of their first difference.

Table 1.9 reports the t value from the second unit root test by Phillips-Perron method. We can reject the unit root hypothesis with 95% confidence interval if the t value without trend is smaller than –1.95; or smaller than –3.41 when the equation including a trend item. Similar to the ADF report, the second unit root test finds that all the spot and forward levels are nonstationary while their first differences items are stationary.

1.6.3. Cointegration test

We need to do the cointegration test before running our error correction models. We use Johansen test and report the results in table 1.10. There are two types Johansen test: trace or eigenvalue. If the trace or eigenvalue is smaller than the critical value, we accept the hypothesis that the cointegrated vector has a rank smaller than a fixed number. For example, we know the trace value for $r \leq 0$ is 322.445, while the critical value with 95% confidence interval is 12.321. We reject the hypothesis that there is no cointegrated relationship.

With different order of time polynomial in the null hypothesis, Johansen test has several equations. We report 3 cases in table 1.10: no deterministic item, with constant term and with constant plus time trend. We use $p = -1$, $p = 0$ and $p = 1$ represent them respectively.

The currencies have 1 cointegrated relationship under each of the three equations, either in trace or eigenvalue measurement. We can run our VECM with confidence.

1.6.4. VECM report

Table 1.11 and table 1.13 report the results of the dynamic macroeconomic factors included in VECM as seen in equation (22) [6]. Table 1.11 has all the returns from the ΔS_t equation, table 1.13 reports the results from the ΔF_t equation. We use lag $k = 5$ for AUD and GBP, $k = 6$ for CAD and JPY. We report VECM only and VECM with extracted news factors. The coefficients, t-probabilities for each coefficient, R squares and the observation numbers are exhibited in the table 1.11 and table 1.13.

Firstly, spot return equations have better explaining power than the forward rate equations through all the currencies. The R squares in the spot return equations are around 10% in all currencies. In particular, CAD has the highest explaining power of 19% while JPY has the lowest R square around 8%. One possible expanation is that the Canadian Dollar is more sensitive to the US macroeconomic information. The equations based on the forward rates have R square from 1% to 5%, lower than the corresponding R square in the spot rates equations.

Secondly, comparing the two vector error correction models for the same currency, we find that the VECM with news factors has better explaining power than the corresponding simple VECM, although all the improvements are samll.

[6] We use the Johansen equation with p = 0 and report the results here. The equations with p = –1 and p = 1 are calculated too. The results are similar.

Thirdly, we use Johansen's trace test at 95% level to automatically find the cointergrating relationship and generate the cointegrating equation z_{t-1} automatically. We find that all coefficients of z_{t-1} items in spot return equations are significantly different from 0. In the forward return equation of AUD and GBP, the coefficients of z_{t-1} is significant too. This suggests that both the spot return and forward return have adjustment from the past variation in the cointegrating relationship between s_t and f_t.

Fourthly, we take a close look at the effect of the news factors. Unfortunately, we find no news factor is significant to zero. That is consistent to the R square comparison. Seems that the contribution from macroeconomic news announcements are limited.

1.7. Out-of-sample forecast with VECM

It is well known that good fitting results for the in sample regression does not mean that the model can provide similar performance in the out of sample forecast. We want to test if the new macroeconomic information also has little effect on the future foreign exchange rates.

We use the root mean square error (RMSE) and the mean absolute error (MAE) as the criteria to measure the accuracy of the forecast. The compared groups are the alternative forecasts coming from VAR and random walk forecast. We follow the methods used by R Clarida and M. Taylor in 1997. The vector autoregression model is an unrestricted fourth order VAR. We update the forecast everyday.[7] In other words, we only forecast one day not from day 1 to day 117.

Panel 1 of table 1.15 reports the RMSE and MAE results from the prediction and that of the compared groups. We multiply all series by 1000 to increase the readability. The first row is for the simple VECM with spot rates and forward rates input only. Then we add in the news factors and report the errors in next row.[8] Row 3 and row 4 are prediction errors from VAR(4) and random walk models.

Here are the findings:

The forecast power of random walk model is fairly. It has moderate prediction errors in all the currencies. It is OK to take it as a benchmark standard. But its performance is not as good as the prior scholars' claim. (e. g., see Meese and Rogoff, 1983; Mark, 1995). We think that is because we take a short forecast horizon.

We found that VECM forecasts have good perfomance in all the currencies. Both error correction models have averaged smaller forecast errors than the random walk models. In AUD and JPY forecsting, the improvement is significant.

[7]Most news are announced in the morning. We can add in our news factors to predict the same day's closing price.

[8]As we did in the VECM regression section, the forecast model applying p = 0 in johansen equation. The other two cases are tried but not reported. The errors ranks in the four models are the same.

However, our VECM add in news factors does not really work better than the simple VECM. Actually, except for the JPY, all the other three currencies have better forecast power from VECM without news input. That is consistent to our finding in the VECM regression.

1.8. Forecast using the non overlapped weekly data

There are too many noises in the overnight foreign exchange fluctuations. For example, oil price, unfavorable speech from some economists, they may affect the value of the US dollar. Compared with the overnight foreign exchange rates, the weekly data are more likely influenced by the pure economic indices such as inflation or growth factors. We run another VECM using the non overlapped weekly spot and forward rates to avoid those uncertainty.

To fulfill this purpose, we aligned the news surprises and exchange rates in another two matrix. Our in sample weekly data begin from Nov. 5th, 1993 and end on May 28th, 2004. The out of sample period is from Jun. 4th to Nov. 17th, 2004. We set a time series which records all the last business date before the weekend[9]. For the foreign exchange part, we aligned the corresponding spot rates and the 1 week forward rates with our date series. For the news surprise part, we

[9]Basically, our date series are the Friday date. However, if it is a holiday on Friday, we save the date before the holiday as the recorded time.

inserted all the announcements occurred in that week to the same row and use the same date series.

Next we generated growth factor and inflation factor from the news surprises matrix, then reran our error correction models with and without news input. This time the vector y_t includes the logarithm of both the spot exchange rates and the 1 week forward rate.

$$y_t = [s_t, f_{t,1w}]' \tag{1.23}$$

The forecast errors are reported in Panel 2 of Table 1.15. The results are encouraging. The error correction models with news have better performance than the simple VECM in CAD and JPY. Actually, in these two currencies, our VECMs with news have smallest forecast errors in all the 4 models. For AUD and GBP cases, VECM with news is still weaker than the pure VECM, but the difference is reduced. Moreover, the VECMs with news have smaller forecast errors than the other two groups. The results proved our assumption. The weekly data are stable and impacted more by the macroeconomic news announcements.

1.9. Conclusion

In this paper we try to track news effects on foreign exchange fluctuations. We align the daily foreign currency spot rates with 27 news deviations. Because the original announcements are on different scales for different news. We use standardized news deviations as our inputs. We use *surprise* describing the news deviations.

Since there are noises in each news release and redundant information in the variables, we applied Kalman filter to filter the news deviations and use maximize likelihood to estimate the unknown parameters. We used growth factor and inflation factor to represent the extracted macroeconomic news.

We checked the loading effect and found the results are satisfactory. Most news variables have a forecast percentage variance (FV) higher than 90%. This shows that our loading matrix is reasonable and the extracted news facters x1 and x2 are reliable too.

We used the vector error correction model (VECM) with the extracted news deviations factors to analyze the foreign exchange spot and forward rates. However, comparing the results with and without news input, we find the improvements coming from the news are limited. Not only the R square has little improvement, but also all the coefficients of the news factors are insignificant.

Next we ran out-of-sample tests on the VECM equations. The comparing groups are VAR(4) and random walk models. We used a dynamic daily updated method to predict next day foreign exchange rate, compared with the out-of-sample real foreign exchange rate. Disappointingly, news implied VECM equations do not outperform the simple VECM equation. But all the VECM forecast errors beat the random walk model.

Considering the noises in the overnight data, we aligned the news surprises, spot rates and the 1 week forward rates in weekly frequency. We extracted growth factor and inflation factor from the weekly news deviations and tried to forecast the next week spot rates. The forecast results are better now. VECMs with news factors have better performance than the comparing groups, especially in the CAD and JPY cases.

In conclusion, we have shown that news has no critical effect to the foreign exchange daily spot returns. The news surprises have some effect on the spot returns but not as large as speculators would like. These results raise the following issues for further empirical and theoretical research.

First, we only analyzed the US domestic news announcements. If we have access to the important releases from the foreign countries, the model will be more interesting.

Secondly, our news surprises only focus on the regularly released macroeconomic indice. It is well known that other shocks affect foreign exchange market as well. For instance, the domestic stock market crash and crude oil price fluctuation could also significantly affect foreign exchange rates. It would be very interesting to study the relationship between foreign exchange market and the commodity markets.

Table 1.1
Summary statistics for news surprises(part 1)

Data are aligned in daily series. News surprises are defined as equation (2). The sample period is from Nov. 2nd, 1993 to Jun. 1st, 2004. Explanation of the news variables: BusInv - business inventories (%change); Capacity - capacity utilizaion(%); ConfidnC - consumer confidence (%); Tbalance - goods and services trade balance ($billion); PCE - personal consumption expenditures (%change); PersInc - personal income (%change); RSXauto - retail sales except auto(%change); RetSls - retail sales (%change); Claims - initial claims (thousands); RGDP - RGDP SAAR (chained after 2Q1995); Construct - construction spending (%change); DurGds - durable goods orders (%change); Hstarts - housing starts (millions of units); IndProd - industrial production (%change); Leaders - index of leading indicators (%change); NewHome - new home sales (K's); GDPPI - GDP price index SAAR; CPI - consumer price index (%change); CPIXFE - CPI core (%change); HrEarn - hourly earnings (%change after Dec. 1989); Nonfarm - nonfarm payrolls (K's); PPI - producer price index (%change); PPIXFE - PPI core (%change); Unemp - civilian unemployment rate. FedRate - fed funds rate(current period); Credit - consumer credit ($bn, monthly change); TBudget - Treasury budget ($B).

Variable	Freq	Obs	Mean	Std. Dev.	Min	Max
BusInv	W	2760	0.004	0.134	-2.433	1.622
Capacity	M	2760	0.000	0.020	-0.188	0.219
ConfidnC	M	2760	0.001	0.042	-0.501	0.513
Tbalance	M	2760	-0.001	0.030	-0.406	0.520
PCE	M	2760	0.002	0.098	-1.849	1.849
PersInc	M	2760	0.004	0.119	-1.920	2.240
RSXauto	M	2760	-0.001	0.155	-2.036	5.657
RetSls	M	2760	-0.002	0.180	-2.611	2.393

Table 1.2
Summary statistics for news surprises(part 2)

Variable	Freq	Obs	Mean	Std. Dev.	Min	Max
Claims	w	2760	-0.001	0.170	-1.375	1.771
RGDP	Q	2760	0.004	0.063	-0.630	0.892
Construct	M	2760	0.006	0.213	-2.364	2.409
DurGds	M	2760	0.000	0.165	-2.254	3.260
Hstarts	M	2760	0.004	0.071	-0.736	0.883
IndProd	M	2760	0.003	0.124	-1.270	1.904
Leaders	M	2760	0.003	0.090	-0.773	2.317
NewHome	M	2760	0.004	0.066	-0.737	0.668
GDPPI	Q	2760	-0.003	0.115	-2.861	0.954
CPI	M	2760	-0.006	0.140	-1.710	1.710
CPIXFE	M	2760	-0.004	0.178	-1.894	1.894
HrEarn	M	2760	0.001	0.192	-2.266	2.720
Nonfarm	M	2760	-0.003	0.147	-1.937	2.412
PPI	M	2760	-0.004	0.167	-2.731	2.521
PPIXFE	M	2760	-0.006	0.199	-3.017	3.017
unemp	M	2760	-0.002	0.032	-0.400	0.300
FedRate	6W	2760	0.000	0.010	-0.164	0.164
Credit	M	2760	0.007	0.200	-2.463	2.960
TBudget	M	2760	0.000	0.028	-0.895	0.266

Table 1.3
Summary statistics for foreign exchange rates

We report the statistics summary of spot rates, forward rates, spot return and forward premium for the 4 currencies respectively. The sample period is from Nov. 2nd, 1993 to Jun. 1st, 2004, in daily data. Spot and forward rates are in natural logarithm. Spot return (SR) is defined by $(\ln S_t - \ln S_{t-1}) \times 1000$

		mean	STD	min	max
AUD	spot	0.463525	0.133866	0.2009	0.7255
	forward	0.463203	0.133683	0.2031	0.7242
	sr	0.025033	7.217598	-48.2481	44.4865
	fp	-0.32191	2.95622	-15.0994	20.3004
CAD	spot	0.379565	0.070393	0.1755	0.4778
	forward	0.379283	0.070347	0.1762	0.4776
	sr	-0.15646	4.431678	-17.4905	15.8897
	fp	-0.28261	1.962343	-11.1374	8.0512
GBP	spot	-0.45856	0.065394	-0.6442	-0.317
	forward	-0.45893	0.065305	-0.6443	-0.3168
	sr	-0.11289	4.882065	-19.9674	21.9074
	fp	-0.37433	2.696881	-23.1961	13.619
JPY	spot	4.727774	0.104639	4.3959	4.9914
	forward	4.72749	0.104631	4.3894	4.992
	sr	-0.18178	7.215082	-56.3021	32.399
	fp	-0.28426	2.638854	-21.9377	20.4307

Table 1.4
The Loading matrix of news announcements

We explain our loading matrix of the 27 news announcements here. h1 represents growth factor and h2 is the inflation factor. The second column exhibits which group the announcement belongs to. ConD is the domestic consumer demand group; g is the economic growth group; inf is the domestic inflation group and intR is the domestic interest rate group. - means negative effect, + is postive influence and 0 means no effect.

	group	news	h1	h2
1	conD	BusInv	0	-
2	conD	Capacity	0	+
3	conD	ConfidnC	0	+
4	conD	Tbalance	0	+
5	conD	PCE	0	+
6	conD	PersInc	0	+
7	conD	RSXauto	+	+
8	conD	RetSls	+	+
9	g	Claims	-	0
10	g	RGDP	+	0
11	g	Construct	+	0
12	g	DurGds	+	0
13	g	Hstarts	+	0
14	g	IndProd	+	0
15	g	Leaders	+	0
16	g	NewHome	+	0
17	inf	GDPPI	0	+
18	inf	CPI	0	+
19	inf	CPIXFE	0	+
20	inf	HrEarn	0	+
21	inf	Nonfarm	0	+
22	inf	PPI	0	+
23	inf	PPIXFE	0	+
24	inf	unemp	-	-
25	intR	FedRate	0	+
26	intR	Credit	0	+
27	intR	TBudget	0	-

Table 1.5
Extracting systematic dynamic factors from macroeconomic announcements

We report the estimates and the t statistics of h in the loading matrix. h1 is the growth factor and h2 is the inflation factor. error is the estimate error while the var is the variance of the original variable. FV is the forecasted percentage variance which is defined in equation 16.

	h1	t1	h2	t2	error	var	fv
BusInv	0	0	-0.053	-340.048	0.0002	0.0297	0.9948
Capacity	0	0	0.012	0.2615	0.0459	0.1507	0.6954
ConfidnC	0	0	2.8474	253.0366	0.0113	0.0866	0.8701
Tbalance	0	0	0.0258	1.2187	0.0212	0.3899	0.9457
PCE	0	0	0.0585	2.0407	0.0287	0.4637	0.9382
PersInc	0	0	0.8379	1031.484	0.0008	0.0094	0.9135
RSXauto	0.4557	156.8857	0.2184	75.1941	0.0029	0.0384	0.9243
RetSls	1.4074	21.766	5.3217	82.303	0.0647	0.9976	0.9352
Claims	-0.0211	-0.6786	0	0	0.0311	0.6514	0.9523
RGDP	1.2372	24.7678	0	0	0.05	1.1933	0.9581
Construct	0.0243	0.3836	0	0	0.0635	0.8585	0.9261
DurGds	0.3596	8.2986	0	0	0.0433	0.7101	0.939
Hstarts	0.1893	128.608	0	0	0.0015	0.0203	0.9275
IndProd	0.0943	1.6094	0	0	0.0586	1.0479	0.9441
Leaders	1.1734	148.4185	0	0	0.0079	0.109	0.9274
NewHome	0.5403	22.338	0	0	0.0242	0.3908	0.9381
GDPPI	0	0	0.2077	16.2781	0.0128	0.2684	0.9525
CPI	0	0	6.3353	240.4415	0.0263	0.0887	0.7031
CPIXFE	0	0	0.0417	1.2189	0.0342	0.4676	0.9268
HrEarn	0	0	0.3977	25.7564	0.0154	0.284	0.9456
Nonfarm	0	0	0.0793	3.5154	0.0226	0.3981	0.9433
PPI	0	0	0.1633	3.7299	0.0438	0.7118	0.9385
PPIXFE	0	0	2.6437	45.7719	0.0578	1.0986	0.9474
unemp	-1.7319	-39.1461	-0.0278	-0.6276	0.0442	0.5889	0.9249
FedRate	0	0	1.9765	44.0327	0.0449	0.8288	0.9458
Credit	0	0	1.0689	739.235	0.0014	0.018	0.9195
TBudget	0	0	-0.5529	-332.346	0.0017	0.0284	0.9415

Table 1.6
Lag checks by AIC method

We use the AIC to measure the goodness of different VAR model with lags from 1 to 8. The last row indicates the lags we pick for each currency.

