ESSAYS ON CARRY TRADE AND EXCHANGE RATE FORECASTING

A Dissertation

Presented to

the Faculty of the Department of Economics

University of Houston

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

By

Gokcen Ogruk

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Abstract

This thesis is the combination of three papers on carry trade strategies and exchange rate forecasting. The first paper evaluates the performance of carry trade strategies with implied Taylor rule interest rate differentials and compares their performance statistics to the naive carry trade strategy with actual interest rates. I argue that the crash risk is reduced with implied Taylor rule interest rate differentials as a trading strategy in Yen and Franc trades for the whole sample period. During the recent financial crisis, the carry trading strategies with an implied Taylor rule interest rate perform best in terms of mean returns, risk adjusted returns and downside risk.

The second paper evaluates the performance of carry trade strategies with Taylor rule fundamentals in a Markov switching dynamic factor augmented regression framework and compares the performance statistics with the benchmark model of a random walk. I make simulations with the Japanese Yen, Swiss Franc and US Dollar as funding currencies against six target currencies. I argue that risk adjusted returns, mean returns and down-side risk perform best when the Taylor rule is used in a regime switching factor augmented regression framework for Yen and Dollar trades. The results are robust to different time periods.

In the third paper, I estimate a dynamic factor from the risk premium of bilateral US Dollar against 15 OECD countries, and augment macro fundamentals suggested by Taylor rule, monetary and purchasing power parity models with that factor. I find evidence of short term predictability of bilateral exchange rates between 1991 and 2012 with factor augmented macro fundamentals.

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1. IS AN IMPLIED TAYLOR RULE INTEREST RATE APPLICABLE AS A CARRY TRADE STRATEGY?

Abstract: This paper evaluates the performance of carry trade strategies with implied Taylor rule interest rate differentials and compares their performance statistics to the naive carry trade strategy with actual interest rates. Carry trade, a currency speculation strategy between high-interest rate and low-interest rate currencies, generates high payoff on average and has a possibility of crash risk. I argue that the crash risk is reduced with implied Taylor rule interest rate differentials as a trading strategy in Yen and Franc trades for the whole sample period. During the recent financial crisis, the carry trading strategies with an implied Taylor rule interest rate perform best in terms of mean returns, risk adjusted returns and downside risk.

1.1 Introduction

This paper studies the comparison between trading strategies based on actual interest rates and implied Taylor rule interest rate differentials. Taylor [1993] rules have been the dominant policy for analyzing and evaluating monetary policy since late 1980s, although no central bank exactly follows a simple Taylor rule at all times. A Taylor rule implied interest rate may be a good candidate as a trading strategy if the trading currency countries determine their nominal interest rate by a type of Taylor rule reaction function.

In this paper, I study the carry trade, a currency trading strategy in which an investor borrows low-interest-rate currencies and lends high-interest-rate currencies. The former currency is often called the funding currency and the latter is called the target currency. The strategy is profitable for an un-hedged carry trade, when the interest rate differentials are high enough to compensate exchange rate fluctuations, so the uncovered interest rate parity (UIP) is not expected to hold. According to UIP, the difference in interest rates between the two countries simply shows how much investors expect the high-interest-rate currency to depreciate against the low-interest-rate currency. Therefore under UIP the profit through interest rate differentials is offset by the exchange rate movements. In reality UIP does not hold, so traders enter into the carry trade market and pretend to make huge profits through carry trade strategies because of this market anomaly.

The profit from carry trading is the sum of interest rate differential and the forward premium between the two currencies. Since the exchange rate moves, carry trading involves exchange rate risk. The target currency may depreciate against the funding currency. In that case, the amount initially borrowed in funding currency will rise in terms of target currency, which increases the cost of borrowing. However, in the literature, many papers showed that the currencies that are at a forward premium and have low interest rates tend to depreciate, not appreciate, as the UIP predicts. Similarly other currencies that are at a forward discount and have high interest rates tend to appreciate, not depreciate. This is called the forward premium puzzle. This forward premium puzzle has been tested extensively in the literature that includes Frankel [1980], Fama [1984] and Flood and Taylor [1996]. However, in the long run it is quite difficult to reject UIP, implying that interest rate differentials are arbitraged. Chinn and Meredith [2004] confirm that UIP holds for periods longer than 5 years.

The original Taylor rule states that the federal funds rate is set as the sum of one, 1.5 times the inflation rate and 0.5 times the percentage deviation of GDP from potential GPD (output gap). This simple rule proposes the usage of short term interest that anticipates the arrangement of the interest rate in accordance with the inflation difference from the target level and the changes in production gap. Many researchers and policy makers assess the validity of Taylor rule in developed and developing countries. Clarida et al. [1998] examines the validity of the rule by using monthly data for USA, Italy, France, United Kingdom and Japan. The conclusion is that, those countries are successful in implementing Taylor rule. Kozicki [1999] finds coefficient estimates very close to the fixed coefficient proposed by Taylor [1993] for the USA. Nelson [2001] assesses the validity of Taylor rule for the United

Kingdom and he concludes that the coefficients he estimated are really close to the fixed coefficients proposed by Taylor [1993]. Osterholm [2005] finds Taylor rule is applicable for countries US, Sweden and Australia. Bhattaraii [2008] finds the applicability of Taylor rule for the countries Germany, France, Japan, the United Kingdom and US.

Why do investors not exploit Taylor rule models as trading strategies, if monetary authorities of these countries are following Taylor rule type of reaction function to determine their nominal interest rate? From the perspective of practitioner, implied Taylor rule interest rate differentials can be a better strategy to follow than actual interest rate differentials for developed countries' currencies. An implied Taylor rule interest rate can be a good candidate for a trading strategy since high inflation countries will follow tighter monetary policies longer term, which will keep their nominal, as well as real, rate higher for a long term, implying traders can exploit the interest rate differentials for a longer time between high inflation prone countries and the low inflation ones assuming that monetary authorities of these countries are following a Taylor rule type of reaction function to determine their nominal interest rate.

The predictive power of Taylor rule fundamentals in exchange rate movements in currency trading have been studied in the literature, however implied Taylor rule interest rates are not used as trading strategies. Recently, combining the failure of UIP with predictive power of fundamentals, Jorda and Taylor [2009] show that the crash risk, or negative skewness, of the carry trade can be greatly reduced using a fundamentals augmented carry trade strategy that takes into account not only interest rate differentials, but also relative Purchasing Power Parity. Li [2011] using Taylor rule fundamentals for forecasting of exchange rate, evaluates the profitability of carry trades. He finds that Taylor rule fundamentals increase the profits of carry trades in a monthly frequency in a factor augmented regression framework. He claims that since Taylor rule fundamentals have better predictive power, practitioners should take into account these fundamentals for the forecasting of exchange rate movements.

The empirical study uses time series data on exchange rates of six major currencies relative to Japanese Yen, Swiss Franc and US Dollars. For each of six currencies we executed individual currency carry trade and calculate the performance statistics of the returns. The carry trades are executed in the naive sense, meaning only interest rate differentials are used for the decision function of the investor. As an alternative strategy to carry trade with actual interest rates (benchmark model), implied Taylor rule interest rates, calculated as proposed by Taylor original formulation, are used as a trading strategy.

The results suggest that crash risk, or negative skewness, of carry trades can be reduced if the investors use implied Taylor rule interest rate differentials as a trading strategy. Taylor rule implied interest rate model for both funding and target currency performs best in Yen and Franc trades. In Dollar carry trades, the crash risk is high for the whole sample period. Risk adjusted returns are higher than the risk adjusted returns of carry trades of the benchmark model.

During the recent financial crises, our results suggest that simple carry trading strategy based on actual rates produces negative returns with negative Sharpe ratios in Yen and Franc trades whereas our proposed strategy of implied Taylor rule interest rates result in positive mean and risk adjusted returns. Given that carry trading strategies have crash risk, the inclusion of an implied Taylor rule interest rate in the trading strategy can reduce this crash risk, making this kind of currency trading strategy less risky, as well profitable during the market turmoil.

The paper organized as follows. The literature review is in section 2. Section 3 briefly describes the Taylor rule. Then in section 4, currency trading strategies are described. Section 5 evaluates the performance of carry trade strategies and compares the payoffs of different strategies of portfolio returns for different time periods. Section 6 concludes.

1.2 Related Literature

The carry trade, buying high interest currencies and selling low interest ones, is a direct consequence of the failure of UIP. The overall impression about UIP is that, it is more likely to hold in the long run than in the short run. A large body of empirical literature documents this fact [Flood and Taylor, 1996, Cheung et al., 2005, Chinn and Quayyum, 2012]. Lewis [1995] presents a survey about the excess return puzzle. By estimating US Dollar (USD)/ Deutsche Mark(DM) and USD/Japanese Yen (JPY) between 1975 and 1989 for 12 month financial instruments, he rejects UIP. Cheung et al. [2005] investigate both 12 month and 5 year term interest rates and their relation with exchange rate movements for the US, Canada, Germany and the UK over the period of 1980-2000. The authors find a negative and significant coefficient of UIP for the short term interest rate. However, the coefficient of UIP has a correct sign and is close to unity for long term bonds. Recently Chinn and Quayyum [2012] examine the failure of UIP for a sample that includes the financial crises of 2007 and find that UIP holds better in the long term than in the short term.

Meese and Rogoff [1983] show that economic models of exchange rates do not outperform the random walk forecast. On the other hand, the recent literature addresses that exchange rate determination is not inconsistent with the macroeconomic fundamentals if the monetary policy is taken to be endogenous with an interest rate feedback rule. Taylor rule models offer a different explanation to the exchange rate determination. The recent work for Taylor rule models include Engel et al. [2007], Molodtsova and Papell [2009]. Engel et al. [2007] use uncovered interest rate parity directly to produce exchange rate forecasts. They replace the interest rate differentials in the UIP with the interest rate differentials implied by the Taylor rule. Molodtsova and Papell [2009] use the variables that enter the Taylor rule to evaluate exchange rate forecast and find that by assessing the out-of-sample performance of 12 currencies, the predictability of these models with Taylor rule fundamentals are stronger for 8 out of 12 currencies.