AIC				
nlag	aud	cad	gbp	jpy
1	6.48	4.544	5.387	6.304
2	6.384	4.47	5.295	6.174
3	6.351	4.438	5.226	6.128
4	6.344	4.423	5.207	6.115
5	6.339	4.421	5.194	6.115
6	6.342	4.417	5.195	6.113
7	6.344	4.418	5.195	6.113
8	6.348	4.425	5.197	6.115
lagcheck	5	6	5	6

Table 1.7
Lag check by LR ratio

We apply LR ratio caculation to confirm the lag check results.

LR ratio											lag check
AUD	nlag	=	8	7	LR	=	2.0754	probability	=	0.7219	
	nlag	=	7	6	LR	=	4.2076	probability	=	0.3786	
	nlag	=	6	5	LR	=	3.7793	probability	=	0.4367	
	nlag	=	5	4	LR	=	16.6505	probability	=	0.00226	5
	nlag	=	4	3	LR	=	18.5424	probability	=	0.000967	
	nlag	=	3	2	LR	=	62.988	probability	=	6.83E-13	
	nlag	=	2	1	LR	=	171.2934	probability	=	0	
CAD	nlag	=	8	7	LR	=	1.2998	probability	=	0.8614	
	nlag	=	7	6	LR	=	6.6439	probability	=	0.1559	
	nlag	=	6	5	LR	=	12.8916	probability	=	0.01182	6
	nlag	=	5	4	LR	=	10.4881	probability	=	0.03296	
	nlag	=	4	3	LR	=	23.8708	probability	=	8.48E-05	
	nlag	=	3	2	LR	=	42.4035	probability	=	1.38E-08	
	nlag	=	2	1	LR	=	87.3104	probability	=	0	
gbp	nlag	=	8	7	LR	=	4.099	probability	=	0.3928	
	nlag	=	7	6	LR	=	9.3066	probability	=	0.05388	
	nlag	=	6	5	LR	=	5.9414	probability	=	0.2036	
	nlag	=	5	4	LR	=	38.2847	probability	=	9.79E-08	5
	nlag	=	4	3	LR	=	51.3644	probability	=	1.87E-10	
	nlag	=	3	2	LR	=	173.8289	probability	=	0	
	nlag	=	2	1	LR	=	229.1571	probability	=	0	
jpy	nlag	=	8	7	LR	=	2.3082	probability	=	0.6793	
	nlag	=	7	6	LR	=	8.4998	probability	=	0.07489	
	nlag	=	6	5	LR	=	12.2384	probability	=	0.01566	6
	nlag	=	5	4	LR	=	8.1377	probability	=	0.08666	
	nlag	=	4	3	LR	=	36.5616	probability	=	2.22E-07	
	nlag	=	3	2	LR	=	112.1308	probability	=	0	
	nlag	=	2	1	LR	=	301.9676	probability	=	0	

Table 1.8
ADF unit root test for exchange rates and extracted factors

We report the unit root test on the 4 currencies, in spot rates and forward rate. We run the ADF test with and without trend respectively. We test the spot and forward rates both on level and on first difference. The critical value in 1% , 5% and 10% levels are -3.358, -2.871 and -2.549.

	without trend		with trend	
	level	first diff	level	first diff
aud spot	-1.6252	-47.3416	-0.8255	-47.3865
cad spot	-0.7812	-36.8793	-1.3118	-36.8762
gbp spot	-1.4459	-55.6642	-1.5017	-55.6597
jpy spot	-1.7809	-53.8378	-1.7925	-53.8298
aud forward	-1.6939	-48.0868	-0.9614	-48.1321
cad forward	-0.9438	-39.4659	-1.5398	-39.4621
gbp forward	-1.7465	-58.6377	-1.8074	-58.6313
jpy forward	-1.9022	-54.7558	-1.9164	-54.7478
x1	-37.7425		-37.7567	
x2	-31.1442		-31.1416	

Table 1.9
Phillips-Perron unit root test for exchange rates and extracted factors

We use Phillips-Perron test to confirm our unit root test. The critical value in 95% without trend is -1.95, with trend is -3.41.

	without trend		with trend	
	level	first diff	level	first diff
aud spot	-1.099	-36.090	-1.688	-36.073
cad spot	-1.008	-29.566	-1.345	-29.559
gbp spot	0.620	-43.029	-2.239	-43.020
jpy spot	-0.633	-42.756	-4.014	-42.765
aud forward	-1.216	-37.969	-1.964	-37.982
cad forward	-1.913	-31.804	-1.363	-31.827
gbp forward	0.749	-48.833	-1.300	-48.860
jpy forward	-0.956	-40.989	-3.375	-40.999
x1	-24.354		-24.354	
x2	-23.140		-23.156	

Table 1.10
Johansen cointegration rank test

The Johansen test is used to check the cointegration rank in our error correction model. We report the trace value and eigen value here. P is the order of time polynomial in the null hypothesis. p = -1 means no deterministic part, p = 0 has constant term, p = 1 has constant plus time trend.

	trace				eigen			
aud	r≤0	crit 95%	r≤1	crit 95%	r≤0	crit 95%	r≤1	crit 95%
p=-1	322.445	12.321	0.255	4.130	322.19	11.225	0.255	4.130
p=0	326.248	15.494	1.191	3.841	325.057	14.264	1.191	3.841
p=1	325.882	18.398	0.730	3.841	325.152	17.148	0.730	3.841
cad								
p=-1	204.762	12.321	0.030	4.130	204.731	11.225	0.030	4.130
p=0	207.509	15.494	2.168	3.841	205.341	14.264	2.168	3.841
p=1	207.709	18.398	2.438	3.841	205.273	17.148	2.436	3.841
gbp								
p=-1	301.662	12.321	0.438	4.130	301.224	11.225	0.438	4.130
p=0	306.495	15.494	2.090	3.841	304.405	14.264	2.090	3.841
p=1	308.449	18.398	2.309	3.841	306.14	17.148	2.309	3.841
jpy								
p=-1	294.463	12.321	0.001	4.130	294.462	11.225	0.001	4.130
p=0	298.054	15.494	3.541	3.841	294.513	14.264	3.541	3.841
p=1	304.088	18.398	3.723	3.841	300.366	17.148	3.723	3.841

Table 1.11
VECM report: Δs_t equationi (part 1)

We report the spot return equations here. The first panel is the simple VECM while the next panel is the VECM with extracted news factors. For each currency, we report the coefficients, P probability, R square and observation numbers.

Panel 1	no news							
	aud		cad		gbp		jpy	
	beta	p-ratio	beta	p-ratio	beta	p-ratio	beta	p-ratio
lag1spot	-0.2117	0.0547	-0.0919	0.4863	-0.1378	0.0453	-0.0859	0.5242
lag1fw	-0.1356	0.1705	-0.1888	0.1178	-0.1799	0.0049	-0.1622	0.193
lag2spot	-0.134	0.118	-0.1613	0.1347	-0.147	0.0099	-0.1046	0.3555
lag2fw	-0.0825	0.2371	-0.1552	0.097	-0.0156	0.7484	-0.0404	0.6843
lag3spot	-0.1169	0.0164	-0.0538	0.4743	-0.0577	0.1029	-0.1155	0.1478
lag3fw	0.2553	0.0213	-0.1104	0.0288	0.2	0.0036	-0.0128	0.8174
lag4spot	0.132	0.1856	0.1113	0.4075	0.185	0.0038	0.0974	0.4723
lag4fw	0.1338	0.1223	0.1856	0.1305	0.093	0.1042	0.1884	0.1338
lag5spot	0.1139	0.1077	0.208	0.0603	0.0724	0.1417	0.0941	0.4103
lag5fw	0.0917	0.073	0.1159	0.2333	0.0541	0.1329	0.0552	0.5833
lag6spot			0.0395	0.6188			0.1286	0.1168
lag6fw			0.1287	0.0211			0.0133	0.8178
ecterm1	-0.0006	0	-0.0006	0	-0.0005	0	-0.0007	0
constant	-0.0002	0.1465	0.0002	0.0355	0.0003	0.0145	-0.0004	0.0163
r2	0.1081		0.1912		0.1014		0.0852	
obs	2195		1625		2563		2466	

Table 1.12
VECM report: Δs_t equationi (part 2)

Panel 2	with news							
	aud		cad		gbp		jpy	
	beta	p-ratio	beta	p-ratio	beta	p-ratio	beta	p-ratio
lag1spot	-0.2115	0.055	-0.0956	0.4699	-0.1379	0.0453	-0.0851	0.5281
lag1fw	-0.1362	0.1687	-0.1912	0.1135	-0.1793	0.005	-0.1598	0.1997
lag2spot	-0.1339	0.1183	-0.1643	0.1282	-0.1472	0.0099	-0.1018	0.3691
lag2fw	-0.0829	0.2347	-0.1574	0.0928	-0.0152	0.754	-0.0398	0.6891
lag3spot	-0.1156	0.0176	-0.0559	0.4574	-0.0572	0.1064	-0.1154	0.1483
lag3fw	0.2558	0.0211	-0.1121	0.0268	0.1994	0.0038	-0.0133	0.8116
lag4spot	0.1325	0.1838	0.1154	0.3909	0.1849	0.0038	0.0965	0.4764
lag4fw	0.1345	0.1205	0.1884	0.1253	0.093	0.1045	0.1863	0.1383
lag5spot	0.1144	0.106	0.2108	0.0573	0.0722	0.1429	0.0913	0.4248
lag5fw	0.0917	0.0728	0.1187	0.2229	0.0542	0.1328	0.0543	0.5898
lag6spot			0.0417	0.6			0.128	0.1186
lag6fw			0.13	0.0199			0.0135	0.8162
ecterm1	-0.0006	0	-0.0006	0	-0.0005	0	-0.0007	0
x1	-0.0237	0.4765	0.0065	0.7619	-0.0128	0.5749	0.028	0.4277
x2	0.026	0.3226	-0.002	0.9021	0.0132	0.4637	-0.017	0.5415
constant	-0.0002	0.1372	0.0002	0.0393	0.0003	0.015	-0.0004	0.0155
r2	0.1088		0.1914		0.1016		0.0856	
obs	2195		1625		2563		2466	

Table 1.13
VECM report: Δf_t equation (part 1)

We report the forward return equations here. The first panel is the simple VECM while the next panel is the VECM with extracted news factors. For each currency, we report the coefficients, P probability and R square.

Panel 1	no news							
	aud		cad		gbp		jpy	
	beta	p-ratio	beta	p-ratio	beta	p-ratio	beta	p-ratio
lag1spot	-0.2061	0.0784	-0.0715	0.6216	0.0698	0.3422	0.0211	0.8829
lag1fw	-0.1043	0.3209	-0.1706	0.1973	-0.0861	0.2062	-0.0646	0.626
lag2spot	-0.1122	0.2178	-0.1706	0.1489	-0.0536	0.3786	-0.065	0.5901
lag2fw	-0.0646	0.3837	-0.1387	0.1761	0.0103	0.8425	-0.0274	0.7957
lag3spot	-0.1494	0.0039	-0.0372	0.652	-0.051	0.1776	-0.1252	0.1408
lag3fw	0.2228	0.0586	-0.1203	0.0298	-0.0192	0.7935	0.008	0.8928
lag4spot	0.0898	0.3968	0.0357	0.8083	0.0738	0.2789	-0.0119	0.9341
lag4fw	0.1072	0.2439	0.1349	0.3162	0.0119	0.8451	0.0613	0.6466
lag5spot	0.1092	0.1465	0.2202	0.0696	0.045	0.3922	0.0507	0.6768
lag5fw	0.1385	0.0108	0.1043	0.3276	0.0411	0.2857	0.0447	0.6772
lag6spot			0.0153	0.8604			0.1359	0.1197
lag6fw			0.146	0.017			0.0062	0.9196
ecterm1	0.0005	0.0004	0.0001	0.5018	0.0005	0	0.0002	0.2504
constant	0.0001	0.3912	0	0.8441	-0.0005	0.0002	0.0001	0.5219
r2	0.0188		0.0187		0.0589		0.0085	

Table 1.14
VECM report: Δf_t equation (part 2)

Panel 2	with news							
	aud		cad		gbp		jpy	
	beta	p-ratio	beta	p-ratio	beta	p-ratio	beta	p-ratio
lag1spot	-0.2056	0.079	-0.0784	0.5886	0.0695	0.3441	0.0221	0.8778
lag1fw	-0.1052	0.3168	-0.1756	0.1847	-0.0862	0.2064	-0.0618	0.6412
lag2spot	-0.1123	0.2175	-0.1767	0.1355	-0.0539	0.376	-0.0615	0.6101
lag2fw	-0.0652	0.3791	-0.143	0.1633	0.0103	0.8419	-0.0266	0.8014
lag3spot	-0.1477	0.0043	-0.041	0.619	-0.0508	0.1791	-0.1251	0.1413
lag3fw	0.2234	0.0579	-0.1235	0.0259	-0.0192	0.7939	0.0074	0.9001
lag4spot	0.0905	0.3927	0.0437	0.7667	0.074	0.278	-0.013	0.9283
lag4fw	0.1082	0.2397	0.1403	0.2974	0.0122	0.8425	0.0588	0.6603
lag5spot	0.11	0.1435	0.2259	0.063	0.045	0.3924	0.0474	0.6973
lag5fw	0.1386	0.0108	0.1094	0.3053	0.0411	0.2858	0.0436	0.6848
lag6spot			0.0192	0.8253			0.1352	0.1217
lag6fw			0.1487	0.0152			0.0064	0.9175
ecterm1	0.0005	0.0004	0.0001	0.468	0.0005	0	0.0002	0.2506
x1	-0.0352	0.3201	0.0066	0.7773	-0.0068	0.7786	0.0328	0.3825
x2	0.0369	0.1862	0.0008	0.9642	0.006	0.7564	-0.0194	0.5115
constant	0.0001	0.4154	0	0.7896	-0.0005	0.0002	0.0001	0.539
r2	0.02		0.0195		0.0589		0.009	

Table 1.15
Forecast errors from different models

We use root mean square error (RMSE) and mean absolute error (MAE) as the criteria to measure the accuracy of the prediction models. Here we have VECM only, VECM with news factors, VAR(4) and random walk models. The first panel uses the daily data to forecast while the second panel has the non overlapped weekly data as input. All the results are multiplied by 1000.

Panel1	aud		cad		gbp		jpy	
return	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
vecm	0.002	0.4072	0.0013	0.2773	0.0007	0.2264	0.0029	0.4591
vnews	0.0023	0.5584	0.0013	0.3622	0.0007	0.2769	0.0029	0.4515
var(4)	0.0038	0.5333	0.0013	0.28	0.0007	0.2458	0.0041	0.5638
rw	0.0039	0.6779	0.0013	0.3674	0.0008	0.2941	0.004	0.5503
Panel2								
weekly								
vecm	0.4557	17.4785	1.6264	36.0747	0.378	16.52	0.9404	28.7045
vnews	0.4619	17.511	1.6244	36.0656	0.3793	16.5523	0.9034	28.0711
var(4)	0.514	19.0058	1.7556	38.3481	0.389	17.1842	0.9668	29.7304
rw	0.4648	17.8504	1.6251	36.2329	0.3793	16.5782	0.9034	28.0749

Chapter 2

The Forward Premium Puzzle When the Forecasting Horizon is Short

2.1. Introduction

It is well known that forward premia fail to forecast future spot returns: in particular, negative estimates from the regression of the spot return on the forward premium suggest that the forward premium predicts changes in the spot rate with the wrong sign[1]. This finding, the so-called "forward premium puzzle", or the rejection of the uncovered interest rate parity (UIP), is both unappealing (as it is easily vulnerable to arbitrage) and difficult to reconcile with underlying theoretical models of exchange rate determination[2].

[1] In a typical regression, the spot return is defined as the ex post change in the (log) spot exchange rate and the forward premium is defined as the current (log) forward exchange rate minus the current (log) spot exchange rate.

[2] See, for example, the survey by Engel (1996).

In recent studies on the "forward premium puzzle", a fair amount of attention has been devoted to the statistical properties of the series that enter the returns regression and the implications that these properties have in interpreting the regression estimates (Baillie and Bollerslev [1994], Crowder [1995], Goodhart *et al*. [1997], Phillips *et al.* [1996])[3]. In particular, the forward premium itself has been shown to have a fractionally nonstationary component. It is therefore argued that the returns regression is not valid in testing the UIP or the unbiasedness (UB) hypothesis of the forward rate because a potentially, stationary variable (spot return) would be regressed on a nonstationary variable (forward premium) (Maynard and Phillips [1998]). Furthermore, it is also argued that the estimated coefficient for the forward premium is biased because of the very persistent autocorrelation in the forward premium and the small sample size of the regression (Baillie and Bollerslev [2000]).

Surprisingly, the uncovered interest rate parity has seldom, if ever, been tested at the very short horizon where the forward rate is calculated in days. Testing whether the unbiasedness hypothesis holds at the extreme short end is important: if it cannot explain how next-day opening spot rates are related to today's closing overnight forward rates, there is little hope that the hypothesis will hold in longer horizons. Moreover, regardless whether the unbiasedness hypothesis holds or not in the short term, testing the hypothesis at the extreme short end would add an entirely new dimension to the important issue of how exchange rates are determined in financial markets.

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[3] A returns regression of the forward rate unbiasedness is to regress the spot return on the forward premium. A levels regression of the forward rate unbiasedness is to regress the future spot rate on the current forward rate.

In this paper, we test the unbiasedness hypothesis using short-term forward rates ranging from overnight to three-day horizons for six currency exchange rates relative to the U.S. dollar. The six currencies are the Australia Dollar, the British Pound, the Canada Dollar, the Euro Dollar, the Japanese Yen, and the Swiss Franc. The forward rates from one week to six month horizons are also examined for comparison purpose. Using this unique data set, we test the implications of the unbiasedness hypothesis at both the levels (unconditional) regression and the returns regression: both types of tests provide insights about the unbiasedness hypothesis.

We present a strikingly different picture about the properties of the spot return, the forward premium and the estimation results from the use of the high-frequency data. In contrast to previous studies where the forward premium is shown to have a nonstationary component, the overnight, tomorrow-next (two-day) and spot-next (three-day) forward premia and their corresponding spot returns are all stationary.

Accordingly, we perform unconditional unbiasedness tests in levels. We find that the log differences between short-term forward rates and their corresponding future spot rates are small in economic terms and statistically insignificant[4]. Thus, at the unconditional level, we cannot reject the null hypothesis that forward rates are the best forecasts for future spot rates. This is in contrast with other studies in which the above null was most frequently statistically rejected[5].

We then conduct unbiasedness tests in the returns regression. Since short-term forward premia are stationary, the OLS estimator with short-term forward premia would be unbiased. This is in sharp contrast with the same but biased estimator when the long-term forward premia are used in the regression. Our estimation

[4]Except that CHF, EUR and JPY have significant forecast errors in overnight prediction.

[5]See, for example, Phillips *et al.* [1996] etc.

results are encouraging. The unbiased estimated coefficients on the overnight forward premia for the six currencies do not show the same strong negative signs as the "forward premium puzzle" indicates, but are all small in economic terms and three of them are statistically close to 1.

Next we run the out of sample test to compare the forecast accuracy by forward premium with the random walk models. We use Root-Mean-Square-Error (RMSE) and Mean-Absolute-Error (MAE) to descibe the forecast errors. The result shows that the short-term return regression has similar performance to the random walk model, and the forecast errors exhibit a strong monotonicity here.

The rest of the paper is organized as the following: section 2 contains some background and discussion; the data are described in section 3; empirical evidence on the stationarity and autocorrelations of the spot returns and forward premia is given in section 4; section 5 presents the unconditional test of the unbiasedness hypothesis; the results from the returns regressions are shown in section 6; section 7 presents the forecast results from the returns regression and compares with the random walk model; concluding remarks are offered in section 8.

2.2. Background and Discussion

In this section we offer a brief summary of the forward rate unbiasedness hypothesis and the two regressions that have been used, almost exclusively, to test for its validity. The hypothesis itself states that the forward exchange rate should provide an unbiased forecast for the future spot exchange rate, and the test is generally interpreted as a *joint* test of market efficiency, risk neutrality and rational expectations. The unbiasedness hypothesis, together with the covered interest parity condition, constitute the uncovered interest rate parity condition.

Let s_t be the (log of the) spot exchange rate, $f_{t,h}$ be the (log of the) h-period forward rate and Ω_t be the information set available up to and including time t. Then, the test for the UB hypothesis using the returns regression is given by:

$$s_{t+h} - s_t = \alpha + \beta(f_{t,h} - s_t) + u_{t+h} \tag{2.1}$$

where $s_{t+h} - s_t$ is the spot return, $f_{t,h} - s_t$ is the forward premium and u_{t+h} is a zero mean stationary process. The null hypothesis to be tested is $\alpha = 0$ and $\beta = 1$ simultaneously. Under the null we have that:

$$E(s_{t+h} - s_t|\Omega_t) = f_{t,h} - s_t \quad \Leftrightarrow \quad E(s_{t+h}|\Omega_t) = f_{t,h}$$

As mentioned in the introduction, most of the previous studies reject the UB hypothesis using the returns regression, and their estimates of β come out to be of the wrong, counter-intuitive negative sign, thus the “forward premium puzzle”.

An alternative model used in testing the UB hypothesis is the levels regression of the future spot rate on the current forward rate as in:

$$s_{t+h} = a + bf_{t,h} + v_{t+h} \tag{2.2}$$

where u_{t+k} is a zero mean stationary process and the joint null hypothesis to be tested is again that $a = 0$ and $b = 1$[6]. As McCallum (1994) notes if the UB

[6]Note that if the UB hypothesis holds, we must have that $\alpha = a$, $\beta = b$ and $v_{t+h} = u_{t+h}$.

regression of equation (1) is appropriate the UB regression of equation (2) would be redundant. However, as we already mentioned, the UB regression of equation (1) has failed in finding economically meaningful estimates for β. Estimation of equation (2) has, in general however, produced estimates of b that are quite close to one but most of the time are statistically different from one.

The contrasting results from the levels and returns regression created a controversy for the interpretation of the UB hypothesis. Moreover, it proves to be extremely difficult to reconcile the two results in a unified framework. Lately, the forward premium in the returns regression has been tested for fractional nonstationarity and was found to indeed have a nonstationary component (Maynard and Phillips [1998]). Thus, it was argued that the returns regression could be statistical unbalanced, as it attempts to explain a dependent variable with a fixed mean using a regressor that wanders randomly.

2.3. Data Description

The uncovered interest rate parity is a theory of exchange rate determination based on the interest rate differential between the relevant currencies. Traditionally, researchers have used one-month, three-month or longer frequencies to test for UIP. This approach is convenient with regard to data availability, as the forward rates and/or interest rate differentials for horizons of a month and longer are readily available.

The objective of this paper is to test the unbiasedness hypothesis at the extreme short end of the forecasting horizon using data with the highest possible frequency. The data for the study consists of daily observations of New York closing spot rates, and closing forward rates including horizons of overnight, tomorrow next (2 day), spot next (3 day), one week, one month, two month, three month and six month. The six currencies used in the paper are the Australia Dollar (AUD), Canadian Dollar (CAD), the Swiss Franc (CHF), Euro (EUR), the British Pound (GBP) and the Japanese Yen (JPY). The US dollar is used as the base currency (denominated as one home currency per U.S. dollar). The period covered by the study is Feb 10th, 1997 through October 31st, 2006. The data are obtained from the Bloomberg system and were collected by Bloomberg as the average of the inter-bank quotes during the New York trading hours. The total number of observations in the sample for the overnight forward rates ranges from 1927 for the Euro to 2324 for the British pound[7].

We take caution in the construction of the forward premia and their corresponding future spot rates and spot returns. Our spot returns are the log changes in spot rates defined over the forecasting horizon (one day, one week, one month, etc.), but sampled at a daily frequency (as in Hansen and Hodrick [1980]). However, we strictly obey the trading rules in the market instead of constructing the spot returns approximately as in the literature. Therefore, our construction of the future spot rates and spot returns are subject to minimal data distortion. In particular, we obey the following rules:

(1) We dropped the weekends and weekdays when there are non-trading holidays in the U.S.;

[7]To avoid the data error and some special events such as 9/11, I use a data filter to skip some special days. I deleted those days the absolute value of overnight spot return are higher than 0.0015 and the absolute value of spot return on tomorrow next higher than 0.001. As a result, I delete 20 days' rates, about 1% of the total data.

(2) If the corresponding future spot date is not on a business day, the next common business day and thus the spot rate are used as the future spot date and rate. For example, for the overnight forward rate on Friday, the corresponding spot date is next Monday or Tuesday if the Monday is a holiday;

(3) One, two, three, six-month forward rates are not a standard 30-day term. Besides following the rules in (2), if today is the last business day, the corresponding future spot dates will be the last business day in the corresponding month as well. For example, if today is March 30 and the last business day of the month, all successive forward dates will be the last common business date in each month, April 30, May 31, June 30, and so on[8].

(4) Markets have specific rules on the transaction date of a contract, the contract date, the value date and the maturity (settlement) date. Basically, the value date is two business days later after the contract date, and the horizon calculation begins from the value date not the contract date. Of course for the overnight and tomorrow next transaction, the value date have to be the same or the next day. Figure 2.1 represents the detailed information on the contract dates, the value dates and the maturiy dates on overnight, tomorrow next, spot next, 1 week and 1 month transaction.

Table 2.1 contains descriptive statistics (annualized means and standard deviations in percentages) for the spot returns and the corresponding forward premia in different forecasting horizons for the six currencies studied. During the sample period, the British Pound, the Euro, the Swiss Franc and the Canadian Dollar appreciated against the U.S. dollar in nearly every return series on average, while the

[8]See Bishop and Dixon (1992) for additional details.

Australian Dollar depreciated against the U.S. dollar on average. For the spot return, the standard deviations of the overnight spot return vary around 2% annually, significantly less than that of the longer return series, which could vary as high as 11%. For the forward premium, the standard deviations are substantially lower, around 1% annually for most of the longer horizon series. The standard deviations are lower for the short-term forward premia than those for the long-term forward premia. Thus, short-term forward premia, or the interest rate differentials, are less volatile together with short-term spot returns compared with their respective long-term series. The means of the two series are both small, less than 5%.

2.4. Tests for Fractional Integration and Autocorrelation

Using the dataset outlined above, we next examine the statistical properties of the spot return and the forward premium[9]. In light of recent papers (Baillie and Bollerslev [2000], Bekaert [1995], and Maynard and Philips [1998]) demonstrating that the highly-persistent nature of the forward premium or the interest rate differential severely affects the estimates of the unbiasedness hypothesis from the returns regression, we pay particular attention to the statistical properties of the spot return and the forward premium. Specifically, we study whether the spot returns and forward premia exhibit nonstationarity and persistent autocorrelations for both the short-term and long-term horizons.

[9] Results for the statistical properties of spot and forward rates are available but we do not report them in the paper, as they conform to the, widely accepted, view that the spot and forward exchange rates contain nonstationary components, and the unit root hypothesis can not be rejected.

We used Robinson's (1995) Gaussian semiparametric estimator to estimate the order of fractional integration for the series studied. If ζ_t is the series of interest then the order of fractional integration is the exponent d in the representation:

$$(1-L)^d(\zeta_t-\mu)=u_t \tag{2.3}$$

where u_t is a short memory time series (e.g. an ARMA process) and μ is the mean of the series ζ_t. The parameter d determines the degree of long run persistence in ζ_t. A value of $d=0$ implies short-memory and stationarity while $d=1$ corresponds to a unit root. For $0<d<1/2$, the process is stationary, but contains long memory, having correlations disappearing hyperbolically rather than geometrically. For $1/2<d<1$, ζ_t is nonstationary, but less than in the case of a unit root. We also computed the standard Ljung-Box portmanteau statistic for autocorrelation, which we denote by Q_{LB}.

We provide quite a different picture for the time series behavior of both the forward premia and spot returns in the short-term as compared with the results from a longer horizon. In the following subsections, the empirical analysis indicates that, when the forward horizon is short ($h=1$ day, 2 days, *or* 3 days), both the forward premia and spot returns are stationary so that the returns regression is appropriate statistically.

To test whether the forward premia are highly persistent, we also use the Ljung-Box Q_{LB} statistics up to lag $h-1$ to provide additional evidence on the time-series properties of the forward premium. These statistics are shown in Table 2.5 along with their respective p-values. Both forward premia and spot returns exhibit persistent autocorrelations, which is consistent with the existing literature (Baillie and Bollerslev, 1994, and Bekaert and Hodrick, 1992).

2.4.1. Spot Return

The results from the fractional order tests on the spot returns for different horizons are presented in Table 2.3. The results indicate a strong rejection of nonstationarity for short-term spot returns, i.e., one-day, two-day, three-day spot returns. For all currencies studied, Robinson's estimator yields fractional orders less than 0.25 for the short-term spot returns. For some of the short-term spot returns, the hypothesis that the fractional order is equal to zero cannot be rejected.

In contrast, the relatively long-term spot returns with horizons greater or equal than one week are nonstationary (i.e. $\widehat{d} > 0.5$) for all currencies studied and are significantly greater than 0.5. The fractional order estimates exhibit strong monotonicity: the longer the forward horizon the higher the fractional order, until reaching unity (indicating a unit root) when the horizon longer than two month.

2.4.2. Forward Premium

Table 2.3 also shows the fractional order estimates of the forward premia. The relevant tests reject the hypothesis of nonstationary for the forward premia when the horizon is 1 day, 2 days and 3 days. The test statistics are all significantly less than 0.5 for these horizons, but are higher than 0.5 for the horizon at one weeks. For the short-term forward premia, the fractional orders are less than 0.3.

The longer term forward premia, especially under horizons longer than one month, however, are nonstationary ($\widehat{d} > 0.5$), consistent with the existing literature. Again, the fractional order tests exhibit strong monotonicity: the longer the horizon is, the higher the fractional order. Note that the fractional order of the two-month forward premium is higher than 0.8, which lies within the area for nonstationarity.

In summary, the test results on the spot return and forward premium indicate that there are significant differences in the time-series properties between the short and long-horizon spot returns and forward premia. For horizons up to three days, both the forward premia and spot returns appear stationary; for the longer horizon, both the forward premia and spot returns appear nonstationary. The time-series properties of the forward premia and spot returns indicate that for short-term horizons, the returns regression is indeed valid to perform and the estimator is most likely unbiased. On the other hand, our results confirm that for longer forward horizons, the estimator from the returns regression is biased given that the longer term spot returns and forward premia are nonstationary and have persistent autocorrelations.

2.4.3. Statistical Issues On the Choice of Forward Horizon

In estimating equation (1), most of the recent studies have used the one-month or three-month spot returns and forward premia, but sampled at a daily frequency. Given the empirical results of the previous subsection, the following discussion focuses around the use of daily data and the implications that they have on the choice of the forward horizon and test outcomes.

It is generally accepted that the spot exchange rate can be adequately modeled as having a unit root, so that we may write:

$$(1-L)s_t = \varepsilon_t \Rightarrow s_t = s_0 + \sum_{j=1}^{t} \varepsilon_j \tag{2.4}$$

where L is the usual lag operator indicating one-month or three-month lags ($L^i s_t = s_{t-i}$), s_0 is assumed for simplicity zero, and ε_j is a stationary process, with unspecified properties at this point.

In testing the UB hypothesis using the returns regression of equation (1), the spot return under forward horizon h is calculated as the log difference of s_{t+h} and s_t. In most studies it is implicitly assumed that this difference is stationary. If the assumption that the daily spot rate has a unit root is correct, the spot return under a forward horizon other than $h = 1$ will be the aggregate of h terms from the ε_j series. Therefore, for fixed t and increasing h the spot return behaves more and more in a nonstationary fashion. To see this, note that:

$$(s_{t+h} - s_t) = \sum_{j=1}^{t+h} \varepsilon_j - \sum_{j=1}^{t} \varepsilon_j = \sum_{j=t+1}^{t+h} \varepsilon_j \tag{2.5}$$

While the number of terms being aggregated at each t is fixed at h, the end effect is to introduce distortion due to aggregation into the return series. Thus, with daily data, the use of a forward horizon other than $h = 1$, to form the return series, may induce such distortions in the series and influence the results of the UB regression of equation (1). In the previous section, the fractional order tests for the long forward horizon indicate a markedly nonstationary behavior for the spot return series, which could be the result of the above temporal aggregation. On the other hand, tests on the short-term return series were clearly stationary. So far, the literature has taken the behavior of the return series as given (as stationary) and claimed that it is the nonstationary property of the forward premium that affects the estimates of the UB returns regression.