Taylor rule fundamentals augmented exchange rate models have stronger predictability power than the random walk in the short run. Li [2011] evaluates exchange rate models with Taylor rule fundamentals from the perspective of the carry trader. The author claims that if the macro fundamental models of exchange rates including Taylor rule fundamentals do better than the random walk, this predictability power of exchange rate models may increase the profitability of carry trade strategies. He finds that carry trades with economic fundamentals have lower Sharpe ratios and better downside risk when the economic fundamentals are used in a factor augmented regression. The results are robust for different time periods and after controlling for the transaction cost.

In this paper, I examine whether Taylor rule fundamentals can be used as a trading strategy and increase the performance of the carry trading in terms of profitability and risk. The reason why implied Taylor rule interest rates may be a good candidate for a trading strategy is related to the predictability power of Taylor rule fundamentals in exchange rate movements. In this perspective, Rosenberg [2008] claims that the Taylor rule can also provide some explanation for the reason why carry trade strategies have permanent excess returns over time. The author states high inflation countries urge nominal interest rates higher in order to bring inflation under control, so that high nominal interest rates result in high real interest rates. The Taylor rule fits in the carry trade excess returns since real interest rate differential is key to the carry trade performance. The countries with high inflation and interest rate should keep their real rates higher than low interest rate countries in order to show their credibility for fighting high inflation. These inflation prone, high interest rate countries should sustain tight monetary policies longer than low interest rate countries. The interest rate policy will be adjusted gradually in both high and low interest rate countries, consequently real interest rate differentials should adjust step by step in response to inflation and output gaps. This gradual adjustment of real rate spreads will result in persistent real exchange rate changes overtime which in turn will lead to persistent positive excess returns between high and low interest rate countries.

The main issue in the carry trade market is to identify the nature of the risk and determine whether this risk is associated with the excess returns in this market. Brunnermeier et al. [2008] show that exchange rate movements of carry trades are negatively skewed and therefore carry trades are subject to crash risk. The authors claim that when there is a change in the availability of funding liquidity, for instance a reduction, there is a rapid unwinding of the trader's position, which leads to crashes in exchange rates. To decrease this risk, Burnside et al. [2007] propose diversification, whereas Jorda and Taylor [2009] propose a strategy based on fundamentals. Burnside et al. [2007] find that an equally weighted portfolio is less skewed than a currency specific carry trade strategy.

Following a fundamentals augmented carry trade strategy, Jorda and Taylor [2009] show that the crash risk of carry trades can be reduced substantially. They find that nominal interest differentials can help predict exchange rate movements in the short run and the forecast of exchange rates can be enhanced by the inclusion purchasing power parity (PPP). The deviation from the PPP helps to forecast the movements of the nominal exchange rate as the real exchange rate adjusts its long run level. The authors show that there is a profitable trading strategy which includes a forecast that the real exchange rate will return its long run level when its deviations from the mean are large.

Crash risk in carry trade strategies may be explained, alternatively, as compensations for the risk of rare disasters with significant loses. This problem is known in the literature as Peso Problem. Burnside et al. [2011] find that large positive payoffs of an equally weighted portfolio are not correlated with standard risk factors and cannot be explained by stochastic discount factors. They argue these large payoffs should be a compensation for the negative payoffs of peso event risk.

In this paper, I will not try to find out the reasons for excess returns from carry trade strategies or try to identify the sources of the prevailing risk in the currency carry trading strategies. However, I will examine whether it is better to use a trading strategy based on Taylor rule fundamentals.

1.3 Taylor Rule

The rule that proposes the usage of short term interest that anticipates the arrangement of the interest rate in accordance with the inflation difference from the target level and the changes in production gap is the Taylor rule.

This paper assesses the performance of Taylor rule implied interest rates as a carry trade strategy. Implied Taylor rule interest rates of eight developed countries are calculated and then used in the execution of carry trades.

Following Taylor [1993], central banks use the reaction function for monetary policy:

$$i_t = \pi_t + \theta(\pi_t - \tilde{\pi}) + \delta y_t + \tilde{r} \tag{1.1}$$

where i_t is the federal funds rate, π_t is the inflation rate, $\tilde{\pi}$ is the target level of inflation, y_t is the output gap and $\tilde{r}$ is the equilibrium level of the real interest rate.

The parameters $\tilde{\pi}$ and $\tilde{r}$ are constant and can be summed up to form a single term, $\mu = \tilde{r} - \theta\tilde{\pi}$. Therefore equation (1.1) can be written as:

$$i_t = \mu + \varphi\pi_t + \delta y_t \tag{1.2}$$

where $\varphi = 1 + \theta$. Assuming that the inflation and output gap have an equal weight of 0.5 in the central banks reaction function and the equilibrium interest and the inflation rates are two percent, the reaction function becomes:

$$i_t = 1 + 1.5\pi_t + 0.5y_t \tag{1.3}$$

1.4 Designing Carry Trade Strategies

Carry trading has become one of the major currency trading strategies since mid 1990s. The currency carry trade is designed to exploit the failure of UIP and consist of borrowing a low interest rate currency and lending a high interest rate currency.

The payoff to an investment in the foreign currency financed by borrowing in the domestic currency is denoted by:

$$x_{t+1} = i_t^\star - i_t + \Delta e_{t+1} \tag{1.4}$$

where e_t is the logarithm of nominal exchange rate (units of foreign currency per domestic currency) , i_t is the interest rate and $i_t^\star$ is the foreign interest rate. Increase in the change in the nominal exchange rate is the appreciation of the foreign currency (i.e., Δe is the change in yen exchange rate). Equation (1.4) is the excess return that is gained from carry trading when UIP is violated. If UIP holds, this excess return will not be forecasted and $E_t(x_{t+1}) = 0$. Therefore, x can be considered as an abnormal return to the carry trade strategy where the foreign currency is the investment currency and Japanese Yen, Swiss Franc and US Dollars are the funding currencies.

In this paper, a carry trade is defined as a binary trading strategy that is based on expected returns. There is a trade between the funding currency country and the target currency country if the interest rate differential between the target country and funding country is positive and the expected return is positive as predicted by the model. The execution of carry trade is denoted by $\hat{b}_{i,t} = 1$:

$$\hat{b}_{i,t} = \begin{cases} 1 & \text{if } i^{\star}_{i,t} - i_{i,t} + E_t(\Delta e_{i,t+1}) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1.5}$$

Consider the case where e_t follows a random walk:

$$E_t(\Delta e_{t+1}) = 0 \tag{1.6}$$

Under the random walk model, the carry trade, in its simplest form, depends solely on the interest rate differentials. This carry trade is called *naive* since it is unrelated to fundamentals other than the interest rate. This naive carry trade with actual rates is the benchmark model (Model 1).

I propose three alternative carry trade strategies . The first one replaces actual interest rate differentials with implied Taylor rule interest rates (Model 2):

$$\hat{b}_{i,t} = \begin{cases} 1 & \text{if } i^{\star implied}_{i,t} - i^{implied}_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1.7}$$

The second strategy employs the difference between the actual interest rate for the target country and implied Taylor rule interest rate for the funding country (Model 3):

$$\hat{b}_{i,t} = \begin{cases} 1 & \text{if } i^{\star}_{i,t} - i^{implied}_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1.8}$$

For this alternative mixed strategy, I am assuming that only the funding currency country follows Taylor rule reaction function for the interest rate determination. The third strategy, on the contrary, assumes only the target currency country follows Taylor rule (Model 4):

$$\hat{b}_{i,t} = \begin{cases} 1 & \text{if } i^{\star implied}_{i,t} - i_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1.9}$$

For one unit of borrowed investment currency, the returns for the different specifications of a carry trade are computed with the realized exchange rates:

$$x_{i,t} = \begin{cases} i^{\star}_{i,t} - i_{i,t} + \Delta e_{i,t+1} & \text{if } \hat{b}_{i,t} = 1 \\ 0 & \text{if } \hat{b}_{i,t} = 0 \end{cases} \tag{1.10}$$

where x_t is the return from binary trading strategy at time t.

1.5 Empirical Results

1.5.1 Data

The empirical analysis uses monthly data. The sample period includes the month end daily exchange rate data from FRED between January 1971 and January 2012 for pairs of the eight major currencies: The Australian Dollar (AUD), the Canadian Dollar (CAD), the Norwegian Krone, the British Pound (GBP), the New Zealand Dollar (NZD), the Japanese Yen (JPY), the Swiss Franc (CHF), and the US Dollar (USD). Exchange rates of the target currency measured in the funding currency are computed as cross rates from their original dollar values. Of the eight currencies, six CHF and JPY cross rates are formed and five USD exchange rates are used. The data for macroeconomic fundamentals are constructed from the International Financial Statistics (IFS) and the OECD Main Economic Indicators (MEI) databases. The seasonally adjusted Industrial Production Index is used for countries' GDP, since GDP data is only available at quarterly frequency[1]. The inflation rate is calculated from the Consumer Price Index and it is the annual rate measured as the 12 month difference of the CPI[2]. The Money Market Rate is used for the monthly interest rate, which central banks set every period.

The output gap calculations are based on potential output. The output gap is

[1] The industrial production series for Australia, New Zealand and Switzerland and the CPI series for Australia and New Zealand are only available at quarterly frequency. They are transformed into monthly frequency data with the quadratic-match average option in E-views 6.0

[2] The Taylor rule estimation for U.S depends on forward looking nature of policymaking. Therefore, using ex-post realized values of inflation, such as in CGG or Greenbook forecast such as in Orphanides [2001] will be appropriate. However, ex-post data and central bank forecasts are not available for other countries; we will use actual inflation rates.

calculated as percentage deviations of actual output from a quadratic time trend, since there is no consensus about which definition of output is used by central banks. We use quasi-real time data in the output gap estimation. The quasi-real time estimate is constructed in two steps. The first step begins with taking the final vintage of the output series with the observations up to, and including, $t-1$ to compute the quasi-real time estimate for period t. Then, in each period, the sample period is extended by one observation and OLS is used for de-trending. In the second step, the first available estimate of the output gap at each point in time that was constructed in the first step is collected. The final sequence of the output gap series will be the quasi-real time estimation of output gap data[3].