The above problem exists even if the UB hypothesis holds at any horizon h greater than one. To see this, consider the simple triangular, cointegrating model:

$$\left\{ \begin{array}{rcl} s_{t+h} & = & f_{t,h} + u_{t+h} \\ f_{t,h} & = & f_{t-1,h} + \eta_{t,h} \end{array} \right\}, E(\eta_{t+j,h}|\Omega_t) = 0 \quad j \geq 0 \text{ , } E(u_{t+h}\eta_{t,h}|\Omega_t) = 0 \tag{2.6}$$

Such a model is feasible as a large body of evidence indicates cointegration between the spot and forward rates (Phillips, McFarland, and McMahon [1996], Hai, Mark and Wu [1997] and others). It is straightforward to show that the h-day spot return behaves in a similar way as in equation (5) by taking differences and using the unit root on the forward rate. We now have that:

$$(s_{t+h} - s_t) = \sum_{j=t-h+1}^{t} \eta_{j,h} + (u_{t+h} - u_t) \tag{2.7}$$

and there is still aggregation of the stationary terms $\eta_{j,h}$. Furthermore, if equation (6) is appropriate we have implications for the forward premium as well. Note that:

$$(f_{t,h} - s_t) = (f_{t,h} - f_{t-h,h}) - u_t \Rightarrow (f_{t,h} - s_t) = \sum_{j=t-h+1}^{t} \eta_{j,h} - u_t \tag{2.8}$$

consequently, the forward premium can also exhibit signs of nonstationarity.

The choice of the forward horizon is important and long horizons may induce distortions and nonstationarities in the spot return and the forward premium: the longer the horizon, the stronger the effect of temporal aggregation on the forward premium series. Again, our empirical results in Table 2.3 point out that such an explanation is quite plausible.

2.5. The Unconditional Tests

Early research in the levels regression $s_{t+h} = a + b f_{t,h} + v_{t+h}$ produced estimates of b close to one. It seems at first to contradict the results from the regression in returns. However, in most of these tests, the hypothesis that b is equal to one is rejected statistically (Phillips *et al*. [1996]).

Under the null hypothesis that the unbiasedness hypothesis holds, both the levels and returns regressions imply that $E[s_{t+h} - f_{t,h}|\Omega_t] = 0$. Taking the expectation over all information sets[10] gives the result that the unconditional mean (forecasting error) of $s_{t+h} - f_{t,h}$ is zero. This is a simple moment restriction that can be tested directly. While unconditional tests like this are usually less powerful than conditional tests, this approach has the advantage of being free from the sample persistence-nonstationarity-induced problems.

The unconditional mean test statistics are reported in Table 2.6.[11] Also reported are the fractional orders and Ljung-Box test statistics for autocorrelations

[10] That is, using the law of iterated expectations.

[11] The test statistics were computed using a variance estimator corrected for heterscedasticity and autocorrelation of order $h-1$.

up to lag $h-1$. The p-values for the hypothesis that the forecasting errors are zero are also reported in table 2.6.

The fractional order tests show that the short-term forecasting errors are stationary ($\widehat{d} < 0.5$) while the long-term forecasting errors are not stationary ($\widehat{d} > 0.5$). The Ljung-Box test statistics and sample autocorrelations (not reported) indicate that almost all the forecasting errors have persistent autocorrelations except the overnight forecasting errors. This evidence is consistent with the results on spot returns and forward premia.

The mean test statistics on the forecasting errors generally cannot reject the hypothesis that the forecasting errors have a zero mean. Surprisingly, the overnight forecasting errors on the Autralian Dollar, Swiss Franc, Euro Dollar and Japenese Yen are statistically different from zero. Nevertheless, the unconditional tests generally support the unbiasedness hypothesis for short-term horizons with the exception for the overnight forecasting errors.

2.6. The Returns Regression

In this section, we test the unbiasedness hypothesis using the returns regression. Since the short-horizon forward premia are mostly stationary, we estimate the equation using the ordinary least squares estimator, and compare our results across forward horizons. Table 2.8 presents the results from the returns regressions. In short-term horizons, the estimated coefficients β are positive except Swiss Franc. As the horizon increases, βs all go to negative and approach a fixed number when the horizon is longer than 1 month.

The results for β for longer horizons confirm the findings of the literature, that for most currencies, one earns more by holding bonds from countries whose interest rates are higher than usual relative to the U.S. interest rates since exchange rates do not adjust to equalize returns. Of course, the longer-horizon results should be interpreted with caution because of the potential bias due to the highly persistence nature of both the spot returns and forward premia. In contrast, compared with the typical negative estimates of β obtained from the regressions in the literature, the so-called "forward premium puzzle" disappears for regressions under overnight regression. Those estimated βs are all positive except Swiss Franc in Table 2.8. Actually, Canada Dollar, British Pound and Japenses Yen have βs close to 1 with high t ratio. Moreover, these estimates are unbiased since the spot returns and forward premia are stationary. It appears that when forward premia are stationary, the estimated βs can go to one as indicated by UIP in some cases.

The $R^2 s$ shown in Table 2.8 are quite low for regressions under most of the horizons, but R^2 increases as the horizon increases. This suggests that the interest rate differential does not have much effect under short horizons, but increases the fit of the model under longer horizons.

2.7. Out-of-sample Forecast

Our finding gives us a different picture from the previous description. The forward premia and spot returns are both stationary in short-term horizons. The forecast errors are stationary too when the forecast horizons are shorter than 1 week. And our return regression indicates that some currencies have significant positive βs in the estimate, moreover, three of the six currencies have βs close to 1. Seems that the notoriously forward premium forecast can be a fine predictor of exchange rate movements in short horizon forecast. Next step we want to use the out-of-sample forecast method to test the power of the return regression.

Scholars agree that random walk model works great in the foreign exchange forecasting problem. It beats almost all the other complicating methods in empirical study and used as the comparing benchmark in many researches (Clarida and Taylor in 1997 and 2003). We use the following equation to predict the spot rate :

$$s_{t+h} = s_t + \alpha + \beta(f_{t,h} - s_t) + \varepsilon \tag{2.9}$$

where α and β are coefficients got from the return regression. We update the spot return in each step, comparing the predicted spot rates with the real spot rates, calculating the root-mean-square-error (RMSE) and mean-absolute-error (MAE) in the end. Then we comparing them with the random walk benchmark, check the accuracy of our forecast.

We apply the rolling regression method to do the out of sample forecast comparing. This procedure allows us to use as much as possible information and only predict 1 step ahead. Here we choose the in-sample size as $N/2$, where N is the total observations of our dependent variable. We use the data from y_1 to $y_{N/2}$ to estimate the parameters $\{\alpha_1, \beta_1\}$ and then have this set of $\{\alpha_1, \beta_1\}$ to generate $\widehat{y_{N/2+1}}$; then have the data from y_2 to $y_{N/2+1}$ to estimate the parameters $\{\alpha_2, \beta_2\}$ and then have this set of $\{\alpha_2, \beta_2\}$ to generate $\widehat{y_{N/2+2}}$; .... repeat the process until we get $\widehat{y_N}$. However, the rolling regression econometrics only works on the return regression forecast, not affect the random walk model.

Table 2.10 reports the predict errors of the return regression and the random walk models.

We use forward premium and random walk methods to make the dynamic out-of-sample forecasts of the spot rates. The forecast horizons vary from 1 day to 1 month ahead[12].

We find that the forecast errors are going up. The RMSE begins from the overnight's 2% to 1 month's 40% to 90%. Similarly, the MAE goes up from overnight's 4 to 1 month's 17 to 21. The forecast errors exhibit strong monotonicity again: the longer the forecast horizon, the higher the forecast errors.

Comparing the forecast errors between random walk and forward premium regression, we find that long-term horizons have better performance than the shorter horizons. The random walk has smaller forecast errors than the return regresiion in the overnight forecast, while the advantage is negligible. When the forecast horizon goes to 1 week or 1 month, the return regression gives better performance than the random walk. The improvement goes significant in 1 month forecast. We think that is because we keep on update our return regression models by the rolling regression method. The forward premium forecast imply more updated information comparing with the simple random walk when the forecast horizon goes longer. Anyway, the forward premium models perform very good, even in the short horizons.

[12]We didn't try the 2, 3 and 6 month forecast because which have to delete a long series data in the end.

2.8. Concluding Remarks

The “forward premium puzzle”–the negative correlation between expected exchange rates changes and the forward premium–has been continuously studied in detail by economists for more than a decade. Using extreme short-term forward rates for six major currencies, we show that the forward premium under this short forward horizon is stationary, as compared with the nonstationary forward premium under longer forward horizons. It is thus the first time that one can estimate the uncovered interest rate parity with certainty that the estimator would be unbiased. Furthermore, the study is able to document that once the interest rate differential becomes the dominant source of information in the market, the interest rate differential (or the forward premium) forecasts future spot returns quite well.

This paper presents some stylized facts about the short-term interest rate differentials, i.e., they are relatively less volatile and more stationary compared with longer term interest rate differentials or forward premia. The results in Table 2.8 indicate that the persistent nature of the longer term forward premia can not be, or at least can not be the only reason, why the uncovered interest rate parity does not hold under longer horizons. Further we compare the forecast power by the forward premium regression with the random walk. The forward premium works pretty good in short horizons. Because we keep on update the parameters in the forward premium models, the long horizon forecasts have smaller errors than the random walk models.

The results from the short-run regressions should help in developing economic models that explore multi-factor explanations of exchange rate determination. The results reported in this paper draw a different picture of the forward premium puzzle. Further empirical work might be addressed toward establishing the robustness of these conclusions, and try to imply these into program trading.

Figure 2.1: The different definitions for contract date, value date and the maturity date

All the contracts start from time t. CD denotes contract date. VD denotes value date and MD denotes maturity date.

Day	t	t+1	t+2	t+3	t+2+1week	t+2+1month
ON	CD/VD	MD				
TN	CD	VD	MD			
SN	CD		VD	MD		
1 week	CD		VD		MD	
1 month	CD		VD			MD

Table 2.1
Summary Statistics for Forward Premia and Spot Returns (part 1)

The data set consists of daily observations of the New York closing spot and forward exchange rates during the period Feb. 10th, 1997 to Oct. 31st, 2006 (See footnote 6 for more detailed explanations). Forward premia (FP) are annualized log differences of daily closing forward rates and daily closing spot rates in percentage. The spot returns (SR) are annualized log difference of the corresponding closing (or opening) spot rates and daily closing spot rates in percentage. N denotes the number of obs. for the overnight FP or the SR, h denotes the forward horizon. ON means overnight horizon, Tnext denotes the tomorrow next and Snext denotes the spot next. The standard deviations is also annualized. In calculating the annualized means and standard deviations, one year represents 264 days, one month 22 days and one week 5 days.(AUD: Australian $, CAD: Canadian $, CHF: Swiss franc, EUR: Euro, GBP: British Pound, JPY: Japanese Yen.)

	AUD		CAD		CHF	
FP						
h	Mean	Std	Mean	Std	Mean	Std
ON	1.342	0.235	0.005	0.107	-2.831	0.187
Tnext	0.446	0.220	-0.028	0.073	-1.336	0.124
SNext	0.335	0.125	-0.053	0.083	-0.895	0.104
1 week	0.947	0.209	-0.116	0.136	-1.852	0.180
1 month	1.240	0.491	-0.145	0.321	-2.381	0.428
2 month	1.273	0.704	-0.143	0.455	-2.428	0.602
3 month	1.265	0.868	-0.135	0.554	-2.432	0.734
6 month	1.251	1.236	-0.109	0.771	-2.415	1.020
SR						
ON	2.705	2.414	0.065	1.235	0.071	2.493
Tnext	-0.007	11.164	-2.000	6.888	-0.022	10.664
SNext	0.029	11.116	-3.196	6.787	-0.682	10.622
1 week	0.690	10.860	-1.348	6.099	-1.127	10.428
1 month	0.529	10.818	-1.872	6.173	-1.653	10.229
2 month	0.507	10.792	-2.048	6.333	-1.739	10.108
3 month	0.302	10.520	-2.143	6.320	-1.914	9.968
6 month	0.153	10.935	-2.235	6.499	-1.799	8.953
N	2282		2186		2201	

Table 2.2
Summary Statistics for Forward Premia and Spot Returns (part 2)

	EUR		GBP		JPY	
FP						
h	Mean	Std	Mean	Std	Mean	Std
ON	-0.497	0.157	1.621	0.143	-4.298	0.229
Tnext	-0.246	0.101	0.626	0.200	-1.924	0.145
SNext	-0.172	0.081	0.453	0.075	-1.371	0.128
1 week	-0.349	0.193	0.914	0.143	-2.745	0.210
1 month	-0.443	0.453	1.180	0.337	-3.544	0.504
2 month	-0.459	0.646	1.226	0.481	-3.685	0.725
3 month	-0.460	0.789	1.242	0.586	-3.725	0.892
6 month	-0.457	1.089	1.265	0.817	-3.786	1.268
SR						
ON	1.776	1.982	1.477	1.609	0.127	2.729
Tnext	-0.831	10.186	-1.257	8.345	1.158	11.099
SNext	-0.931	10.078	-1.323	8.296	1.077	11.047
1 week	-0.856	10.029	-1.573	8.175	0.118	11.215
1 month	-1.054	10.084	-1.493	7.929	-0.130	11.359
2 month	-1.551	10.417	-1.604	7.515	-0.423	11.284
3 month	-1.862	10.459	-1.713	7.084	-0.794	11.324
6 month	-2.188	9.874	-1.519	6.930	-0.356	10.954
N	1927		2324		2240	

Table 2.3

Estimates of Fractional Order for the Forward Premia and Spot Returns (part 1)

Robinson's (1995) Gaussian semiparametric estimator is used to test for the fractional order. d denotes the fractional order and std denotes the standard deviation. N is the observation numbers for the overnight SR or FP.

	AUD		CAD		CHF	
FP						
h	d	Std	d	Std	d	Std
ON	0.294	0.023	0.303	0.023	0.211	0.023
Tnext	0.286	0.022	0.334	0.023	0.234	0.022
SNext	0.296	0.023	0.229	0.025	0.214	0.022
1 week	0.558	0.022	0.669	0.024	0.609	0.027
1 month	0.761	0.022	0.884	0.028	0.739	0.032
2 month	0.876	0.022	0.972	0.035	0.863	0.051
3 month	0.953	0.022	1.024	0.040	0.945	0.069
6 month	1.017	0.022	0.989	0.036	0.987	0.097
SR						
ON	0.046	0.023	0.045	0.023	0.016	0.023
Tnext	0.050	0.022	0.038	0.023	0.030	0.022
SNext	0.145	0.023	0.111	0.025	0.135	0.022
1 week	0.722	0.022	0.680	0.022	0.754	0.022
1 month	0.914	0.022	0.889	0.022	0.893	0.021
2 month	0.975	0.022	0.948	0.022	0.951	0.022
3 month	0.941	0.022	0.933	0.022	0.983	0.022
6 month	0.948	0.022	0.967	0.022	0.953	0.022
N	2282		2186		2201	

Table 2.4
Estimates of Fractional Order for the Forward Premia and Spot Returns (part 2)

	EUR		GBP		JPY	
FP						
h	d	Std	d	Std	d	Std
ON	0.268	0.024	0.255	0.023	0.211	0.023
Tnext	0.283	0.024	0.146	0.022	0.227	0.023
SNext	0.287	0.024	0.261	0.022	0.216	0.023
1 week	0.667	0.025	0.707	0.021	0.645	0.031
1 month	0.821	0.030	0.856	0.020	0.720	0.036
2 month	0.946	0.040	0.966	0.018	0.865	0.064
3 month	1.005	0.046	1.025	0.014	0.925	0.095
6 month	1.071	0.064	1.048	0.016	0.997	0.136
SR						
ON	0.003	0.024	0.017	0.023	0.025	0.023
Tnext	0.074	0.024	0.041	0.022	0.036	0.023
SNext	0.182	0.024	0.144	0.022	0.137	0.023
1 week	0.755	0.023	0.777	0.022	0.719	0.022
1 month	0.905	0.023	0.919	0.021	0.901	0.022
2 month	0.970	0.023	0.979	0.021	0.954	0.022
3 month	0.992	0.023	0.963	0.021	0.953	0.022
6 month	0.961	0.023	0.930	0.020	0.974	0.022
N	1927		2324		2240	

Table 2.5
Estimates of Autocorrelations for the Forward Premia $p_{t,h} = f_{t,h} - s_t$

Q_lb is the Ljung-Box statistics for autocorrelations up to lag $h-1$ except for the overnight case that $h=1$ is used, the P denotes the P value.

	AUD		CAD		CHF	
FP	Q_lb	P	Q_lb	P	Q_lb	P
ON	616	6.3E-136	507	0	133	0
Tnext	716	2.7E-156	921	0	302	0
SNext	1475	0	338	0	374	0
1 week	14296	0	15207	0	15317	0
1 month	55046	0	53658	0	54842	0
2 month	104856	0	98643	0	103688	0
3 month	152826	0	138735	0	148728	0
6 month	279536	0	225449	0	262577	0
	EUR		GBP		JPY	
FP	Q_lb	P	Q_lb	P	Q_lb	P
ON	680	0	552	0	357	0
Tnext	974	0	29	0	244	0
SNext	1484	0	784	0	265	0
1 week	12897	0	15669	0	15396	0
1 month	44955	0	54516	0	53150	0
2 month	84302	0	101286	0	101040	0
3 month	120117	0	141703	0	145891	0
6 month	206850	0	232209	0	261590	0

Table 2.6

Estimates of the Forecasting Error: $u_{t+h} = s_{t+h} - f_{t,h}$ (part 1)

Fractional Orders are estimated using Robinson's gaussian semiparametric estimator, the standard errors are reported too. Q_lb is the Ljung-Box statistics for autocorrelations up to $h-1$ except for the overnight case that $h=1$ is used, the P is the P value. H_o : $Eu_{t+h} = 0$ is the mean test statistics.