1.5.2 Statistical Evaluations of Carry Trades

The carry trades are executed with Japanese Yen, Swiss Franc, and US dollars as funding currencies. For Japanese Yen, six carry trades are executed with Australia, Canada, England, New Zealand, Norway, and the US as target currency countries. For Switzerland, six carry trades are executed with all countries except Japan, and for the US five carry trades are executed excluding Japan and Switzerland.

Performance statistics of carry trade returns include *Mean Return*, *Standard Deviation*, *Sharpe Ratio*, *Return Skewness*, *Return Kurtosis* and *Maximum Drawdown* of returns from the period 1986:1 to 2012:01.

[3] Policy makers estimate output gaps using the data available to them at the time they are making decision. However, real time data is not available for most of the countries throughout the period that we are studying. Orphanides and Simon van [2002] finds the correlation between real time and quasi-real time output gap is high. Thus, using quasi-real time output gap will be appropriate. The output gap for the first series is calculated from 1971:1 to 1980:1.

The *Sharpe Ratio* is calculated as a ratio of returns normalized by the standard error. The Sharpe ratio is good for evaluating how well the return of an asset compensates the investor for the risk taken. A portfolio, or a return may have high mean returns; however it is better when it does not have additional risk.

The exchange rate movements are not symmetric. This asymmetry is associated with a crash risk. Return *Skewness* and *Kurtosis* are used as measures of the risk of large amounts of losses. Skewness shows the risk of large losses to carry traders in the case of a market crash and kurtosis shows whether these changes are abrupt or not. Large negative skewness means that there is higher probability of these large losses, while large kurtosis shows that these changes are fast. *Maximum Drawdown* measures the largest single drop from the peak to bottom before a new peak is reached. Large maximum drawdowns indicate higher risk.

1.5.3 Performance Statistics of Carry Trades

The sample period goes 1986 to 2011. I choose this period, since it is emphasized that the Taylor rule is followed by the central banks of the countries of interest between the early 1990s and the early 2000s in the literature.

In practice an investor can apply the carry trade to individual currencies or to portfolios of currencies. Burnside et al. [2011] claims that the risk in carry trade strategies is reduced with diversification across different currencies. They claim that the gains from diversification are large. This paper takes the perspective of an individual currency trader and examines whether this trader gains more by diversifying carry trades across different currencies. We consider equally weighted carry trade strategies where Yen, Franc and Dollar positions give equal weight at each point in time to all the currencies for which x_t is not equal to zero.

The performance statistics of equally weighted portfolio returns for Japanese Yen are shown in Table 1 Panel A. Carry trade strategies with implied Taylor rule interest rate differentials have identical mean returns and lower standard errors.

One of the important measures of return per unit of risk is the Sharpe ratio. It is the ratio of mean excess return per unit of volatility. Although mean excess returns for carry trade strategies are high, the Sharpe ratios of carry trade strategies are usually small, since the volatility for those returns is high. It is shown that carry trade strategies with both actual interest rates and implied Taylor rule interest rates (Model 2) have small Sharpe ratios (Table 1). The standard errors for the Taylor rule models are lower than the benchmark model (Model 1); and the mean returns for Taylor rule strategies are similar to the naive strategy with actual rates (Model 1). This results in larger Sharpe ratios for the Taylor rule models (Model 2, Model 3, and Model 4).

While the Sharpe ratios suggest that all carry trade strategies do not have attractive risk return profiles, they do not account for the crash risk or downside risk, which is also crucial for the trader. The maximum drawdown measures the largest possible loss, whereas skewness measures the possibility of large losses or gains during the market crashes. Table 1 shows that all carry trade returns are negatively skewed and have excess kurtosis, implying carry trade returns have a crash risk and fat tails.

The recent literature emphasizes the importance of market wide distress in carry trading strategies. Carry traders have significant losses during the periods of market distress. This is the main reason why the returns of carry trades are negatively skewed. The results show that the negative skewness is improved when the traders use implied Taylor rule interest rate as a trading strategy for both the funding and target currencies in Table 1 (Model 2). The skewness of the returns is improved more than 50 percent.

Table 1 Panel B shows the performance statistics of carry trade returns with the Swiss Franc as the funding currency. The results are similar to the case where Japanese Yen used as funding currency. Carry trade strategies with implied Taylor rule interest rate differentials have lower standard errors and similar mean returns. The crash risk for the carry trades with actual interest rate is improved with the trading strategies using implied Taylor rule interest rate for both the funding and target currency countries (Model 2).

The payoffs in Swiss Franc trades have high probability of large losses in a case of market crash. The portfolio returns with all models are negatively skewed. The implementation of Taylor rule interest rates in both the funding and target currency countries as a trading strategy improves the downside risk: Table 1 (Panel B) shows skewness is improved 30 percent and the maximum drawdown drops 2 percent.

Table 1, Panel C show the performance of Dollar carry trades. The results are similar to Yen and Franc trades. Taylor rule models have identical mean returns. The trade strategy with implied interest rates for both the funding and target currency has a larger Sharpe ratio, lower standard error and lower maximum drawdown (Model

2).

The results with the implied Taylor rule interest rate model (Model 2) display a clear pattern. For all funding currencies, the mean return is similiar to the benchmark model, while standard errors are lower. Model 2 performs relatively better in terms of risk adjusted returns, however the Sharpe ratios are not large enough for an investor to invest in a carry trade. In Yen and Franc trades, this model has better skewness and kurtosis than the naive model with actual rates. The model using implied interest rates in the funding currency (Model 3) is similiar to the benchmark model in terms of mean retun, standard error and Sharpe ratio. This model performs better in terms of downside risk for Yen and Franc trades.

I argue that, with the implied Taylor rule interest rate as a trading, carry trade is as profitable as the benchmark model. In Yen and Franc trades, the crash risk of carry trading improves with implemented interest rate models. The results are similar for Dollar trades in terms of mean return and the Sharpe ratio, but not in terms of downside risk.

1.5.4 Performance Statistics of Carry Trades Before and During the Recent Financial Crisis

The performance statistics of carry trade returns before the financial crisis are presented in Table 2. Yen and Franc trades have similar results. For the benchmark model, mean returns are higher, standard errors are lower, and the Sharpe ratio is larger. Implied Taylor rule interest rates for both the funding and target currencies as a strategy does not perform as well as the benchmark model in mean returns and risk adjusted returns.

Dollar trades follow a relatively different pattern than Yen and Franc trades during this period.The Taylor rule implied interest rate strategy performs best when the Taylor rule is implemented for both funding and target currency countries' interest rates (Model 2). The Sharpe ratio exceeds one, skewness is positive, and maximum drawdown decreases to six percent.

The Taylor rule is a policy that is designed to respond both to the deviations of inflation from its target level and the output from its natural level. During the financial crisis of 2008, when the federal funds rate hit the zero lower bound, it was assumed that the Taylor rule was no longer a relevant policy for Fed. Thus, it would be expected that carry trade strategies with implied Taylor rule interest rates may not perform as well as the naive model with actual rates during this period.

The 2008-2009 financial crisis is a telling example of a severe period of market stress or tail event. The carry traders have high probability of crash risk in this period. The performance statistics of portfolios are presented in Table 3. For our benchmark model, mean returns are negative, implying a negative Sharpe ratio for Yen and Franc trades. The payoffs to portfolios are negatively skewed except for Franc trades. The returns have fat tails for all funding currencies.

The Taylor rule implied interest rate strategy for both funding and target currency surprisingly performs well in terms of mean returns, downside risk and risk adjusted returns during the financial crisis except for Dollar trades (Model 2). The mean returns of these strategies are positive and higher than our benchmark model. The returns for Model 2 are positively skewed and do not have fat tails. For Dollar trades, the best performance comes with the strategy where a Taylor rule implied interest rate is followed by the funding currency country, but not followed by the target currency country (Model 3). In this case, Panel C of Table 3, the payoffs to portfolio returns with US Dollar as funding currency are two percent higher than the benchmark model. This is interesting since, contrary to arguments that the Fed does not follow a Taylor rule during the financial crisis, the payoffs to portfolio with US Dollar as funding currency perform better than the benchmark model.

Implied Taylor rule interest rate differentials are successful as a carry trading strategy compared to our benchmark model during the financial crisis and before the financial crisis for Dollar trades. However, their performance is not as good as the benchmark model for Yen and Franc trades before the financial crisis. The returns have a lower Sharpe Ratio, due to lower mean returns and they are negatively skewed and have fat tails.

1.6 Conclusion

This paper provides evidence of applicability of implied Taylor rule interest rates as currency trading strategies. We design alternative carry trading strategies with interest rate differentials implied by the Taylor rule, and document that these alternative trading strategies are as profitable as the naive carry trade strategy with actual rates. These strategies are performing better than the benchmark model in terms of risk adjusted returns and downside risk in Franc and Yen trades. The crash risk of Japanese Yen carry trades are reduced by 50 percent. In case of Franc trades, crash risk is reduced by 30 percent. In Dollar trades, the implied Taylor rule interest rate model performs well except for the case where the implied Taylor rule interest rate strategy is followed by only the target currency country (Model 4). This result is parallel to the argument that the US follows Taylor rule type of reaction function for determining its interest rate during the sample period.

While we provide returns with better performance in terms of downside risk and risk adjusted returns with implied Taylor rule interest rates in Yen and Franc trades, my analysis does not find profitable payoffs to these trading strategies when we consider the period before the financial crisis of 2008-2009. Dollar trades follow a different pattern and have identical mean returns to the benchmark model, but better risk adjusted returns with Taylor rule implied interest rates. The Sharpe ratio of Model 2 exceeds one during that period.

The recent literature emphasizes the importance of market wide distress in carry trade strategies. Carry traders have significant losses during periods of market distress. During the recent crisis, the mean returns and adjusted risk returns are negative for the benchmark model. The returns have negative skewness and fat tails. Although the 2008-2009 financial crisis was clearly not a good period for carry trade investors, the implied Taylor rule interest rate model (Model 2) for both funding and target currencies performs surprisingly well (see Table 3). Mean returns, the Sharpe ratio and skewness turn into positive numbers. These results hold for all funding currencies and the crash risk during the periods of market distress can be decreased with the adoption of an implied Taylor rule interest rate as a carry trading strategy.

Overall, the results are consistent with the view that returns to carry trade have high mean returns and small Sharpe ratios with a possibility of crash risk. This crash risk is reduced with the Taylor rule implied interest rate trading strategies for the whole sample in Yen and Franc trades. My finding that trading strategies with implied Taylor rule interest rates have better performance in terms of crash risk, would be helpful to the practitioner, since these trading strategies are as profitable, on average, as the benchmark model and they provide better statistical performance in terms of downside risk, especially during market distress.

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Tab. 1.1: PERFORMANCE STATISTICS OF CARRY TRADE RETURNS (1986-2012)

	Actual Interest Rates (Model1)	Implied Interest Rates (Model2)	Implied Rate Funding (Model3)	Implied Rate Target (Model4)
Panel A: Japanese Yen is the Funding Currency				
Mean Return	0.02	0.02	0.02	0.02
Standard Error	0.09	0.08	0.08	0.08
Sharpe Ratio	0.18	0.24	0.20	0.23
Skewness	-1.02	-0.35	-0.55	-1.31
Kurtosis	3.70	1.69	1.62	6.46
Max. Drawdown	0.38	0.39	0.41	0.35
Panel B: Swiss Franc is the Funding Currency				
Mean Return	0.02	0.02	0.02	0.02
Standard Error	0.07	0.06	0.07	0.06
Sharpe Ratio	0.27	0.37	0.26	0.30
Skewness	-0.31	-0.21	-0.22	-0.45
Kurtosis	1.42	1.95	1.24	2.78
Max. Drawdown	0.27	0.22	0.24	0.25
Panel C: US Dollar is the Funding Currency				
Mean Return	0.04	0.04	0.04	0.02
Standard Error	0.06	0.05	0.06	0.05
Sharpe Ratio	0.66	0.73	0.74	0.44
Skewness	-1.02	-1.78	-1.07	-2.34
Kurtosis	6.72	16.39	8.14	17.90
Max. Drawdown	0.27	0.24	0.26	0.25

[1] The sample period is from 1986:01 to 2012:01. The total number of observations is 312.
[2] The Sharpe Ratio is the mean returns divided by standard deviations.
[3] All returns are annualized.
[4] Equally weighted portfolio is calculated as giving equal weight to each currency trade in time (Funding currencies are: the Australian Dollar, Canadian Dollar, UK Pound, Norwegian Krone ,New Zealand Dollar, US Dollar for Panel A and B).

Tab. 1.2: PERFORMANCE STATISTICS OF CARRY TRADE RETURNS (1986-2007)

	Actual Interest Rates (Model1)	Implied Interest Rates (Model2)	Implied Rate Funding (Model3)	Implied Rate Target (Model4)
Panel A: Japanese Yen is the Funding Currency				
Mean Return	0.03	0.02	0.02	0.04
Standard Error	0.09	0.08	0.08	0.08
Sharpe Ratio	0.39	0.25	0.29	0.52
Skewness	-0.54	-0.46	-0.49	-0.52
Kurtosis	1.06	1.43	1.14	1.89
Max. Drawdown	0.38	0.39	0.41	0.25
Panel B: Swiss Franc is the Funding Currency				
Mean Return	0.03	0.02	0.03	0.03
Standard Error	0.07	0.06	0.07	0.06
Sharpe Ratio	0.43	0.37	0.34	0.48
Skewness	-0.43	-0.44	-0.40	-0.52
Kurtosis	0.67	1.03	0.33	1.87
Max. Drawdown	0.16	0.22	0.24	0.18
Panel C: US Dollar is the Funding Currency				
Mean Return	0.04	0.04	0.04	0.03
Standard Error	0.05	0.03	0.05	0.04
Sharpe Ratio	0.89	1.12	0.95	0.89
Skewness	0.22	0.43	0.32	0.15
Kurtosis	0.64	1.46	1.32	1.14
Max. Drawdown	0.14	0.06	0.11	0.11

[1] The sample period is from 1986:01 to 2007:01. The total number of observations is 252 .
[2] The Sharpe Ratio is the mean returns divided by standard deviations.
[3] All returns are annualized.
[4] Equally weighted portfolio is calculated as giving equal weight to each currency trade in time (Funding currencies are: the Australian Dollar, Canadian Dollar, UK Pound, Norwegian Krone ,New Zealand Dollar, US Dollar for Panel A and B).

Tab. 1.3: PERFORMANCE STATISTICS OF CARRY TRADE RETURNS (2007-2011)

	Actual Interest Rates (Model1)	Implied Interest Rates (Model2)	Implied Rate Funding (Model3)	Implied Rate Target (Model4)
Panel A: Japanese Yen is the Funding Currency				
Mean Return	-0.05	0.01	-0.01	- 0.07
Standard Error	0.13	0.06	0.09	0.10
Sharpe Ratio	-0.40	0.22	-0.12	-0.62
Skewness	-1.34	0.65	-0.82	-2.41
Kurtosis	3.89	3.20	3.35	9.41
Max. Drawdown	0.37	0.09	0.23	0.35
Panel B: Swiss Franc is the Funding Currency				
Mean Return	-0.02	0.02	-0.01	-0.02
Standard Error	0.09	0.06	0.08	0.07
Sharpe Ratio	-0.22	0.34	-0.08	-0.33
Skewness	0.10	1.18	0.46	-0.14
Kurtosis	2.19	8.23	4.59	4.87
Max. Drawdown	0.27	0.13	0.21	0.25
Panel C: US Dollar is the Funding Currency				
Mean Return	0.02	0.02	0.04	-0.03
Standard Error	0.09	0.09	0.09	0.07
Sharpe Ratio	0.25	0.26	0.44	-0.49
Skewness	-1.46	-1.73	-1.46	-3.34
Kurtosis	4.26	6.80	4.39	14.29
Max. Drawdown	0.27	0.24	0.26	0.25

[1] The sample period is from 1986:01 to 2007:01. The total number of observations is 60 .
[2] The Sharpe Ratio is the mean returns divided by standard deviations.
[3] All returns are annualized.
[4] Equally weighted portfolio is calculated as giving equal weight to each currency trade in time (Funding currencies are: the Australian Dollar, Canadian Dollar, UK Pound, Norwegian Krone ,New Zealand Dollar, US Dollar for Panel A and B).

2. CARRY TRADE STRATEGIES WITH TAYLOR RULE FUNDAMENTALS AND MARKOV SWITCHING DYNAMIC FACTOR

Abstract: This paper evaluates the performance of carry trade strategies with Taylor rule fundamentals in a Markov switching dynamic factor augmented regression framework and compares the performance statistics with the benchmark model of a random walk. We make simulations with the Japanese Yen, Swiss Franc and US Dollar as funding currencies against six target currencies. Carry trade, a currency speculation strategy between the high-interest rate and low-interest rate currencies, generates high payoffs on average but has a possibility of crash risk. We argue that risk adjusted returns, mean returns and down-side risk perform best when the Taylor rule is used in a regime switching factor augmented regression framework for Yen and Dollar trades. The results are robust to different time periods.

2.1 Introduction

Persistent interest differentials and low exchange rate volatility have underpinned significant cross-currency positioning in recent years. One of the basic principles in finance is if investors have zero-cost investment, the expected return for that investment should be zero; otherwise there will be an arbitrage opportunity. The carry trade is an example of zero-cost investment, where the investors borrow from low-interest rate currencies and invest in high interest rate currencies in order to profit from the interest rate differentials. Carry trade is profitable contrary to economic and financial theories. Since traders invest in risk-free deposits, the only source of risk comes from exchange rate volatility.

This paper studies currency carry trade strategies based on macro fundamentals and regime switching factor models in exchange rate forecasting. Our starting point is to forecast exchange rates with macro fundamentals, focusing on Taylor rule models. Recent studies show that Taylor rule fundamentals have predictive power in exchange rate determination [Molodtsova and Papell, 2009]. We utilize factor models in exchange rate forecasting in order to capture co-movements of the excess returns of carry trades, consequently the factor that is derived from the excess return is used as an explantory variable in the forecasting equation of the exchange rate. The factor is also subject to regime switches to capture the asymmetries involved in exchange rate movements.

According to uncovered interest parity (UIP), the difference in interest rates between the two countries simply shows how much investors expect the high-interest-rate currency to depreciate against the low-interest-rate currency. If UIP holds, the carry trade strategy does not work, as higher yielding currencies will depreciate against lower yielding ones at a rate equal to the interest differential, equalizing expected returns for a given currency. The interest rate differential is expected to be fully offset by currency movements, neutralizing any profitable arbitrage opportunities from carry trading.

A large body of empirical literature documents that UIP fails at short and medium horizons but holds in the long term [Flood and Taylor, 1996, Chinn and Meredith, 2004]. Recently, the failure of UIP in short and medium horizons is examined to include the financial turmoil of 2007 [Chinn and Quayyum, 2012] . Indeed, in the rest of the cases the relationship is precisely the opposite of that predicted by UIP: currencies with high interest rate tend to appreciate, not depreciate, while other currencies with low interest rates tend to depreciate, not appreciate. This failure of UIP is so well established that the phenomenon is called the forward premium puzzle. This forward premium puzzle has been tested by an extensive literature that includes Frankel [1980] and Fama [1984].

Carry trading is profitable for an unhedged currency strategy, when the interest rate differentials are high enough to compensate for exchange rate fluctuations. The profit from the carry trade is the sum of the interest rate differential and the forward premium between the two currencies. Carry trade involves risk due to potential exchange rate movements. In fact, the high yield currency may depreciate against the low yield currency, increasing the amount initially borrowed in the funding currency in terms of target currency, and driving up the cost of borrowing. Since exchange rate movements are not offset by the interest rate differentials between the countries, carry traders tend to make huge profits.

It has been known that carry trades are profitable on average since the seminal paper by Meese and Rogoff [1983], who argue that the best predictor of next month's exchange rate is today's exchange rate. Thus, investors can make money on average by borrowing in currencies with low interest rates and investing in currencies with high interest rates. With the random walk model of exchange rates, the profit of carry trade comes from the yield spreads.