		AUD		CAD		CHF
Forder						
h	d	std	d	std	d	std
ON	0.075	0.023	0.042	0.023	0.025	0.023
Tnext	0.054	0.022	0.041	0.023	0.032	0.022
SNext	0.146	0.023	0.112	0.025	0.135	0.022
1 week	0.722	0.022	0.680	0.022	0.754	0.022
1 month	0.914	0.022	0.889	0.022	0.893	0.021
2 month	0.975	0.022	0.948	0.022	0.951	0.022
3 month	0.941	0.022	0.932	0.022	0.983	0.022
6 month	0.947	0.022	0.966	0.022	0.955	0.022
Q_lb						
	Q_lb	p	Q_lb	p	Q_lb	p
ON	0.183	0.669	1.784	0.182	0.446	0.504
Tnext	523	0.000	516	0.000	480	0.000
SNext	1073	0.000	765	0.000	1131	0.000
1 week	3803	0.000	2934	0.000	3965	0.000
1 month	16602	0.000	15924	0.000	16583	0.000
2 month	30168	0.000	31043	0.000	30789	0.000
3 month	52378	0.000	50874	0.000	42452	0.000
6 month	138110	0.000	102562	0.000	86142	0.000
H0:	Eu(t+h)=0					
	mean	p	mean	p	mean	p
ON	1.650	0.099	0.138	0.890	3.372	0.001
Tnext	-0.135	0.893	-0.939	0.348	0.417	0.677
SNext	-0.094	0.925	-1.453	0.146	0.070	0.944
1 week	-0.084	0.933	-0.779	0.436	0.251	0.802
1 month	-0.238	0.812	-1.023	0.306	0.260	0.795
2 month	-0.258	0.796	-1.093	0.274	0.252	0.801
3 month	-0.315	0.752	-1.113	0.266	0.194	0.846
6 month	-0.313	0.754	-1.096	0.273	0.242	0.809

Table 2.7
Estimates of the Forecasting Error: $u_{t+h} = s_{t+h} - f_{t,h}$ (part 2)

	EUR		GBP		JPY	
Forder						
h	d	std	d	std	d	std
ON	0.023	0.024	0.013	0.023	0.019	0.023
Tnext	0.076	0.024	0.043	0.022	0.038	0.023
SNext	0.183	0.024	0.145	0.022	0.138	0.023
1 week	0.755	0.023	0.777	0.022	0.719	0.022
1 month	0.904	0.023	0.919	0.021	0.901	0.022
2 month	0.969	0.023	0.980	0.021	0.953	0.022
3 month	0.992	0.023	0.964	0.021	0.953	0.022
6 month	0.962	0.023	0.930	0.020	0.974	0.022
Q_lb						
	Q_lb	p	Q_lb	p	Q_lb	p
ON	0.005	0.945	0.341	0.559	1.640	0.200
Tnext	409	0.000	540	0.000	495	0.000
SNext	984	0.000	1230	0.000	1123	0.000
1 week	3397	0.000	4418	0.000	3601	0.000
1 month	15498	0.000	15223	0.000	14622	0.000
2 month	28208	0.000	26477	0.000	30833	0.000
3 month	38416	0.000	40706	0.000	47530	0.000
6 month	92499	0.000	98602	0.000	71981	0.000
H0:						
	mean	p	mean	p	mean	p
ON	3.094	0.002	-0.269	0.788	4.673	0.000
Tnext	-0.174	0.862	-0.751	0.452	0.916	0.360
SNext	-0.234	0.815	-0.737	0.461	0.757	0.449
1 week	-0.163	0.870	-1.077	0.281	0.923	0.356
1 month	-0.192	0.848	-1.272	0.204	1.111	0.267
2 month	-0.334	0.738	-1.467	0.142	1.045	0.296
3 month	-0.431	0.667	-1.568	0.117	0.922	0.356
6 month	-0.511	0.609	-1.382	0.167	1.174	0.241

Table 2.8
Estimates of the returns regression $\triangle_h s_{t+h} = \alpha + \beta p_{t,h} + u_{t+h}$ (part 1)

h is the forecasting horizon, $\nabla_h s_{t+h}$ is the spot return, $p_{t,h}$ is the forward premium, N denotes the number of observations. I use Newey-West robustness correction to solve the serial correlation problems.

	AUD		CAD		CHF	
α						
h	coef	t	coef	t	coef	t
ON	0.000	2.73	0.000	0.14	0.000	-0.42
Tnext	0.000	0.70	0.000	-1.28	-0.001	-1.92
SNext	0.000	1.00	0.000	-2.22	0.000	-1.23
1 week	0.002	4.42	-0.001	-2.42	-0.003	-4.06
1 month	0.007	8.33	-0.002	-5.62	-0.010	-8.47
2 month	0.013	11.57	-0.004	-8.23	-0.020	-12.0
3 month	0.018	14.59	-0.007	-10.4	-0.031	-15.6
6 month	0.033	20.03	-0.013	-15.0	-0.060	-25.6
β						
ON	0.243	1.13	0.668	2.70	-0.199	-0.70
Tnext	-4.215	-4.04	-3.972	-2.02	-4.930	-2.79
SNext	-6.707	-3.61	-2.345	-1.22	-3.062	-1.46
1 week	-7.267	-6.77	-4.700	-5.07	-5.005	-4.22
1 month	-5.633	-12.8	-3.393	-8.67	-4.093	-8.43
2 month	-5.347	-17.9	-3.424	-12.2	-4.012	-11.9
3 month	-5.337	-23.5	-3.364	-14.8	-4.119	-15.3
6 month	-5.113	-33.4	-3.620	-22.4	-4.123	-25.2
	R^2	N	R^2	N	R^2	N
ON	0.001	2282	0.003	2186	0.000	2201
Tnext	0.007	2347	0.002	2310	0.003	2360
SNext	0.006	2274	0.001	1821	0.001	2366
1 week	0.020	2292	0.011	2322	0.008	2357
1 month	0.065	2334	0.031	2337	0.029	2350
2 month	0.122	2307	0.060	2314	0.057	2331
3 month	0.194	2293	0.087	2295	0.092	2309
6 month	0.334	2232	0.184	2233	0.221	2248

Table 2.9
Estimates of the returns regression $\triangle_h s_{t+h} = \alpha + \beta p_{t,h} + u_{t+h}$ (part 2)

	EUR		GBP		JPY	
α						
h	coef	t	coef	t	coef	t
ON	0.000	2.40	0.000	0.48	0.000	2.58
Tnext	0.000	-0.83	0.000	-0.31	0.000	-0.73
SNext	0.000	-1.04	0.000	-0.06	0.000	-0.68
1 week	-0.001	-2.31	0.000	1.27	-0.002	-1.97
1 month	-0.003	-4.64	0.001	2.04	-0.005	-2.87
2 month	-0.007	-7.27	0.003	3.05	-0.009	-3.82
3 month	-0.011	-9.76	0.005	4.53	-0.015	-5.33
6 month	-0.024	-18.0	0.012	7.98	-0.036	-9.38
β						
ON	0.035	0.12	0.717	3.09	0.827	3.30
Tnext	-5.816	-2.53	-0.985	-1.15	-2.141	-1.34
SNext	-7.978	-2.81	-2.684	-1.18	-2.413	-1.34
1 week	-7.132	-6.07	-3.780	-3.23	-2.472	-2.22
1 month	-5.700	-11.6	-2.619	-5.43	-1.459	-3.10
2 month	-5.538	-15.9	-2.644	-8.29	-1.265	-3.87
3 month	-5.548	-19.9	-2.888	-11.8	-1.361	-5.10
6 month	-5.685	-34.1	-3.000	-17.9	-1.787	-9.85
	R^2	N	R^2	N	R^2	N
ON	0.000	1927	0.004	2324	0.005	2240
Tnext	0.003	1929	0.001	2372	0.001	2286
SNext	0.004	1929	0.001	2374	0.001	2289
1 week	0.019	1925	0.004	2374	0.002	2287
1 month	0.066	1908	0.012	2358	0.004	2275
2 month	0.118	1888	0.029	2338	0.007	2256
3 month	0.175	1865	0.057	2316	0.012	2233
6 month	0.393	1802	0.125	2253	0.043	2173

Table 2.10
Out-of-sample forecast accuracy report

(We use rolling regression method to make the out of sample test. The fixed in sample data length is N/2. rw denotes random walk and fp denotes forward premium regression. We use root mean square error (RMSE) and mean absolute error (MAE) indicate the forecast errors. They are multiplied by 1000 to increase the readableness. The forecast horizons are from 1 day in advance to 1 month ahead.)

		aud		cad		chf	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
1 day	rw	0.0428	5.034	0.0263	4.0299	0.0456	5.1763
	fp	0.0429	5.0339	0.0263	4.0274	0.0457	5.1811
2 day	rw	0.0835	7.1342	0.0491	5.5099	0.0819	7.1192
	fp	0.0834	7.0958	0.0491	5.5085	0.0823	7.1375
3 day	rw	0.124	8.7329	0.0703	6.6643	0.119	8.6806
	fp	0.1239	8.6925	0.0701	6.6536	0.1196	8.6978
1 week	rw	0.2764	13.357	0.1311	9.2886	0.2763	13.336
	fp	0.2733	13.103	0.1293	9.1688	0.2752	13.288
1 month	rw	0.8989	24.039	0.4773	17.523	0.9135	24.187
	fp	0.8429	23.095	0.4511	17.047	0.8872	23.932
		eur		gbp		jpy	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
1 day	rw	0.0377	4.7132	0.0276	4.112	0.0339	4.5015
	fp	0.0377	4.7004	0.0277	4.1238	0.034	4.4975
2 day	rw	0.0704	6.6226	0.0544	5.7805	0.0652	6.2954
	fp	0.0705	6.6165	0.0545	5.7649	0.0654	6.3078
3 day	rw	0.1031	8.076	0.0811	7.0395	0.0969	7.8119
	fp	0.1032	8.0247	0.0812	7.0065	0.0971	7.8134
1 week	rw	0.2366	12.506	0.1935	11.051	0.2285	11.983
	fp	0.2329	12.353	0.1918	11.003	0.2287	11.878
1 month	rw	0.8399	23.346	0.6704	21.034	0.7628	22.217
	fp	0.7943	22.919	0.6508	20.652	0.7592	21.914

Figure 2.2: Time series graph for overnight forward premium

The data set consists of daily observations of the New York closing and forward exchange rates during the period Feb. 10th, 1997 to October 31st, 2006 (See footnote 6 for more detailed explanations).(AUD: Australian Dollar, CAD: Canadian Dollar, CHF: Swiss franc, EUR: Euro, GBP: British Pound, JPY: Japanese Yen.)

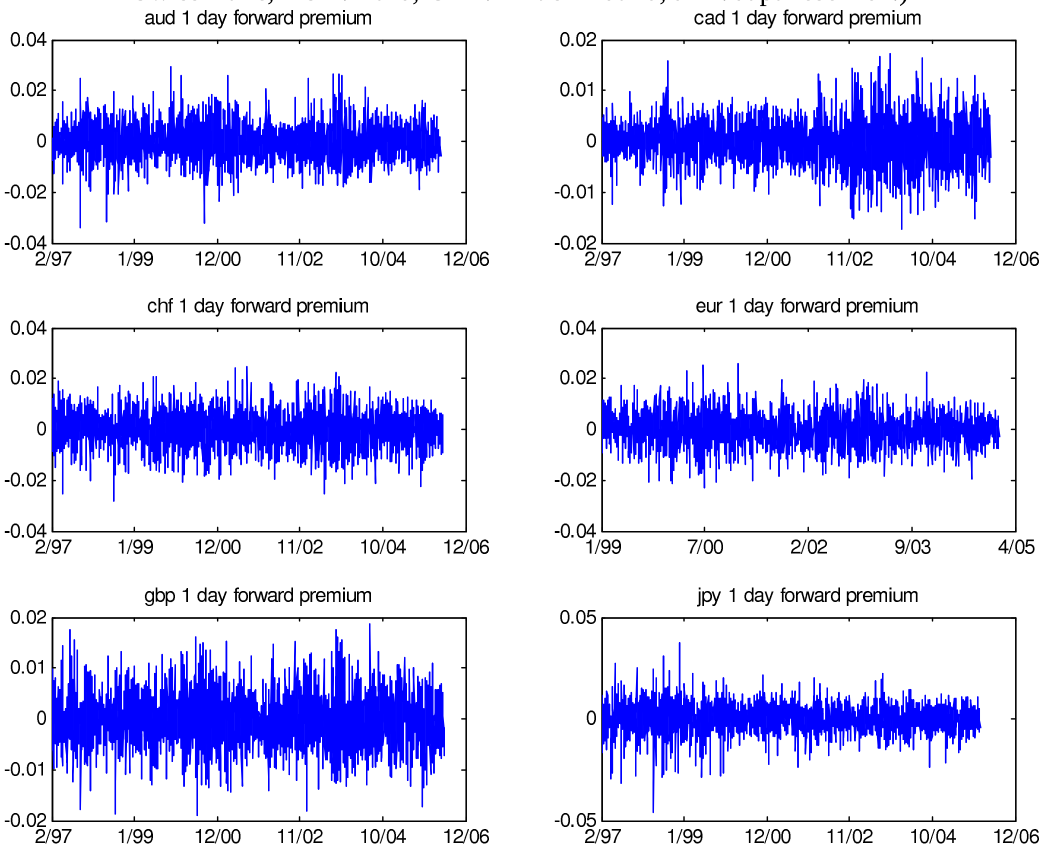


Figure 2.3: Time series graph for 1 week forward premium

The data set consists of daily observations of the New York closing and forward exchange rates during the period Feb. 10th, 1997 to October 31st, 2006 (See footnote 6 for more detailed explanations).(AUD: Australian Dollar, CAD: Canadian Dollar, CHF: Swiss franc, EUR: Euro, GBP: British Pound, JPY: Japanese Yen.)