Even though Meese and Rogoff [1983] show that economic models of exchange rates do not outperform the random walk forecast, many studies show the predictive ability of macro fundamentals for currency movements. Fundamental based models performed well in exchange rate forecasting during the 1980s and 1990s, however, their predictive ability declined with the availability of new data on exchange rates from the 1990s and 2000s [McGrevy et al., 2012]. Earlier research focused on the PPP and monetary approach in exchange rate forecasting, and recent studies have success in the prediction of exchange rate movements using the endogenity of monetary policy with interest rate feedback rules such as Taylor rules [Molodtsova and Papell, 2009].

While the predictive power of Taylor rule and other macro fundamentals in exchange rate movements has been studied in the literature, these macro fundamentals and their predictive powers are not emphasized much as currency trading strategies.

Jorda and Taylor [2009] show that the crash risk, or negative skewness, of the carry trade can be greatly reduced using fundamentals augmented carry trade strategies that take into account not only interest rate differentials, but also relative Purchasing Power Parity. Li [2011] evaluates the profitability of the carry trades using Taylor rule fundamentals in exchange rate forecasting. He claims factor augmented Taylor rule fundamentals increase the profits of carry trade in a monthly frequency.

Our argument comes from the claim that excess returns from currency trading are empirically characterized by a regime switching dynamic factor model. The dynamic factor that is derived from the risk premium summarizes the comovements between the excess returns. This factor is subject to regime switches in order to capture asymmetries in the exchange rate movements. Two ideas, nonlinearities in exchange rates and an unobservable common component in the macro data, are the fundamental elements of Engel and Hamilton [1990] and Stock and Watson [1989, 1993], respectively. Stock and Watson [1989] developed a model where the factors are extracted from the co-movements of various economic activities in order to obtain an alternative index to the Department of Commerce indicators. These factors summarize the information contained in a large set of predictors. Engel and Hamilton [1990] take into account asymmetries in exchange rates by assuming a two state Markov switching random walk model.

This paper estimates a Markov switching dynamic factor model where the factor is derived from the excess carry trade returns by maximizing its likelihood function. We utilize the methods proposed by Kim and Nelson in order to estimate the unobserved regime switching factor. Chauvet [1998] popularized the use of dynamic factors with

Markov switching to characterize business cycles, however there is no paper in the literature that utilizes the nonlinear factor models to characterize the risk premium of currency trading. The goal in building a Markov switching dynamic factor is to capture both the nonlinearities in the currency market and the co-movements in the excess returns of the currency carry trading. The information extracted from the risk premium has the potential to increase the forecasting ability of macro fundamentals in exchange rate determination.

Our empirical study uses time series data on the exchange rates of six major currencies against the Japanese Yen, Swiss Franc and five major currencies against the US Dollar. For each of the six currencies, we generate equally weighted portfolios and calculate the performance statistics of the returns. Our benchmark model is the naive carry trade model. The carry trades are executed in the naive sense, implying the investor's decision to execute carry trade depends on only interest rate differentials. Alternative strategies to the naive strategy are the models incorporating macro fundamentals and/or estimated factors in exchange rate forecasting. We have a total of seven alternative trading strategies that are simulated for the out of sample forecasting of the exchange rates.

Our empirical findings suggest that the mean returns, risk adjusted returns, downside risk, or negative skewness and maximum drawdown, of the carry trades can be improved if the investors use Taylor rule fundamentals that are augmented with a regime switching dynamic factor. This result holds for both Yen and Dollar carry trades. In Franc trades, Taylor rule fundamentals perform better than other models in the simulation. Taylor rule fundamentals model with a Markov switching factor also boosts the profit of carry trades in Dollar trades during the financial crisis of 2007. The profits of Dollar trades increase by 2%, implying Markov switching factor augmented Taylor rule fundamentals model also performs better in abnormal times.

Our results have important implications for the carry trade investors. Given that carry trade strategies are profitable, some authors, notably Brunnermeier et al. [2008], have remarked that these strategies have crash risk due to exchange rate volatility. Using both Taylor rule fundamentals and Markov switching factor in exchange rate forecasting not only increases the profit, but can reduce the risk of carry trading.

The paper is organized as follows. We review the related literature in section 2. In section 3, we explain macro fundamentals augmented carry trade strategies. In section 4, we describe the model that characterizes the risk premium. In section 5, we explain the design of carry trade strategies. Section 6 evaluates the performance of the carry trade strategies, and compares the payoffs of different strategies of portfolio returns for the different time periods. Section 7 concludes.

2.2 Related Literature

The original academic literature claims that macroeconomic variables offer little help in exchange rate forecasting. Meese and Rogoff [1983] show that economic models of exchange rates do not outperform the random walk forecast. Frankel and K. Rose [1994], based on a survey, found that the driftless random walk explains exchange rate movements better than standard models with macroeconomic fundamentals. Cheung et al. [2005] find that none of the macro fundamental models used in 1990s such as PPP fundamentals, sticky price monetary, productivity differential, uncovered interest rate parity and composite model of fundamentals can be successfully used by examining five developed countries' currency markets.

Exchange rate determination can be consistent with macroeconomic fundamentals when monetary policy is taken to be endogenous with an interest rate feedback rule. Taylor rule models offer a different explanation to the exchange rate determination. Engel and West [2005], using Taylor rule model as an example of present values, state that if the fundamentals have an I(1) process and the discount factor is near one then the exchange rate will nearly follow a random walk. Engel and West [2006] specify the monetary policy in a two country perspective and construct a model based real exchange rate where the real exchange rate is defined as the deviation of the nominal exchange rate from the Purchasing Power Parity. Model based real exchange rate is determined by the set of fundamentals that include country differentials in the deviation of inflation from the target level as well as the output gap. They find positive correlation between the model based and the actual dollar-mark real exchange rate to be around 30 percent. Mark [2009] shows that linking the real dollar-mark exchange rate to Taylor rule fundamentals may provide a solution to the exchange rate puzzle. Engel, Mark and West [2007] use uncovered interest rate parity directly to produce exchange rate forecast. They replace the interest rate differentials in the UIP by the interest rate differentials implied by Taylor rule, whereas Molodtsova and Papell [2009] used the variables that enter Taylor rule to evaluate the exchange rate forecast. Molodtsova and Papell [2009] find out that by assessing the out of sample performance of 12 currencies, the predictability of these models with Taylor rule fundamentals are stronger for 8 out of 12 currencies.

Taylor rule fundamentals augmented exchange rate models have stronger predictability power than a random walk in the short run. Li [2011] evaluates exchange rate models with Taylor rule fundamentals from the perspective of the carry trader. The author claims that if the macro fundamental models of exchange rate including Taylor rule fundamentals do better than a random walk, this predictability power of exchange rate models may increase the profitability of carry trade strategies. He finds that carry trade models, using economic fundamentals in a factor augmented regression framework, have lower Sharpe Ratio and better downside risk. The results are robust to different time periods.

Jorda and Taylor [2009] show that the crash risk of the carry trade can be reduced substantially by following macro fundamentals augmented carry trade strategies. They find that the nominal interest differential can help to predict exchange rate movements in the short run, but the forecast of exchange rates can be enhanced by including purchasing power parity (PPP). The deviation from PPP helps to forecast movements of the nominal exchange rate as the real exchange rate adjusts to its long run level. The authors show that there is a profitable trading strategy which includes a forecast that real exchange rate will return its long run level when its deviations from the mean are large.

A very large literature has found that factor models do well at forecasting basic macro variables. Stock and Watson [1989] extract factors from the comovements of various components of economic activity in order to form an alternative index to the Department of Commerce indicators. Stock and Watson [2002] apply the factor models to the analysis of large data sets, where each of a large set of variables is split into a common component, driven by unobservable factors and an idiosyncratic component. The basic idea is to get information from the estimated factors for predicting the future developments in the variables. These factors are the summary of the information contained in a large set of predictors. Thus, factor analysis is purely a statistical method, in which unobservable characteristics account for the variation and covariation across the observed variables.

Factor model forecasts of exchange rate are inspired by Engel et al. [2007]. The authors mention that exchange rates themselves have an unobservable common component which may contain useful information for prediction. Engel et al. [2012] construct factors from a cross section of exchange rates and then use these estimated factors in the forecast equation of exchange rates. Using quarterly data from 1973 to 2007, factor augmented macro fundamentals model of exchange rate forecasts tends to improve on the forecasts of a random walk model in mean square error for their late sample, starting from 1999 and ending at 2007, although the factors themselves are not statistically significant. Using monthly data from 1999 to 2010, McGrevy et al. [2012] perform a factor analysis on a panel of 23 nominal exchange rates where the factors are extracted from the exchange rate itself. The authors identify the Euro/Dollar, the Swiss-Franc/Dollar and the Yen/Dollar exchange rates as the empirical counterparts to these common factors and find that the exchange rate factor augmented PPP Model has significant in sample and out of sample predictive power.

Lustig et al. [2011] extract common factors from the excess currency returns associated with the carry trade. They claim that the global risk factor is the dominant factor. However they do not use this factor for explaining the variation in exchange rates. Verdelhan [2011] uses these common risk factors that are derived from excess returns from carry trade to explain the variations in bilateral exchange rates. However, Verdelhan [2011] did not take into account these factors in exchange rate forecasting.

Engel and Hamilton [1990] consider nonlinearities in exchange rates by assuming a simple two state Markov switching random walk with drift which allows both the constant term and the variance of disturbance term to take two distinct values during times of appreciation and depreciation. The authors find that the US Dollar/German Mark, the US Dollar/UK Pound and the US Dollar/French Franc exchange rates can be described well by Hamilton's [1989] Markov switching model. Engel [1994] incorporates this model for the out of sample exchange rate predictability. Using quarterly nominal exchange rate data from 1973 to 1991, he fits the Markov switching model for 7 USD and 11 non USD exchange rate series and finds that the model fits well in sample for many exchange rates, but this model is not able to generate forecasts superior to the random walk in mean square prediction error.

Chauvet [1998] integrates the two ideas by extracting a two state Markov switching dynamic factor from the various components of economic activity in order to obtain an alternative index to the Department of Commerce indicators. She characterizes the business cycles with this unobservable variable that summarizes the comovements of some coincident macro variables. This factor is subjected to swings in order to capture asymmetric features of business cycles.

In this paper, we examine whether the Markov switching factor that is derived from the excess returns can increase the performance of carry trade in terms of profitability and risk. Specifically, we will determine whether Markov switching factor augmented Taylor rule models can beat the naive carry trade strategy.

We utilize both Taylor rule and PPP models of exchange rate forecasting. However, our focus will be on the Taylor rule models because of the predictability power of Taylor rule fundamentals in exchange rate movements. Rosenberg [2008] claims that the Taylor rule can also provide some explanation for why carry trade strategies have permanent excess returns over time. The author states that high inflation countries push nominal interest rates higher in order to bring inflation under control, resulting in high real interest rates. The Taylor rule fits in the carry trade excess returns since the real interest rate differential is key to carry trading performance. Countries with high inflation and interest rates should keep their real rates higher than low interest rate countries in order to show their credibility for fighting high inflation. Therefore these inflation prone, high interest rate countries should sustain tighter monetary policies longer than low interest rate countries. The interest rate policy will be adjusted gradually in both high and low interest rate countries. Consequently, real interest rate differentials should adjust step by step in response to inflation and output gaps. This gradual adjustment of real rate spreads will result in persistent real exchange rate changes overtime, which in turn will lead to persistent positive excess returns between high and low interest rate countries.

The main issue in the carry trade market is to identify the nature of the risk and determine whether this risk is associated with the excess returns in this market. Brunnermeier, Nagel, and Pedersen [2008] show that exchange rate movements of carry trades are negatively skewed and therefore carry trades are subject to crash risk. The authors claim that when there is a reduction in the availability of funding liquidity, then there is a rapid unwinding of the traders position, which leads to crashes in exchange rates. To decrease this risk, Burnside et al. [2007] propose diversification, whereas Jorda and Taylor [2009] propose a strategy based on fundamentals. Burnside et al. [2007] find that equally weighted portfolio is less skewed than a currency specific carry trade strategy.

An alternative explanation to observable risks such as crash risk in carry trade strategies, these excess returns of carry trade might be compensation for the risk of rare disasters with significant loses that do not occur in sample. This problem is known in the literature as Peso Problem. Burnside et al. [2011] find that large, positive payoffs of an equally weighted portfolio are not correlated with standard risk factors and cannot be explained by stochastic discount factors. Therefore, they argue, these large payoffs should be a compensation for the negative payoffs of peso event risk.

Based on the literature, in this paper we will not try to find out the reasons of excess returns to carry trading strategies, however we will model excess return or the risk premium by a Markov switching dynamic factor. This factor will capture comovements in the excess return. We wil then use this estimated factor with Taylor rule fundamentals in the forecasting equation of exchange rate. Our proposed carry trading strategy will utilize the information that is derived from the risk premium and the macro fundamentals of exchange rate forecasting.

2.3 Carry Trade Strategies

2.3.1 Benchmark and Momentum Models

Our benchmark model is the naive carry trade strategy. Under the random walk theory, the carry trade, in its simplest form, depends solely on the interest rate differentials. This carry trade is called naive since it is unrelated to fundamentals other than interest rates. The second trading strategy is the Momentum model of exchange rates. This strategy simply takes the current value of the change in exchange rate to be the best forecast of the change in exchange rate the next period. The naive and the momentum carry trade strategies can be described as:

Naive (Random Walk) (Model 1): The strategy focuses on only interest rate differentials.

$$\Delta \hat{e}_{t+1} = 0 \tag{2.1}$$

Momentum (Model 2): The strategy takes the current value of exchange rate change as the best predictor of future exchange rate.

$$\Delta e_{t+1} = \beta_e \Delta e_t + \epsilon_{t+1} \tag{2.2}$$

2.3.2 PPP Fundamentals Augmented Models

Purchasing Power Parity (PPP) holds in the long run, as many studies have confirmed. Under PPP, the exchange rate forecasting equation includes the price differences of the two countries. Following Jorda and Taylor [2009], we will incorporate PPP into uncovered interest parity condition by expressing UIP in real, rather than nominal terms. Specifically, $r_t = i_t - \pi_{t+1}$ with $\pi_{t+1} = \Delta p_{t+1}$ and p_t is the log of national price level of the funding currency country. Thus, PPP signal as a currency trading strategy is:

PPP Signal (Model 3):

$$\Delta e_{t+1} = \beta_1(q_t - \bar{q}) + \epsilon_{t+1} \tag{2.3}$$

Jorda and Taylor [2009] form vector time series with changes in nominal exchange rates, differences in inflation rates and nominal interest rates between countries, where the levels of first two entries are I(1) variables which will be cointegrated if the PPP condition holds with cointegrating vector $q_t = e_t + p_t - p_t^\star$. Jorda and Taylor [2009] use the weak PPP condition, $q_t = \bar{q} + \psi(p_t - p_t^\star)$, as a cointegrating vector, where $\bar{q}$ is the mean fundamental equilibrium exchange rate, and the Vector error correction model (VECM) as a currency trading strategy is expressed as : *VECM (Model 4):*

$$\Delta e_{t+1} = \beta_0 + \beta_e \Delta e_t + \beta_1(\pi_t - \pi_t^\star) + \beta_2(i_t - i_t^\star) + \beta_3(q_t - \bar{q} - \psi(p_t - p_t^\star) + \epsilon_{t+1} \tag{2.4}$$

2.3.3 Taylor Rule Fundamentals Augmented Models

The Taylor rule relates changes in the interest rate to inflation and the output gap. Many researchers and policy makers assess the validity of the Taylor rule in both developed and developing countries. Clarida et al. [1998] have examined the validity of the rule by using monthly data for the USA, Italy, France, United Kingdom and Japan. They conclude that those countries are successful in implementing the Taylor rule. Kozicki [1999] finds coefficient estimates very close to the fixed coefficient proposed by Taylor [1993] for the USA. Nelson [2001] assesses the validity of Taylor rule for United Kingdom and concludes that the estimated coefficients are really close to the fixed coefficients proposed by Taylor [1993]. Osterholm [2005] finds the Taylor rule is applicable for the USA, Sweden and Australia. Moreover, Bhattaraii [2008] finds the applicability of Taylor rule for Germany, France, Japan, UK and USA.

Following Taylor (1993), central banks follow the below reaction function for the monetary policy rule:

$$i_t = \pi_t + \theta(\pi_t - \tilde{\pi}) + \delta y_t + \tilde{r} \tag{2.5}$$

where i_t is the federal funds rate, π_t is the inflation rate, $\tilde{\pi}$ is the target level of inflation, y_t is the output gap and $\tilde{r}$ is the equilibrium level of real interest rate.

The parameters $\tilde{\pi}$ and $\tilde{r}$ are constant and can be sum up to form single term $\mu = \tilde{r} - \theta\tilde{\pi}$. Therefore the equation (2.5) can be written as:

$$i_t = \mu + \varphi\pi_t + \delta y_t \tag{2.6}$$

where $\varphi = 1 + \theta$. Clarida et al. [1998] assume that the actual observable interest rate gradually adjust to its target level. Therefore, the Taylor's original formulation with interest rate smoothing becomes as follows:

$$i_t = (1-\rho)(\mu + \varphi\pi_t + \delta y_t) + \rho i_{t-1} \tag{2.7}$$

Following Molodtsova and Papell [2009], we will use Taylor rule fundamentals for exchange rate determination. The interest rate differentials between the target currency and the funding currency will be replaced by the Taylor rule fundamentals. Although Molodtsova and Papell [2009] consider different specifications for the Taylor rule fundamentals, we will follow the formulation with interest rate smoothing, where the interest rate is characterized by the inflation gap, the output gap, the equilibrium interest rate, and the lagged interest rate. We will assume both central banks follow a similar rule and they respond identically to the inflation and the output gaps. Therefore, the Taylor rule coefficients will be identical for both countries. We will also assume the two central banks have different inflation targets and equilibrium interest rates. With these assumptions, the Taylor rule as a currency trade strategy is:

Taylor Rule Fundamentals Only (Model 5):

$$\Delta e_{t+1} = \beta_0 + \beta_1(\pi_t - \pi_t^\star) + \beta_2(y_t - y_t^\star) + \beta_3(i_{t-1} - i_{t-1}^\star) + \epsilon_{t+1} \tag{2.8}$$

The variable e_t is the log of the funding currency in units of target currency, so that an increase in e_t is a depreciation of the funding currency. Star indicates the values for the target currency country. π_t and y_t are the inflation and output gaps respectively.

Alternative models with Taylor rule fundamentals are also considered. For instance, Taylor rule fundamentals in a non-switching factor augmented regression framework and Taylor Rule fundamentals combined with Momentum strategy are used as forecasting equation for the exchange rates[1]:

Momentum and Taylor Rule Fundamentals Model (Model 6):

$$\Delta e_{t+1} = \beta_0 + \beta_e \Delta e_t + \beta_1(\pi_t - \pi_t^\star) + \beta_2(y_t - y_t^\star) + \beta_3(i_{t-1} - i_{t-1}^\star) + \epsilon_{t+1} \tag{2.9}$$

Taylor Rule Fundamentals with Non-Switching Factor (Model 7):

$$\Delta e_{t+1} = \beta_0 + \beta_C \hat{C}_t + \beta_1(\pi_t - \pi_t^\star) + \beta_2(y_t - y_t^\star) + \beta_3(i_{t-1} - i_{t-1}^\star) + \epsilon_{t+1} \tag{2.10}$$

where $\hat{C}_t$ is the non-switching dynamic factor that is estimated by maximum likelihood estimation.

The last model with Taylor rule fundamentals is Markov switching (MS) factor augmented Taylor rule model. The MS-factor augmented Taylor rule model of exchange rate as a currency trading strategy is expressed as:

Taylor Rule Fundamentals with Markov-Switching (MS) Factor (Model 8):

$$\Delta e_{t+1} = \beta_0 + \beta_F \hat{F}_t + \beta_1(\pi_t - \pi_t^\star) + \beta_2(y_t - y_t^\star) + \beta_3(i_{t-1} - i_{t-1}^\star) + \epsilon_{t+1} \tag{2.11}$$

In equation (2.11), the Markov switching factor, $\hat{F}_t$, is estimated by approximate MLE using both the Kalman Filter and the Hamilton Filter together.