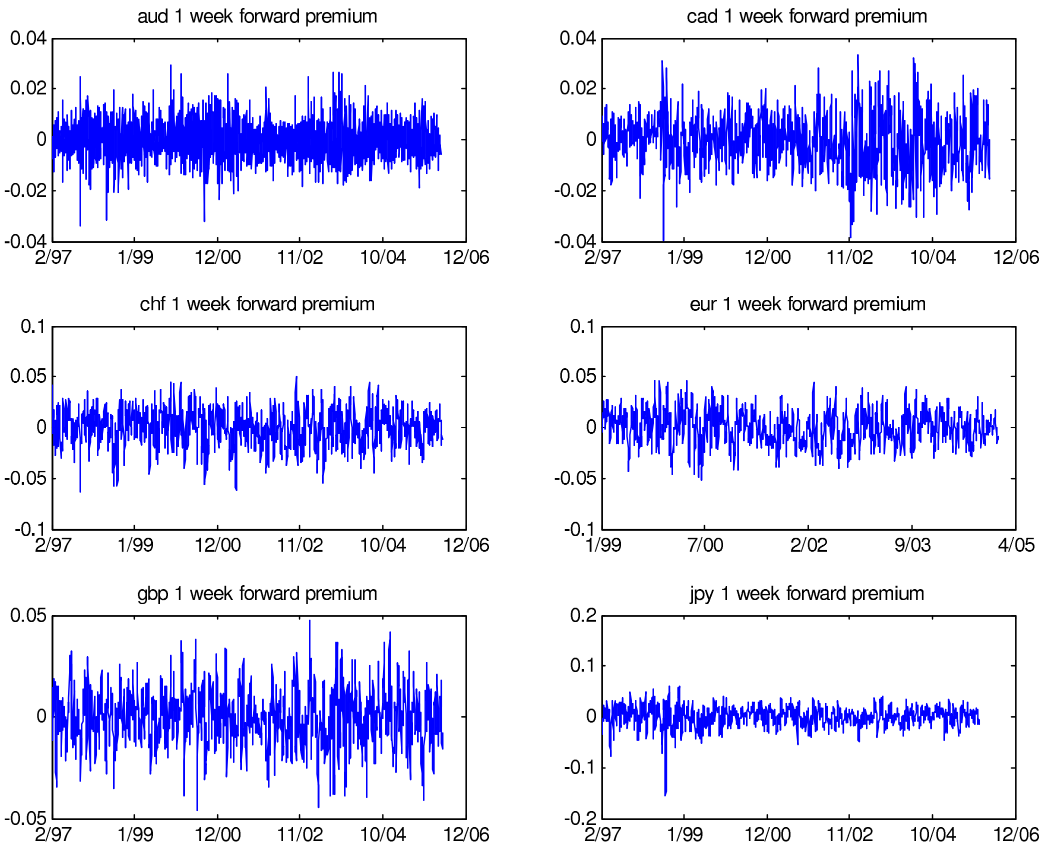
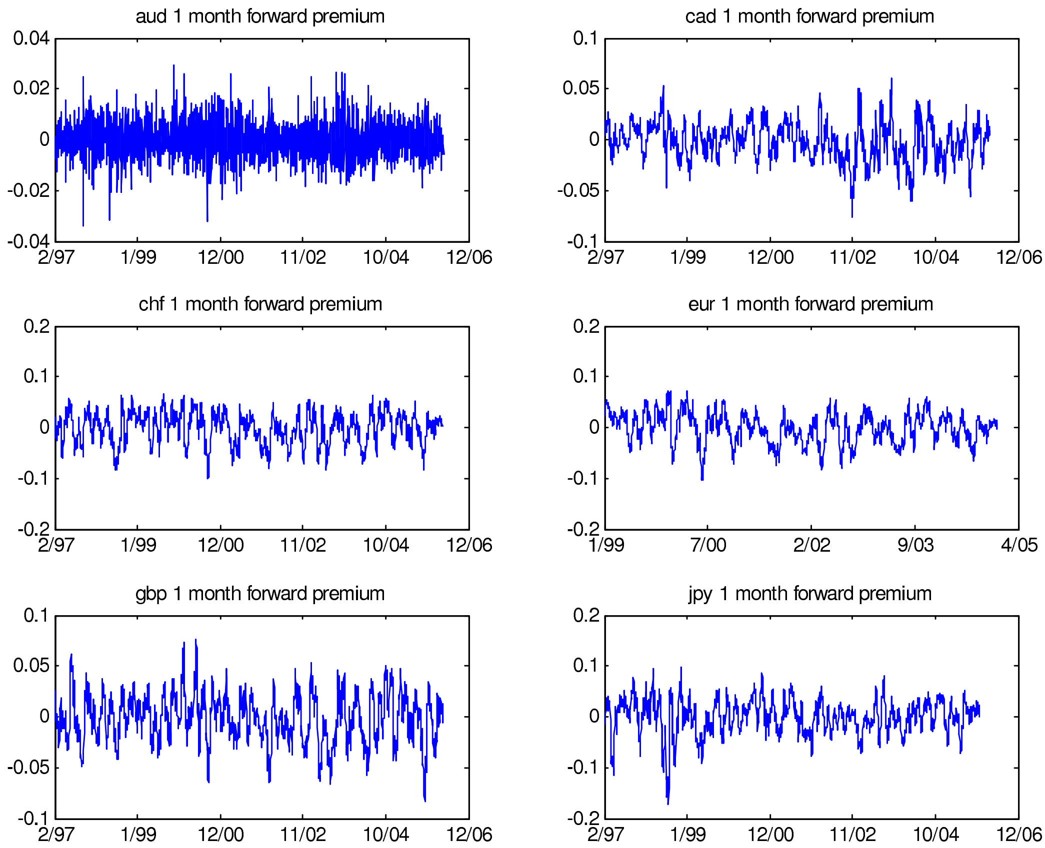


Figure 2.4: Time series graph for 1 month forward premium

The data set consists of daily observations of the New York closing and forward exchange rates during the period Feb. 10th, 1997 to October 31st, 2006 (See footnote 6 for more detailed explanations).(AUD: Australian Dollar, CAD: Canadian Dollar, CHF: Swiss franc, EUR: Euro, GBP: British Pound, JPY: Japanese Yen.)



Chapter 3

The Profitability of Using VECM Strategy

3.1. Introduction

Whether the foreign exchange rate fluctuations are predictable or not has been discussed for a long time. Scholars have tried many complex models to forecast the future foreign exchange spot rates. However, empirical studies found that a simple random walk forecast outperforms almost all the other complex exchange rate models (e.g., see Meese and Rogoff , 1983; Mark, 1995). In addition the forward premium puzzle has been proved as an inaccurate predictor for future spot exchange rates (e. g., see Hansen and Hodrick, 1980; Baillie and Bollerslev, 1994; Phillips, 1996).

Does this suggest that the foreign exchange market violate the efficient market hypothesis? Scholars tried the term structure models in the late of 1990's. They found that vector error correction model (VECM) works better than the simple random walk forecast, especially in longer horizon such as 13-week or even 52-week (e. g., see Clarida and Taylor 1997 and 2003). However, due to limited data accessibility and technical constraints, their works focused on medium and long horizon forecasts, which are 1 month and up.

The VECM gained great success and became popular in economics of foreign exchange and global finance. Many works tried to enrich the model to explain the spot and forward exchange rates better (e. g., see Simpson, Ramchander and Chaudhry in 2005). However, for the foreign exchange traders, they do not need to know the exact number of the next rate. Knowing the sign of the position is good enough for medium term trading. In this regard, simple VECM forecast used by Clarida and Taylor can fulfill this purpose.

Using a comprehensive set of foreign exchange spot and forward rates from 10 industrial countries, we forecast future rates with the vector error correction model. The difference from prior works is that we use the rolling regression technology to run the out-of-sample forecasts. By repeatingly estimate the parameters we only need to forecast 1 step ahead. That can increase our forecasting accuracy.

We check the forecast errors first. The VECM estimates show smaller forecast errors than the random walk models, but the improvement is insignificant when the horizon gets longer. In our simulation, we determine the sign of position with the VECM forecasts, and clear the position at the end of the simulation period. Comparing the mean forecast trading return (MFTR) and the mean correct forecast direction (MCFD) of the simulation, we find that the strategy based on rolling VECM forecast is more profitable than the buy and hold strategy in short horizons.

In section 2 we briefly discuss the data and the rolling regression technology involved. In section 3, we review the VECM method and define the criteria we will use. Section 4 reports our simulation results and section 5 gives our conclusion.

3.2. Description of Data and rolling regression

3.2.1. Data description

We collect foreign exchange spot and forward rates from Bloomberg, which were saved by Bloomberg as the average of the inter-bank quotes during New York trading hours. We study the following 10 industrial countries' currencies as our subjects:

1) Australia Dollar (AUD)
2) Canada Dollar (CAD)
3) Swiss Franc (CHF)
4) Danish Krone (DKK)
5) Euro (EUR)
6) British Pound (GBP)
7) Japanese Yen (JPY)
8) Norwegian Krone (NOK)
9) New Zealand Dollar (NZD)
10) Swedish Krona (SEK)

Because we choose United States Dollar (USD) as the domestic currency, we invert the original AUD, EUR, GBP and NZD data. The data starts on Oct. 28th, 1996 and end on May 15th, 2009. It covers more than 10 years' fluctuations and includes 3277 business days. For EUR, the data begins on Jan. 1st, 1999.[1] We have forward rates of 1 week, 2 week, 3week, 1 month, 3month and 6 month.[2] The spot and forward rates are in daily frequencies.

3.2.2. Rolling regression

Different from Clarida's work, we make out-of-sample forecasts with the rolling regression technique.

Rolling regression is an econometric procedure that allows us to estimate a series of parameters based on the same equation over multiple date ranges. In this procedure, we use a fixed length window of past data as inputs rather than the full set of previous data.

For example, if the available data has length L, the traditional method will allocate L_1 observations from the beginning as the in-sample data, and the remaining L_2 as the out-of-sample data set. Here the in-sample period always uses the vast majority of the full data set. This method generates a set of parameters using time series L_1 and apply them to produce all the out-of-sample forecasts. Although this method can also dynamically generate the one step ahead forecast, the forecast model itself is out-of-date.

[1]EUR has only 2660 business days.

[2]The forward rates are not always available in these horizons. For example, Swedish Krona only has 1538 days with the 6 kinds of forward rates although there are 3277 business days.

On the contrary, the rolling regression method we apply here updates the forecast models every day. We choose an in-sample size N, where $N < L$, the procedure of the rolling VECM is as the following:

1) Use data from y_1 to y_N to estimate the parameters Θ_1 for our VECM;

2) Apply Θ_1 to generate one step ahead forecast for period $N+1$ and save the results $\widehat{y_{N+1}}$;

3) Use data from y_2 to y_{N+1} to estimate a new set of parameters Θ_2;

4) Apply Θ_2 and the real spot and forward rates from date 2 to date $N+1$ to forecast $\widehat{y_{N+2}}$;

5) $\ldots$

6) Repeat the above procedure until the in sample data is y_{L-N} to y_{L-1}, we obtain the last $\widehat{y_L}$.

In the rolling VECM method, the fixed length window N is very important. We need sufficient number of observations to estimate the models, while leaving enough out-of-sample size $L-N$ to measure the forecasting performance. Here we choose $N = 2/3L$ and select $N = 3/4L$ and $N = 4/5L$ as robustness test.

3.3. Econometric method

Let s_t denote the logarithm of the spot exchange rate at time t and $f_{n,t}$ the logarithm of the n period forward rate at time t. Numerous research have demonstrated that the spot and forward exchange rates exhibit a unit root and become stationary under first difference (e.g., see Clarida 1997 and Simpson 2002). We set up a vector y_t comprising s_t and $f_{n,t}$ for a particular currency,

$$y_t = [s_{t,}, f_{(1,t)}, f_{(2,t)}, f_{(3,t)}, f_{(4,t)}, f_{(13,t)}, f_{(26,t)}]' \tag{3.1}$$

Here $f_{(1,t)}$, $f_{(2,t)}, f_{(3,t)}$ are the logarithm of the 1 week, 2 week and 3 week forward rates at time t respectively, $f_{(4,t)}$ is the logarithm of the 1 month forward rate at time t, $f_{(13,t)}$ is the logarithm of the 3 month forward rate at time t, and $f_{(26,t)}$ is the logarithm of the 6 month forward rate at time t.

We ran cointegration tests between $f_{n,t}$ and s_t for each foreign currency using the maximum likelihood tests suggested by Johansen (1991)[3]. The result shows that there exist a linear combination of the spot and forward rates that is stationary. Evidence of cointegraion suggests that there is a long run statistical relationship between the spot rate and term structure. Therefore the short term fluctuations of spot and forward rates are affected by the lagged deviation from the inherent relationship between spot and forward rates.

The VECM can be written as

$$\Delta y_t = \mu + \sum_{i=1}^{k-1} \alpha_i \Delta y_{t-i} + \Pi y_{t-k} + \varepsilon_t \tag{3.2}$$

Where Δ is the first-difference operator. We have show that y_t is a cointegrated vector so the matrix Π has reduced rank $r < 7$.

[3]Not shown in the appendix.

Using the rolling VECM method we generate Θ_1, Θ_2 ... and $\widehat{y_{N+1}}$, $\widehat{y_{N+2}}$ ... We check the accuracy of our prediction with mean squared forecast error (MSFE) and mean absolute forecast error (MAFE);

Because foreign exchange market is volatile, forecast errors can be quite large from period to period. The traders only care about whether the foreign currency will appreciate or depreciate. If we know the foreign currency will go up for sure, we will buy and hold; otherwise, we will short the foreign currency. We use another two criteria to measure the trading return: the mean forecast trading return (MFTR) and the mean correct forecast direction (MCFD). The former is defined as:

$$MFTR \equiv \frac{1}{L-N} \sum_{t=N}^{L-1} sign(\widehat{r_{t+1}}) r_{t+1} \tag{3.3}$$

Where L is the observation numbers of the full set, N is the fixed length of in-sampler data, $r_t = s_t - s_{t-1}$. Here $sign(\widehat{r_{t+1}}) = 1$ if $\widehat{r_{t+1}} \geq 0$ and $sign(\widehat{r_{t+1}}) = -1$ if $\widehat{r_{t+1}} < 0$.

The latter is defined as:

$$MCFD \equiv \frac{1}{L-N} \sum_{t=N}^{L-1} 1[sign(\widehat{r_{t+1}}) sign(r_{t+1}) > 0] \tag{3.4}$$

Here $1[.]$ is the indicator function which give 1 if the statement in the braket is true and 0 otherwise.

We have different benchmarks for these criteria. For the forecast errors, we use the random walk model as the benchmark. For the trading simulation, we use the ‘buy and hold’ strategy as our benchmark. In the former case, we prefer a smaller forecast error. In the latter case the higher profit will be better. MFTR is the average return we can get by that strategy. MCFD represents the frequency the traders take a correct positions.

3.4. Forecast errors and trading simulation

In table 3.1 we report the comparison of our forecasts of the future spot rates by rolling regression and that by the random walk model. Table 3.4 gives the simulated trading returns of error correction models and the ‘buy and hold’ strategies.

3.4.1. Forecast errors

Going over table 3.1, we note that the forecast errors in VECM are always be smaller than the corresponding errors from the random walk model. In both models, the errors increase monotonically when the forecast horizon increases. However, the improvement from the VECM is not consistent when the forecast horizon gets longer. This is a little different from Clarida’s work. Apparently, when the forecast horizon goes up, the models involves more variables and the simple VECM is not good at describing the complex long term foreign exchange markets. However for short run traders the VECM is still quite valuable.

We note another interesting fact here. For the more popular currencies, the random walk works relatively better, especially for the 1 week forecast. For example, EUR and GBP’s mean squared forecast errors are as low as 0.0001. While for the less popular currencies such as AUD, CHF and CAD, the MSFEs are in the range from 0.0003 to 0.001. The least popular currencies, such as DKK, SEK, NZD and NOK, all have error higher than 0.001. [4] We also observe that the forecast errors of the VECM forecasts exhibit the similar character. This may be explained by more consumption of tradable signals in the more popular currencies due to competition.

We use Diebold-Mariano test to examine the forecast accuracy. We define the error loss function as the squared error loss. The null hypotheses is that the squared error loss from random walk is the same to the loss from the VECM. Table 3.3 reports the Diebold-Mariano test statistic. If the S value is higher than 1.96, then we reject the null hypotheses in 95% level. We find that the popular European currencies are all reject the null hypotheses, JPY has significant S value too. The other 5 currencies exibit smaller S values. However, Most currencies reject the null in 90% level. We can say with confidence that the VECM has better predictive accuracy than the random walk model.

3.4.2. The simulated trading profitability

The averaged forecast errors is not a direct measurement of the medels profitability. The MFTR and MCFD are more directly related to real profitability of the model.

Table 3.4 describes the results from the trading simulation. MFTR shows the average trading returns and MCFD exhibits the probability the traders take a correct position. We compute the performance of two strategies: trading based on

[4] JPY exhibits different behavior here. Becasue its rate is measured in high magnitude.

the VECM forecast, and the buy and hold strategy. We denote these two strategies as VECMT and BAH respectively.

The VECMT strategy works as the following: buy the foreign currency with \$1 if our VECM gives a positive forecast; short \$1's foreign currency if the VECM prediction is negative. The BAH just buys \$1 foreign currency and sells it the next period.

We note that the average returns from the VECMT strategy beat that of BAH strategy, especially in short horizon. In the meanwhile, the VECMT strategy has a higher MCFD than the BAH strategy. For all 10 currencies, the VECMT is more profitable than the simple BAH strategy.

Trading by the VECMT strategy always yields positive return in medium horizon. The BAH strategy is quite volatile. 5 currencies of the 10 simulations report negative returns in our test. We find that when the horizon gets longer, trading return in the VECMT strategy goes down dramatically. In the 6-month trading, the return is insignificant to 0.

For the correct holding direction measurement, we note that the BAH strategy hold a correct position for around 50% of times, VECMT strategy is correct than 60% of times in 1 week predictions.

3.4.3. Robustness testing

For robustness test we use $N = 3/4L$, and $4/5L$ to rerun the above measurements of $N = 2/3L$. These results are reported from table 3.6 through table 3.12.

Table 3.6 reports different forecast errors in random walk and VECM models; table 3.8 discusses the trading results in VECMT and BAH strategy. Both using the fixed in sample data length $3/4L$.

Comparing table 3.6 with table 3.1, we get the similar results in these two split methods: VECM has smaller forecast errors than the RW model. With shorter predict horizon, the improvement is better than those under long horizons. We also find that the forecast errors in table 3.6 is bigger than those in table 3.1, especially in the unpopular currencies such as DKK, NOK and SEK.

Trading simulation works a little better with $N = 3/4L$. In table 3.8 we note that the VECMT strategy in 1week trading always has higher MFTR than its comparable value as table 3.4. Besides that, table 3.8 exhibits the similar characters with table 3.4: VECMT strategy always runs better than BAH strategy, but the advantage only holds in medium horizons.

Table 3.10 and table 3.12 reports the results for the fixed in sample data length of $4/5L$. The forecast errors continue to increase, as do the trading returns. It seems with the longer in sample data, the forecast accuracy reduces while the trading performance gets more profitable.