[1] Diifferent specifications with Taylor rule fundamentals are used. For instance, non-linearity in interest rates is introduced to both the Taylor rule model (Model 4) and MS-factor augmented Taylor rule model (Model 8). The results do not outperform the factor augmented macro fundamentals models so we do not report these results.

2.4 Modelling and Estimating the Factor

2.4.1 Model

A vector of excess returns is modeled as a combination of two stochastic autoregressive processes; a single unobserved component, which is the common factor for the observable variable (risk premium), and an idiosyncratic component. The empirical analysis is done by using the log of first difference of the spot exchange rates, and the interest rate differentials of target and funding countries. The sum of these two macroeconomic data is defined as the observable variable displaying comovements with the aggregate economic conditions.

The model is:

$$y_{i,t} = i^{\star}_{i,t} - i_{i,t} + \Delta e_{i,t+1} \qquad \text{for } i = 1, 2, ..., n \tag{2.12}$$

$$y_{i,t} = \lambda_i f_t + \varepsilon_{i,t} \qquad \text{for } i = 1, 2, ..., n \tag{2.13}$$

$$f_t = \mu_{st} + \phi f_{t-1} + v_t \qquad \text{for } S_t = 0, 1 \tag{2.14}$$

$$\varepsilon_{i,t} = \gamma_i \varepsilon_{i,t-1} + \xi_{i,t} \qquad \text{for } i = 1, 2, ..., n \tag{2.15}$$

The assumptions of the model are:

$$v_t \sim i.i.d.\ N(0, 1)$$

$$\xi_{i,t} \sim i.i.d.\ N(0, \Sigma)$$

$$p_{ij} = Prob[S_{t=j}|S_{t-1=i}] \qquad \sum_{j=1}^{M} p_{ij} = 1 \qquad \forall i \in MStates$$

$Y_{i,t}$ is the excess return, the parameters λ_i are the factor loadings,which measure the sensitivity of the ith series to the contractions and expansions in the economy, and

F_t is the common factor. The idiosyncratic term $\varepsilon_{i,t}$ is serially uncorrelated at all leads and lags, $\xi_{i,t}$ is the measurement error.

A nonlinear structure is introduced in the unobserved component in the form of a first order two state Markov switching process. There are two states in the economy: a contraction,($S_t = 0$) or an expansion, ($S_t = 1$). We model the excess returns of the currency trading such that the only source of comovements comes from the unobservable dynamic factor. The basic idea of the model is to allow the mean of unobservable common factor to take two distinct values during the times of expansions and contractions. The regime at any given time is presumed to be the outcome of a Markov chain whose realizations are unobserved. The two regimes at any given time are characterized by the transition probabilities of the Markov process. For example, $Prob[S_t = 1 \mid S_{t-1} = 1] = p$ is the probability of an expansion, and $Prob[S_t = 0 \mid S_{t-1} = 0] = q$ is the probability of contraction.

The state space representation for the switching dynamic factor (10) - (13) with the AR(1) process for the factor and the AR(1) process for the disturbance term is explained in Appendix A.

The AR(1) MS-factor and the AR(1) error terms are used for modeling the risk premium when the funding currency is the USD and the CHF. We can write the measurement equation and the transition equation in vector notation:

$$Y_t = HB_t \tag{2.16}$$

$$B_t = \alpha_{st} + ZB_{t-1} + u_t \tag{2.17}$$

2.4.2 *Estimation*

With the dynamic factor model of Stock and Watson [1989, 1993] and the regime switching model of Hamilton [1989], excess returns of the observed currency pairs from the carry trade depend on the current and lagged values of an unobserved common factor. This common factor captures the comovements between the risk premium of each currency trading and is dependent on whether the economy is in the recession state or in the boom state.

The dynamic factor model with regime switching is estimated by maximizing its likelihood function. We used Kim's algorithm [1999] to estimate the model. Kim extended Hamilton's Markov switching Model to a linear dynamic state space representation. He allows the regime switching in both the transition and measurement equation. His algorithm combines nonlinear discrete Kalman Filter with Hamilton's nonlinear filter, which allows both the estimation of an unobserved state vector and the transition probabilities.

The procedure to estimate the model starts with recursively calculating one step-ahead predictions and updating equations of the dynamic factor, given the starting values and the probabilities of the Markov States. The probability terms are calculated using Hamilton's Filter. This nonlinear filter computes for the two state Markov switching process four forecasts at each date and the number of cases is multiplied by two at each iteration. Since this approach makes the Kalman Filter computationally infeasible, Kim [1999] proposes an approximation consisting of taking weighted averages of updating equations by the probabilities of Markov States.

As a by product of the filter, the conditional density of the observable variables that is calculated will then be used to estimate the unknown parameters of the model. These parameter estimates will be recursively substituted into Kalman Filter until the estimates of parameters converge. The maximum likelihood estimators and the sample data are then used in the final application of the filter to draw inferences about the dynamic factor and the probabilities. The estimation procedure is discussed in details in the Appendix B.

2.5 Designing Carry Trade Strategies

Carry trading has become one of the major currency trading strategies since mid-1990s. The currency carry trade is designed to exploit the failure of UIP and consists of borrowing in a low interest rate currency and lending in a high interest rate currency.

$$X_t = \begin{cases} > 0 & \text{if } I_t < I_t^\star \\ < 0 & \text{if } I_t > I_t^\star \end{cases} \tag{2.18}$$

Ignoring the transaction costs, the payoff to the carry trade in domestic currency is:

$$X_t \left[E_t (1 + I_t^\star) \frac{1}{E_{t+1}} - (1 + I_t) \right] \tag{2.19}$$

The variable E_t denotes the spot exchange rate, expressed as domestic currency per foreign currency unit, and X_t is the amount of domestic currency borrowed. The variables, I_t and $I_t^\star$, represent the domestic and foreign interest rate, respectively.

Thus, the return of an investment in the foreign currency financed by the domestic currency consists of both interest rate differentials between the two countries and the changes in the exchange rate.

We denote the logarithm of nominal exchange rate (units of foreign currency per domestic currency) by e_t, interest rate by i_t and foreign interest rate by $i_t^\star$. The return of an investment in the foreign currency financed by borrowing in the domestic currency is denoted by:

$$x_{t+1} = i_t^\star - i_t + \Delta e_{t+1} \tag{2.20}$$

where $\Delta e_{t+1} = e_{t+1} - e_t$ is the appreciation of the foreign currency (e.g,. Δe is the change in yen exchange rate). Equation (2.20) is the excess return that is gained from carry trading when UIP is violated. If UIP holds, this excess return will not be forecasted and $E_t(x_{t+1}) = 0$. Therefore, x can be considered as an abnormal return to the carry trade strategy where foreign currency is the investment currency and Japanese Yen, Swiss Franc and US Dollars are the funding currency.

In this paper, a carry trade is defined as a binary trading strategy that is based on expected returns. There is a trade between the funding currency country and the target currency country if the interest rate differential between the target country and funding country is positive and the expected return is positive as predicted by the model. The execution of carry trade is denoted by $\hat{b}_{i,t} = 1$:

$$\hat{b}_{i,t} = \begin{cases} 1 & \text{if } i_{i,t}^\star - i_{i,t} + E_t(\Delta e_{i,t+1}) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.21}$$

Consider the case where e_t follows a random walk:

$$E_t(\Delta e_{t+1}) = 0 \tag{2.22}$$

Under the random walk model, the carry trade, in its simplest form, depends solely on the interest rate differentials. This carry trade is called "naive" since it is unrelated to fundamentals other than the interest rate.

For one unit of borrowed investment currency, the returns for the different specifications of a carry trade are computed with the realized exchange rates:

$$x_{i,t} = \begin{cases} i^{\star}_{i,t} - i_{i,t} + \Delta e_{i,t+1} & \text{if } \hat{b}_{i,t} = 1 \\ 0 & \text{if } \hat{b}_{i,t} = 0 \end{cases} \tag{2.23}$$

where x_t is the return from binary trading strategy at time t.

2.6 Empirical Results

2.6.1 Data

The empirical analysis uses monthly data. The sample period includes the month end daily exchange rate data from FRED between January 1971 and January 2012 for pairs of the eight major currencies: The Australian Dollar (AUD), the Canadian Dollar (CAD), the Euro (EUR), the British Pound (GBP), the New Zealand Dollar (NZD), the Japanese Yen (JPY), the Swiss Franc (CHF), and the US Dollar (USD). Exchange rates of the target currency measured in the funding currency are computed as cross rates from their original dollar values. Of the eight currencies, six CHF and JPY cross rates are formed and five USD exchange rates are used. The data for macroeconomic fundamentals are constructed from the International Financial Statistics (IFS) and OECD Main Economic Indicators (MEI) databases. The seasonally adjusted Industrial Production Index is used as for countries GDP, since GDP data is only available at quarterly frequency[2]. The inflation rate is calculated from the Consumer Price Index, and is the annual rate measured as the 12 month difference of the CPI[3]. The Money Market Rate is used for the monthly interest rate, which central banks set every period. German exchange rates and macro fundamentals are substituted for those of the Euro Zone before January, 1999.

The output gap calculations are based on potential output. The output gap is calculated as percentage deviations of actual output from a quadratic time trend, since there is no consensus about which definition of output is used by central banks. We use quasi real time data in the output gap estimation. The quasi real time estimate is constructed in two steps. The first step begins with taking the final vintage of the output series with the observations up to, and including, $t-1$ computing the quasi-real time estimate for period t. Then, in each period, the sample period is extended by one observation and OLS is used for detrending. In the second step, the first available estimate of the output gap at each point in time that is constructed in the first step is collected. The final sequence of output gap series will be the quasi

[2] The industrial production series for Australia, New Zealand and Switzerland and the CPI series for Australia and New Zealand are only available at quarterly frequency. They are transformed into monthly frequency data with the quadratic-match average option in E-views 6.0

[3] The Taylor Rule estimation for U.S depends on forward looking nature of policymaking. Therefore, using ex-post realized values of inflation, such as in CGG or Greenbook forecast such as in Orphanides (2001) will be appropriate. However, ex-post data and central bank forecasts are not available for other countries; we will use actual inflation rates.

real time estimation of output gap data[4].