3.5. Concluding Remarks

In this paper, we replicate the method Clarida and Taylor used in 1997. We have a longer data set which start from 1996 and end in 2009. We use the daily forward rates with horizons from 1 week to 6 month. To investigate the power of VECM in more detail, we test not only the popular currencies such as GBP and JPY, but also some less traded currencies such as DKK and SEK.

To increase the accuracy of our model, we use the rolling regression technique. We keep on updating our parameters and use the updated model to predict the next period's foreign exchange rates. This method allows us to incorporate as much as possible information into the models.

We use the mean square forecast errors (MSFE) and mean absolute forecast errors (MAFE) to describe the forecast accuracy of our model, and take the random walk model as the benchmark. The results show that VECM beats the random walk in all the 10 currencies. In the medium horizon, the VECM displays obvious improvement over the random walk model.

Then we run a trading simulation to test the profitability of the VECM prediction. We choose our long or short position by the sign of next period's forecast, and clear the position later. We call it VECMT strategy. Comparing the profit of VECMT with that of the simple 'buy and hold (BAH)' strategy, we observe the VECMT performs better in medium horizon than BAH strategy.

We try the data in 3:1 and 4:1 for the in-sample and out-of-sample groups respectively. All these yields similar as that of the 2:1 splitting. With more in-sample data, the forecast error gets higher but the profitability in 1 week horizon gets higher too.

Our experiment proves that the VECM performs better than random walk in foreign exchange forecast studying. The VECM shows strong advantage in medium horizon, especially in the 1-week prediction.

Table 3.1
Forecast Errors from VECM and RW models (with 2:1 data split) (part 1)

We reports the forecast errors from vector error correction model (VECM) and random walk model here. We use rolling regression method to generate paramaters. This table we have the in-sample data length as 2/3 of the total observations. MSFE is the mean squared forecast error and MAFE is the mean absolute forecast error. We have the forecast horzion from 1 week to 6 month here. (AUD: Australia ,*CAD* : *Canada*, DKK: Danish Krone, EUR: Euro, GBP: British Pound, JPY: Japenese Yen, NOK: Norwegian Krone, NZD: New Zealand Dollar, SEK: Swedish Krona)

AUD		1w	2w	3w	1m	3m	6m
RW	MSFE	0.001	0.0019	0.0028	0.0041	0.0124	0.0275
	MAFE	0.0201	0.0283	0.0349	0.0423	0.0655	0.1081
VECM	MSFE	0.0008	0.0018	0.0026	0.0039	0.0125	0.0282
	MAFE	0.0182	0.027	0.0339	0.0412	0.0643	0.1044
CAD							
RW	MSFE	0.0004	0.0008	0.0011	0.0015	0.0046	0.0112
	MAFE	0.0144	0.0201	0.0237	0.027	0.0481	0.0809
VECM	MSFE	0.0004	0.0008	0.0011	0.0015	0.0047	0.0111
	MAFE	0.013	0.0198	0.0235	0.0269	0.0479	0.0809
CHF							
RW	MSFE	0.0003	0.0006	0.0009	0.0012	0.0026	0.006
	MAFE	0.0131	0.0183	0.0224	0.0268	0.0387	0.0632
VECM	MSFE	0.0002	0.0005	0.0008	0.0012	0.0028	0.0064
	MAFE	0.0116	0.0175	0.0217	0.0264	0.0407	0.0665
DKK							
RW	MSFE	0.0107	0.0225	0.0341	0.0513	0.1182	0.2753
	MAFE	0.0755	0.1094	0.1383	0.171	0.2495	0.4568
VECM	MSFE	0.0084	0.0208	0.0324	0.0499	0.1208	0.2814
	MAFE	0.0657	0.1047	0.1342	0.1678	0.2518	0.4553

Table 3.2
Forecast Errors from VECM and RW models (with 2:1 data split) (part 2)

EUR		1w	2w	3w	1m	3m	6m
RW	MSFE	0.0001	0.0003	0.0004	0.0006	0.0014	0.0032
	MAFE	0.0081	0.0115	0.0145	0.0178	0.026	0.0464
VECM	MSFE	0.0001	0.0002	0.0004	0.0006	0.0014	0.0034
	MAFE	0.0072	0.011	0.0142	0.0176	0.0271	0.0481
GBP							
RW	MSFE	0.0001	0.0002	0.0002	0.0003	0.0013	0.0037
	MAFE	0.0067	0.0092	0.0104	0.0123	0.0224	0.0394
VECM	MSFE	0.0001	0.0002	0.0002	0.0003	0.0014	0.0037
	MAFE	0.006	0.0089	0.0102	0.0121	0.0227	0.0403
JPY							
RW	MSFE	2.6599	4.8865	7.7295	11.1873	34.2303	59.2261
	MAFE	1.2371	1.7556	2.2166	2.6696	4.6438	6.1011
VECM	MSFE	2.1801	4.4199	7.1418	10.5557	33.7153	58.9843
	MAFE	1.1092	1.6527	2.1319	2.5951	4.6132	6.0846
NOK							
RW	MSFE	0.0239	0.0393	0.0558	0.0826	0.3482	0.8144
	MAFE	0.1118	0.1408	0.1637	0.2027	0.4049	0.6999
VECM	MSFE	0.0192	0.0383	0.0535	0.08	0.3542	0.8382
	MAFE	0.1002	0.1391	0.1593	0.1984	0.4048	0.6883
NZD							
RW	MSFE	0.0016	0.003	0.0045	0.0065	0.0166	0.044
	MAFE	0.0275	0.0386	0.0468	0.0563	0.0963	0.1538
VECM	MSFE	0.0013	0.0028	0.0043	0.0065	0.0179	0.0479
	MAFE	0.0245	0.0373	0.0461	0.0559	0.0987	0.1562
SEK							
RW	MSFE	0.0337	0.0662	0.0988	0.1391	0.3963	1.0879
	MAFE	0.1282	0.1779	0.2233	0.2728	0.4362	0.7684
VECM	MSFE	0.0264	0.0607	0.094	0.1352	0.3947	1.072

Table 3.3
Diebold-Mariano test with VECM and RW models (with 2:1 data split)

We use Diebold-Mariano test statistic for comparing predictive accuracy. The two forecast models are random walk and VECM respectively. We use squared error loss as our loss function. The critical value is 1.96 at 95% level.

	1w	2w	3w	1m	3m	6m
AUD	1.6848	1.7714	1.7397	1.6731	1.3067	1.2261
CAD	1.6087	1.6812	1.8225	1.8641	2.2421	1.6567
CHF	6.236	5.546	3.7456	3.7786	5.1163	3.5547
DKK	2.1324	2.0705	2.0844	2.1548	7.2026	2.7849
EUR	2.9986	2.2352	2.2081	2.2609	4.1044	2.6582
GBP	2.0179	2.4368	2.8187	2.3842	1.5028	1.43
JPY	4.3268	4.4042	3.8556	4.0561	2.8588	5.7442
NOK	1.9532	2.1237	2.3546	2.6839	2.2178	1.8261
NZD	1.8671	1.9118	2.1351	2.1483	2.0598	2.1365
SEK	1.6208	1.6053	1.6428	1.7868	2.0121	1.4578

Table 3.4
Trading returns from VECMT and BAH strategies (with 2:1 data split) (part 1)

We reports the simulated trading returns from two strategies here. The first one is based on the vector error correction model (VECM) prediction. We buy the foreign currency if it will appreciate or short if it will depreciate. We call this strategy as VECMT. The second strategy is just buy and hold, sell it next period. We call it BAH strategy. This table we have the in-sample data length as 2/3 of the total observations. MFTR is the mean squared forecast trading return and MCFD is the mean correct forecast direction. We have the forecast horzion from 1 week to 6 month here. (AUD: Australia ,*CAD* : *Canada*, DKK: Danish Krone, EUR: Euro, GBP: British Pound, JPY: Japenese Yen, NOK: Norwegian Krone, NZD: New Zealand Dollar, SEK: Swedish Krona)

AUD		1w	2w	3w	1m	3m	6m
BAH	MFTR	0.0003	0.0002	0.0001	0.0001	-0.002	-0.007
	MCFD	0.5474	0.5304	0.5325	0.5304	0.6251	0.6262
VECMT	MFTR	0.0076	0.0069	0.0072	0.008	0.0081	0.0134
	MCFD	0.6677	0.6081	0.5911	0.5761	0.606	0.655
CAD							
BAH	MFTR	-0.0001	-0.0003	-0.0007	-0.0013	-0.0058	-0.0085
	MCFD	0.5232	0.5286	0.5113	0.5126	0.4369	0.4728
VECMT	MFTR	0.0053	0.004	0.0032	0.0034	0.0027	0.0009
	MCFD	0.6401	0.5803	0.5392	0.5299	0.5618	0.5007
CHF							
BAH	MFTR	0.0007	0.0009	0.0011	0.0017	0.0078	0.0139
	MCFD	0.4921	0.5058	0.4889	0.5121	0.5913	0.5892
VECMT	MFTR	0.0043	0.005	0.0051	0.0048	-0.0019	-0.0023
	MCFD	0.6367	0.603	0.5871	0.5628	0.4456	0.4467
DKK							
BAH	MFTR	0.0002	0.0003	0.0004	0.0002	-0.0016	0.0022
	MCFD	0.5364	0.5094	0.5198	0.5281	0.605	0.6466
VECMT	MFTR	0.0058	0.0059	0.0069	0.0057	0.0035	0.0072
	MCFD	0.6424	0.5967	0.5904	0.5551	0.5156	0.5447

Table 3.5
Trading returns from VECMT and BAH strategies (with 2:1 data split) (part 2)

EUR		1w	2w	3w	1m	3m	6m
BAH	MFTR	0.001	0.0021	0.0028	0.0037	0.0082	0.0156
	MCFD	0.5524	0.5592	0.5614	0.5795	0.699	0.7238
VECMT	MFTR	0.0044	0.0041	0.0047	0.0039	-0.0033	-0.0063
	MCFD	0.628	0.5817	0.5817	0.5423	0.4036	0.3935
GBP							
BAH	MFTR	-0.0008	-0.0016	-0.0025	-0.0037	-0.0134	-0.026
	MCFD	0.503	0.4812	0.497	0.5049	0.5583	0.4862
VECMT	MFTR	0.0051	0.0045	0.0042	0.004	-0.0031	-0.0067
	MCFD	0.6482	0.5998	0.583	0.5741	0.498	0.4713
JPY							
BAH	MFTR	0.0007	0.0013	0.002	0.0028	0.0072	0.0166
	MCFD	0.4612	0.4791	0.4722	0.4831	0.4891	0.501
VECMT	MFTR	0.0046	0.0048	0.0053	0.0054	0.006	0.0062
	MCFD	0.6282	0.5845	0.5716	0.5636	0.5467	0.5328
NOK							
BAH	MFTR	-0.0004	-0.0008	-0.0015	-0.0024	-0.0075	-0.0146
	MCFD	0.5692	0.5049	0.4834	0.5263	0.6218	0.6608
VECMT	MFTR	0.0086	0.0071	0.0081	0.0078	0.0075	0.0084
	MCFD	0.6745	0.5945	0.614	0.5867	0.5497	0.6043
NZD							
BAH	MFTR	-0.0006	-0.0012	-0.0019	-0.0029	-0.013	-0.0249
	MCFD	0.5144	0.5086	0.4983	0.5155	0.4799	0.5029
VECMT	MFTR	0.0082	0.0075	0.0081	0.0066	0.0009	-0.0098
	MCFD	0.651	0.6005	0.5809	0.5672	0.5189	0.5293
SEK							
BAH	MFTR	-0.001	-0.0018	-0.0031	-0.0055	-0.0187	-0.0311
	MCFD	0.5205	0.501	0.4737	0.4776	0.4815	0.5984
VECMT	MFTR	0.0076	0.0079	0.0087	0.0085	0.008	0.0151
	MCFD	0.6491	0.6023	0.6101	0.5712	0.5127	0.5692

Table 3.6
Forecast Errors from VECM and RW models (with 3:1 data split) (part 1)

We reports the forecast errors from vector error correction model (VECM) and random walk model here. We use rolling regression method to generate paramaters. This table we have the in-sample data length as 3/4 of the total observations. MSFE is the mean squared forecast error and MAFE is the mean absolute forecast error. We have the forecast horzion from 1 week to 6 month here. (AUD: Australia ,*CAD* : *Canada*, DKK: Danish Krone, EUR: Euro, GBP: British Pound, JPY: Japenese Yen, NOK: Norwegian Krone, NZD: New Zealand Dollar, SEK: Swedish Krona)

AUD		1w	2w	3w	1m	3m	6m
RW	MSFE	0.0013	0.0023	0.0034	0.005	0.0162	0.0361
	MAFE	0.0222	0.0309	0.0379	0.0467	0.0787	0.1327
VECM	MSFE	0.001	0.0021	0.0032	0.0048	0.0164	0.037
	MAFE	0.0202	0.0294	0.0367	0.0452	0.0767	0.1267
CAD							
RW	MSFE	0.0006	0.001	0.0014	0.002	0.0059	0.0143
	MAFE	0.0167	0.0235	0.0276	0.0316	0.0565	0.0958
VECM	MSFE	0.0004	0.001	0.0014	0.002	0.006	0.0143
	MAFE	0.015	0.0232	0.0276	0.0316	0.0568	0.096
CHF							
RW	MSFE	0.0003	0.0006	0.0009	0.0013	0.0029	0.0066
	MAFE	0.0132	0.0185	0.0231	0.0278	0.0409	0.0661
VECM	MSFE	0.0003	0.0005	0.0009	0.0013	0.0029	0.0071
	MAFE	0.0118	0.0176	0.0224	0.0274	0.0422	0.0706
DKK							
RW	MSFE	0.0132	0.028	0.042	0.0628	0.1401	0.3296
	MAFE	0.0858	0.1234	0.1547	0.19	0.2693	0.5029
VECM	MSFE	0.0104	0.0257	0.0397	0.0605	0.1422	0.3346
	MAFE	0.0746	0.1175	0.1497	0.1851	0.269	0.4966

Table 3.7
Forecast Errors from VECM and RW models (with 3:1 data split) (part 2)

EUR		1w	2w	3w	1m	3m	6m
RW	MSFE	0.0001	0.0003	0.0005	0.0007	0.0016	0.0038
	MAFE	0.0085	0.0124	0.0159	0.0196	0.0284	0.0507
VECM	MSFE	0.0001	0.0003	0.0004	0.0007	0.0016	0.0039
	MAFE	0.0075	0.0118	0.0154	0.0193	0.029	0.0516
GBP							
RW	MSFE	0.0001	0.0002	0.0002	0.0004	0.0016	0.0046
	MAFE	0.0071	0.0094	0.0104	0.0125	0.0244	0.0441
VECM	MSFE	0.0001	0.0002	0.0002	0.0004	0.0016	0.0047
	MAFE	0.0063	0.0091	0.0103	0.0122	0.0247	0.0451
JPY							
RW	MSFE	2.8407	5.1167	8.1749	11.7545	38.4686	61.2976
	MAFE	1.2603	1.7782	2.2501	2.7012	4.9404	5.8891
VECM	MSFE	2.3311	4.6319	7.5661	11.0452	37.856	61.2467
	MAFE	1.1331	1.6792	2.1662	2.6154	4.9106	5.8831
NOK							
RW	MSFE	0.0296	0.0481	0.067	0.0981	0.4326	1.0042
	MAFE	0.126	0.156	0.1794	0.2215	0.4477	0.781
VECM	MSFE	0.0239	0.0473	0.0649	0.0956	0.4415	1.0377
	MAFE	0.1135	0.1556	0.176	0.2182	0.4488	0.7677
NZD							
RW	MSFE	0.0019	0.0037	0.0054	0.0078	0.0194	0.0533
	MAFE	0.0302	0.0423	0.0508	0.0613	0.1034	0.1673
VECM	MSFE	0.0015	0.0034	0.0052	0.0077	0.0208	0.0572
	MAFE	0.0268	0.041	0.0501	0.0609	0.1052	0.1672
SEK							
RW	MSFE	0.0423	0.0824	0.1213	0.1691	0.5073	1.4205
	MAFE	0.1473	0.1999	0.2475	0.3	0.5147	0.9335
VECM	MSFE	0.0331	0.0748	0.1148	0.1637	0.5023	1.3911
	MAFE	0.1298	0.19	0.2374	0.2933	0.5124	0.9108

Table 3.8
Trading returns from VECMT and BAH strategies (with 3:1 data split) (part 1)

We reports the simulated trading returns from two strategies here. The first one is based on the vector error correction model (VECM) prediction. We buy the foreign currency if it will appreciate or short if it will depreciate. We call this strategy as VECMT. The second strategy is just buy and hold, sell it next period. We call it BAH strategy. This table we have the in-sample data length as 3/4 of the total observations. MFTR is the mean squared forecast trading return and MCFD is the mean correct forecast direction. We have the forecast horzion from 1 week to 6 month here. (AUD: Australia ,*CAD* : *Canada*, DKK: Danish Krone, EUR: Euro, GBP: British Pound, JPY: Japenese Yen, NOK: Norwegian Krone, NZD: New Zealand Dollar, SEK: Swedish Krona)

AUD		1w	2w	3w	1m	3m	6m
BAH	MFTR	0.0004	0.0004	0.0002	0.0001	-0.0018	-0.005
	MCFD	0.5611	0.5568	0.5724	0.5682	0.6761	0.7472
VECMT	MFTR	0.0083	0.0076	0.0081	0.0095	0.0113	0.0191
	MCFD	0.6577	0.6094	0.6023	0.5994	0.6449	0.7457
CAD							
BAH	MFTR	0.0003	0.0005	0.0004	0.0001	-0.0032	-0.009
	MCFD	0.5451	0.5735	0.577	0.5717	0.5044	0.4867
VECMT	MFTR	0.0062	0.0045	0.0041	0.0039	0	-0.0014
	MCFD	0.6407	0.5735	0.5381	0.531	0.5133	0.485
CHF							
BAH	MFTR	0.0008	0.0009	0.0011	0.0017	0.0071	0.0202
	MCFD	0.5056	0.5056	0.4887	0.5254	0.5873	0.6451
VECMT	MFTR	0.0044	0.005	0.0055	0.0049	-0.0003	-0.0063
	MCFD	0.6352	0.5972	0.5831	0.5549	0.4549	0.3958
DKK							
BAH	MFTR	-0.0004	-0.0013	-0.0024	-0.0043	-0.0142	-0.0173
	MCFD	0.5069	0.4626	0.4626	0.4543	0.4792	0.5291
VECMT	MFTR	0.007	0.0079	0.0087	0.0071	0.0068	0.0136
	MCFD	0.6648	0.6427	0.6205	0.5651	0.554	0.6094

Table 3.9
Trading returns from VECMT and BAH strategies (with 3:1 data split) (part 2)

EUR		1w	2w	3w	1m	3m	6m
BAH	MFTR	0.0009	0.0017	0.002	0.0025	0.005	0.0108
	MCFD	0.5594	0.5519	0.5429	0.5684	0.6737	0.7293
VECMT	MFTR	0.0047	0.0055	0.0058	0.0051	0.0003	0.0022
	MCFD	0.6271	0.6075	0.597	0.5459	0.4406	0.4256
GBP							
BAH	MFTR	-0.0011	-0.0024	-0.0039	-0.0056	-0.0163	-0.0269
	MCFD	0.502	0.469	0.4875	0.5007	0.5968	0.5679
VECMT	MFTR	0.0052	0.0038	0.0034	0.0039	-0.0031	-0.0067
	MCFD	0.6443	0.5889	0.5744	0.5705	0.5033	0.4743
JPY							
BAH	MFTR	0.0011	0.0022	0.0034	0.0045	0.0149	0.0363
	MCFD	0.4808	0.5073	0.4927	0.4887	0.5563	0.6212
VECMT	MFTR	0.0045	0.0045	0.0047	0.0051	0.0045	0.004
	MCFD	0.6119	0.5748	0.5576	0.5629	0.5219	0.5258
NOK							
BAH	MFTR	-0.0019	-0.004	-0.0064	-0.0094	-0.0264	-0.0465
	MCFD	0.5299	0.4494	0.4286	0.4571	0.4961	0.5481
VECMT	MFTR	0.0094	0.007	0.0074	0.008	0.0051	0.008
	MCFD	0.6623	0.5818	0.6	0.574	0.5506	0.6338
NZD							
BAH	MFTR	-0.0005	-0.0012	-0.002	-0.0031	-0.0128	-0.0184
	MCFD	0.5299	0.5069	0.4946	0.4977	0.5253	0.5819
VECMT	MFTR	0.0092	0.0084	0.009	0.0078	0.0036	0.0023
	MCFD	0.6646	0.6003	0.5712	0.5712	0.562	0.611
SEK							
BAH	MFTR	-0.0025	-0.0046	-0.0071	-0.0112	-0.0343	-0.0539
	MCFD	0.4792	0.4583	0.4193	0.4245	0.3594	0.5208
VECMT	MFTR	0.0088	0.0096	0.0097	0.0108	0.0098	0.0244
	MCFD	0.6484	0.6068	0.612	0.5833	0.5469	0.638

Table 3.10

Forecast Errors from VECM and RW models (with 4:1 data split) (part 1)

We reports the forecast errors from vector error correction model (VECM) and random walk model here. We use rolling regression method to generate paramaters. This table we have the in-sample data length as 4/5 of the total observations. MSFE is the mean squared forecast error and MAFE is the mean absolute forecast error. We have the forecast horzion from 1 week to 6 month here. (AUD: Australia ,$CAD : Canada$, DKK: Danish Krone, EUR: Euro, GBP: British Pound, JPY: Japenese Yen, NOK: Norwegian Krone, NZD: New Zealand Dollar, SEK: Swedish Krona)

AUD		1w	2w	3w	1m	3m	6m
RW	MSFE	0.0016	0.0028	0.0042	0.0061	0.02	0.0445
	MAFE	0.0251	0.0349	0.0437	0.054	0.0917	0.1554
VECM	MSFE	0.0013	0.0026	0.0039	0.0059	0.0202	0.0458
	MAFE	0.0227	0.0332	0.0421	0.0522	0.0897	0.1492
CAD							
RW	MSFE	0.0007	0.0012	0.0017	0.0023	0.0061	0.0161
	MAFE	0.0186	0.0256	0.0295	0.0334	0.0548	0.1017
VECM	MSFE	0.0005	0.0012	0.0017	0.0022	0.0061	0.016
	MAFE	0.0165	0.0252	0.0294	0.0332	0.0546	0.1015
CHF							
RW	MSFE	0.0004	0.0007	0.001	0.0015	0.0034	0.0079
	MAFE	0.0141	0.0198	0.0245	0.0297	0.0462	0.075
VECM	MSFE	0.0003	0.0006	0.001	0.0015	0.0035	0.0082
	MAFE	0.0125	0.0187	0.0238	0.0294	0.048	0.0783
DKK							
RW	MSFE	0.0152	0.0325	0.0484	0.0726	0.1629	0.3648
	MAFE	0.0912	0.1332	0.1694	0.2078	0.291	0.5219
VECM	MSFE	0.0118	0.0298	0.0458	0.0701	0.1676	0.3799
	MAFE	0.079	0.1265	0.1639	0.2032	0.2941	0.5243

Table 3.11
Forecast Errors from VECM and RW models (with 4:1 data split) (part 2)

EUR		1w	2w	3w	1m	3m	6m
RW	MSFE	0.0002	0.0004	0.0006	0.0008	0.0019	0.0046
	MAFE	0.0094	0.0136	0.0173	0.0214	0.0317	0.0578
VECM	MSFE	0.0001	0.0003	0.0005	0.0008	0.0019	0.0046
	MAFE	0.0082	0.0128	0.0167	0.0209	0.0321	0.0576
GBP							
RW	MSFE	0.0001	0.0002	0.0003	0.0005	0.002	0.0055
	MAFE	0.0077	0.0103	0.0114	0.0135	0.0271	0.0476
VECM	MSFE	0.0001	0.0002	0.0003	0.0004	0.002	0.0056
	MAFE	0.0069	0.01	0.0112	0.0132	0.0274	0.0487
JPY							
RW	MSFE	3.2089	5.7658	9.4145	13.6662	46.2695	74.1551
	MAFE	1.3366	1.8893	2.44	2.9674	5.602	6.7517
VECM	MSFE	2.6099	5.1764	8.625	12.7676	45.5228	74.0214
	MAFE	1.1938	1.7753	2.3401	2.865	5.5618	6.7502
NOK							
RW	MSFE	0.0343	0.0556	0.0775	0.1159	0.532	1.203
	MAFE	0.135	0.1665	0.1933	0.2428	0.5232	0.8647
VECM	MSFE	0.0279	0.0548	0.0756	0.1134	0.5446	1.2578
	MAFE	0.1221	0.1656	0.1905	0.2395	0.5251	0.8623
NZD							
RW	MSFE	0.0023	0.0043	0.0065	0.0093	0.023	0.0614
	MAFE	0.0335	0.0463	0.0563	0.0692	0.1134	0.1743
VECM	MSFE	0.0018	0.0041	0.0062	0.0094	0.025	0.0675
	MAFE	0.03	0.045	0.0555	0.0692	0.1177	0.1789
SEK							
RW	MSFE	0.0502	0.0981	0.145	0.2047	0.6185	1.7161
	MAFE	0.1623	0.2196	0.2775	0.342	0.6006	1.0546
VECM	MSFE	0.0392	0.0893	0.1379	0.1986	0.6111	1.6827
	MAFE	0.143	0.209	0.2673	0.3345	0.5956	1.0313

Table 3.12
Trading returns from VECMT and BAH strategies (with 4:1 data split) (part 1)

We reports the simulated trading returns from two strategies here. The first one is based on the vector error correction model (VECM) prediction. We buy the foreign currency if it will appreciate or short if it will depreciate. We call this strategy as VECMT. The second strategy is just buy and hold, sell it next period. We call it BAH strategy. This table we have the in-sample data length as 4/5 of the total observations. MFTR is the mean squared forecast trading return and MCFD is the mean correct forecast direction. We have the forecast horzion from 1 week to 6 month here. (AUD: Australia ,*CAD* : *Canada*, DKK: Danish Krone, EUR: Euro, GBP: British Pound, JPY: Japenese Yen, NOK: Norwegian Krone, NZD: New Zealand Dollar, SEK: Swedish Krona)

AUD		1w	2w	3w	1m	3m	6m
BAH	MFTR	0.0003	0.0001	-0.0005	-0.0009	-0.0069	-0.0143
	MCFD	0.5595	0.5684	0.5808	0.5702	0.6359	0.6998
VECMT	MFTR	0.0097	0.0091	0.0099	0.0108	0.0119	0.017
	MCFD	0.6661	0.6288	0.6128	0.6075	0.6323	0.7247
CAD							
BAH	MFTR	-0.0008	-0.0016	-0.0029	-0.0047	-0.0186	-0.0258
	MCFD	0.5022	0.5265	0.5221	0.5066	0.385	0.4115
VECMT	MFTR	0.0071	0.0057	0.0046	0.0048	0.0046	0.0057
	MCFD	0.646	0.5863	0.5442	0.5398	0.5553	0.5133
CHF							
BAH	MFTR	0.001	0.0013	0.0015	0.0023	0.009	0.022
	MCFD	0.5106	0.4982	0.5	0.5493	0.6303	0.6602
VECMT	MFTR	0.0047	0.0052	0.0058	0.0048	-0.0005	-0.0041
	MCFD	0.6338	0.6021	0.5775	0.5387	0.4243	0.3944
DKK							
BAH	MFTR	-0.0021	-0.0046	-0.007	-0.0104	-0.0265	-0.043
	MCFD	0.4533	0.4014	0.4048	0.3668	0.4014	0.4118
VECMT	MFTR	0.0078	0.0075	0.0085	0.007	0.0022	-0.0003
	MCFD	0.6644	0.6298	0.6159	0.5606	0.5329	0.5433

Table 3.13
Trading returns from VECMT and BAH strategies (with 4:1 data split) (part 2)

EUR		1w	2w	3w	1m	3m	6m
BAH	MFTR	0.0004	0.001	0.0009	0.0009	0.002	0.0063
	MCFD	0.5357	0.515	0.5132	0.5376	0.6504	0.6842
VECMT	MFTR	0.0055	0.0063	0.0072	0.0065	0.0039	0.0082
	MCFD	0.6429	0.6165	0.6165	0.5677	0.4718	0.5
GBP							
BAH	MFTR	-0.0019	-0.0038	-0.0061	-0.0087	-0.0269	-0.048
	MCFD	0.4843	0.4498	0.4679	0.4761	0.5025	0.4596
VECMT	MFTR	0.0056	0.0043	0.004	0.0049	-0.0026	-0.0049
	MCFD	0.6474	0.5783	0.575	0.5848	0.5272	0.5041
JPY							
BAH	MFTR	0.0018	0.0036	0.0055	0.0075	0.0213	0.048
	MCFD	0.4917	0.5414	0.5315	0.5199	0.6192	0.6805
VECMT	MFTR	0.005	0.0053	0.0057	0.0061	0.0045	0.0041
	MCFD	0.6209	0.5861	0.5629	0.5596	0.5166	0.5116
NOK							
BAH	MFTR	-0.0034	-0.0066	-0.0097	-0.0133	-0.0369	-0.0787
	MCFD	0.4968	0.4351	0.4091	0.4383	0.4578	0.4351
VECMT	MFTR	0.01	0.0074	0.0073	0.0084	0.0071	-0.0025
	MCFD	0.6656	0.5779	0.5974	0.5779	0.5584	0.5844
NZD							
BAH	MFTR	-0.0016	-0.0034	-0.0055	-0.0082	-0.0271	-0.0478
	MCFD	0.5019	0.4732	0.4655	0.4291	0.4176	0.477
VECMT	MFTR	0.0097	0.0086	0.0099	0.0083	-0.0031	-0.0199
	MCFD	0.6552	0.5862	0.5709	0.5517	0.4923	0.5249
SEK							
BAH	MFTR	-0.0035	-0.0064	-0.0097	-0.0146	-0.047	-0.0844
	MCFD	0.4545	0.4513	0.3961	0.3831	0.3052	0.4026
VECMT	MFTR	0.01	0.0106	0.0109	0.0128	0.0154	0.0311
	MCFD	0.6429	0.6071	0.6104	0.5942	0.5714	0.6558

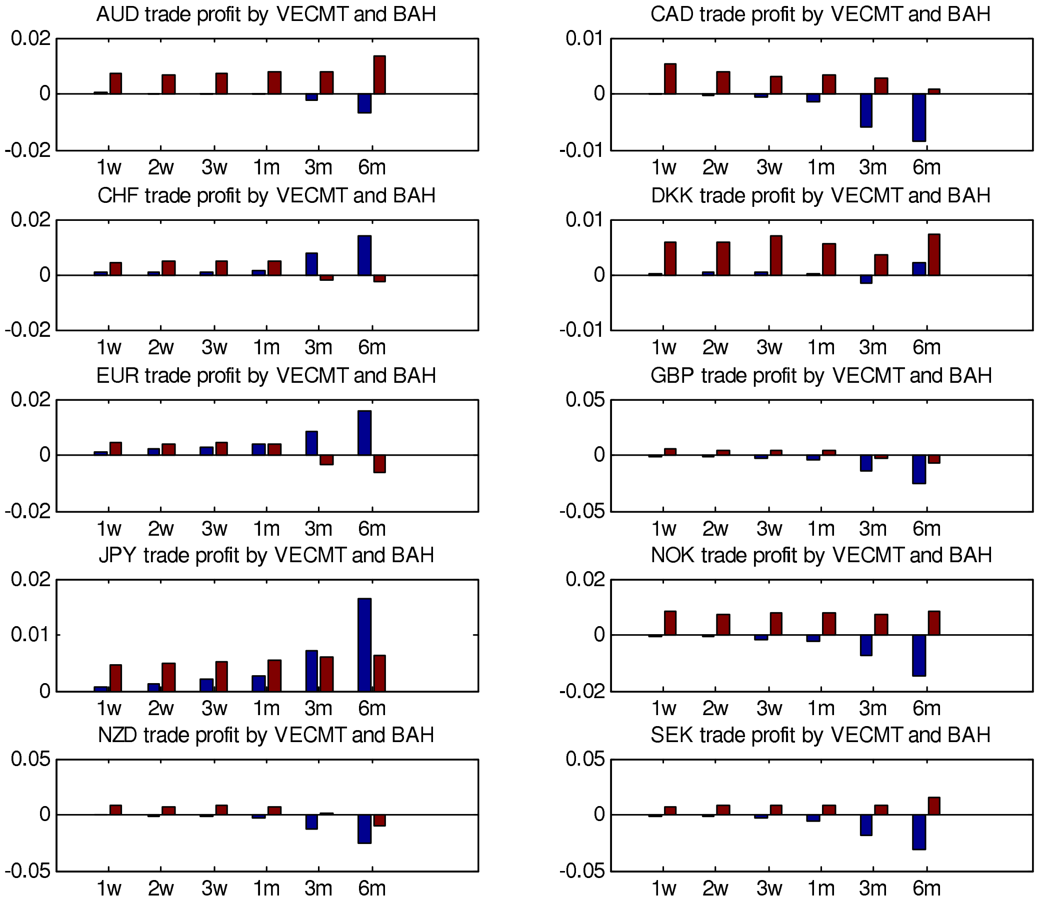


Figure 3.1: Average profit by two trading strategy

We buy or short by our VECM prediction, comparing with the simple buy and hold strategy. This graph shows the averaged profit of these two strategy in the 2:1 data split. The red bars are the profit from VECMT, and the blue bars are BAH average profit.

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