Some basic statistics for the sample from 1975 to 2011 are presented in Table 1. The basic statistics indicate that since the standard deviations are high, all variables are volatile. Target currencies on average have higher interest rates than funding currencies (note that the interest rate differential is defined as the difference between the target currency country and the funding currency country) which indicates that there is a profit opportunity in borrowing from the funding currency and investing into the target currency. However, due to depreciation of the funding currency over the sample period, which does not fully offset the interest rate differential in most cases, the gain (the sum of interest rate differentials and change in exchange rate in Table 1) from carry trade is positive, but less than interest rate differentials. For instance, the Australian Dollar, a typical investing currency, has a sizeable interest rate differential, which is not offset by the appreciation of funding currency.

Table 1 shows that there is a positive correlation between average interest rate differentials and average excess returns, which points to the violation of UIP in the data. The currencies with the average positive interest rate differentials against the funding currencies have positive average excess returns and the currencies with average negative interest differentials have negative average excess returns. For instance, an investor making a carry trade in investing in AUD financed by borrowing JPY during our sample period would have earned the sum of the average interest rate

[4] Policy makers estimate output gaps using the data available to them at the time they are making decision. However, real time data is not available for most of the countries throughout the period that we are studying. Orphanides and Simon van [2002] finds the correlation between real time and quasi real time output gap is high. Thus, using quasi real time output gap will be appropriate. The output gap for the first series is calculated from 1971:1 to 1980:1.

differential and the change in exchange rate, which is 2% annually.

2.6.2 Model Selection and Specification Tests

Several different specifications of the model are estimated, including an AR(1) and an AR(2) factor with an AR(1) and an AR(2) idiosyncratic terms for the observables. Combinations of these models are also tested. However, highly parameterized models with higher dynamic orders have coefficients that are not significant at the 5% significance level. The likelihood ratio test is used to choose among the alternative specifications of the model.

For the adequacy of the model selection, the disturbances in the observable variables are analyzed. The correctly specified model has estimated disturbances that are not serially uncorrelated implying the sample autocorrelations should be zero and the disturbances should be white noise[5]. The diagnostic tests for the data state that the specifications that are selected for the model are adequate.

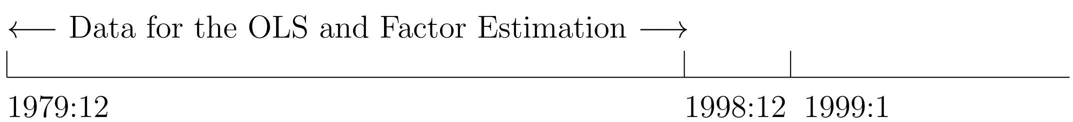
Identifying the number of common factors that explain common variations in a set of observable variables is one of the major tasks of factor analysis. The most widely used is the Scree test of Cattell [1966]. The Scree test is a visual test based on the behaviors of the eigenvalues of the second moment matrix of the observable variables. In this paper, the number of factors is verified by checking the eigenvalues of the correlation matrix containing the total variance of the observables and for visual inspection the Scree test is used. The magnitude of the eigenvalues, which contains

[5] For Franc data, error terms are contemporaneously correlated. In the literature, the Approximate Factor Models are used in order to estimate the existence of cross correlation between the disturbances. We are working to improve the results in Franc trades.

information about how much of the correlations among the observable variables is explained by a particular factor, shows there is a single factor in the data.

2.6.3 Forecasting and Statistical Evaluations of Carry Trades

The out-of-sample performance starts in January 1999, when the Euro became official. We first estimate the non-linear unobservable factor and factor loadings. After obtaining the sequence of factors and factor loadings, we estimate the coefficients of the models, which include the factor as an explanatory variable, using the OLS method to forecast exchange rates for that month. As depicted in (2.24), we use data from 1979:12 through 1998:12 to estimate factors and factor loadings and construct $\hat{F}_{i,t} = \hat{\lambda}_i \hat{f}_t$ for all cross currencies.



(2.24)

The forecasting equation is combining both the macro fundamentals and the estimated factors in a single equation;

$$\hat{e}_{i,t+1} - \hat{e}_{i,t} = E_t(\beta_i + \beta_F \hat{F}_{i,t} + z_{i,t}) \qquad t = 1999:1, ..., 2011:12 \qquad (2.25)$$

where $z_{i,t}$ is the different specification of the macro fundamentals.

The out of sample forecast is done by estimating each equation by OLS in a rolling regression framework. Each model is initially estimated using the first 228 data points to generate the one-period-ahead forecast. Then the first data point is dropped, an additional data point is added at the end of sample and the model is reestimated. A one month ahead forecast is generated at each step. The out of sample forecast is then used to determine the value of b_t, the binary decision making function of the carry trade at time t.

With JPY and CHF as the funding currencies, this process is performed for each of the six nations, whereas when using USD it is performed for each of 5 nations. 156 months of trade decisions are computed from 1999:1 to 2011:12. The out of sample period includes the 2007 financial crises, in which several crash episodes took place, providing a realistic assessment of the crash episode returns at that time.

Performance statistics of the carry trade returns include the *Mean Return*, *Standard Deviation*, *Sharpe Ratio*, *Return Skewness*, *Return Kurtosis* and *Maximum Drawdown* of returns from the period 1999:1 to 2011:12. The performance statistics are based on an equally weighted portfolio of 6 currencies against the JPY and the CHF, 5 currencies against the USD.

One of the popular methods of summarizing the properties of a return of an asset or an investment is *Sharpe Ratio*. It is calculated as a ratio of returns normalized by the standard error. The Sharpe Ratio is good for evaluating how well the return of an asset compensates the investor for the risk taken. A portfolio or a return may have higher mean returns than its peers, however, it is better when it does not have additional risk. Therefore, the greater the Sharpe Ratio, the better its risk adjusted performance is.

In this paper, *Return Skewness* and *Kurtosis* are used as measures of the risk of large amount of losses. Skewness is a measure of degree of asymmetry of a distribution while Kurtosis measures the height and sharpness of the peak. A negative Skewness implies that the left hand side tail of the probability density function is longer than the right hand side tail, and the mass of values lies to the left of the mean of the distribution. A large positive number for the Kurtosis shows a higher and sharper peak.

The exchange rate movements are not symmetric when they go up and down. This asymmetry of exchange rate movement is associated with a crash risk. Brunnermeier, Nagel, and Pedersen [2008] claim that the movements of exchange rates between high yield and low yield currencies are negatively skewed and, therefore, are subject to crash risk. Consequently, in this paper, we used Skewness to show the risk of large losses by carry traders in case of market crashes and Kurtosis to show that whether these changes are abrupt or not. Large negative Skewness implies that there is higher probability of these large losses, while positive big Kurtosis shows that these changes are fast.

The *Maximum Drawdown* is also an important performance statistics for the risk of a portfolio. It measures the largest single drop from the peak to bottom before a new peak is reached. Therefore the Maximum Drawdown measures the largest possible loss since the beginning of the portfolio. Large Maximum Drawdowns indicate higher risk.

We report all performance statistics for an equally weighted portfolio returns for each of the models described. The financial crisis of 2007 is considered separate and the performance statistics of that period are also reported.

2.6.4 Empirical Results of MS-Dynamic Factor Model

We use monthly exchange rate and interest rate data for calculating risk premium. The inferred probabilities, parameter estimates and factor loadings are estimated from the switching dynamic factor. The estimates obtained through numerical maximization of the conditional log likelihood function are presented in Table 2. There is significantly positive growth in state 1 and significantly negative growth in state 2 for all currency returns except the US Dollar. The asymmetries in the phases of the states are well defined by the switching dynamic factor. The probability of staying in expansion, p, is higher than the probability of staying in contraction, q except for the USD. The estimated transition probabilities for the expansion state are highly significant and persistent for the Japanese Yen and the USD. For Franc trades, the expansion state is not as persistent as the other currency trades, that is why the graph of the smoothed probabilities of the expansion state is very volatile, $p = 0.88$.

With respect to the factor loadings of the Yen carry trade; the Canadian and the US Dollar excess returns have the highest coefficients, supporting the observation that they are the most sensitive returns to expansions and contractions. Overall, all factor loadings are highly significant, implying the risk premium for all currencies is highly sensitive to the regime switches in the economy. The same results are true for the Franc and the US Dollar trades. The US and the Canadian Dollar have the highest significant factor loadings for the Franc carry trade returns. The New

Zealand Dollar has the highest parameter estimates for the US Dollar trade returns, and all of the excess returns are significantly affected by the state of the economy.

In this paper, inferences of the smoothed probabilities can be used to identify large gains or losses from carry trading. Figure 1 graphs the estimated probabilities that the economy is in an expansion state at time t, based on information using whole sample, $Prob(S_t = 1|\Theta_T)$, for the Yen, Franc and Dollar trades, respectively. Figure 1 shows that the Asian Crises of 97-98 was not a good period for Yen trade investors. The investors also had large losses in the 2008 financial crisis, although after and before the crisis they profited from carry trading. Figure 3 shows that the mid-80s, the early 2000s and the financial crisis of 2007-2010 were good periods for Dollar traders due to the low interest rates of 2000s and financial crisis period.

The MS-Dynamic Factor Model for the risk premium is very useful in several aspects. First, there is a significant unobservable component that is derived from the excess returns of carry trading and this unobservable component's conditional mean changes depending on the contractions and expansions of the economy for all currency pairs. This result implies that the currency risk premium is sensitive to regime switches in the economy. Moreover, the expansion state is persistent for both Yen and Dollar returns, indicating that if the economy is in a state of expansion, the duration of that expansion is long.

2.6.5 Performance Statistics of the Carry Trade Returns

The carry trades are constructed with the target currency countries that have higher interest rate differentials on average than the funding currency country. There are six individual carry trades with the Yen and the Franc and five individual trades with the Dollar. In practice an investor can apply the carry trade strategy either to individual currencies or to portfolios of currencies. Burnside et al. [2011] claims that the risk in carry trade strategies is reduced by diversifying the carry trade across different currencies. They claim that the gains from diversification are large, since diversification increases the Sharpe Ratio by fifty percent. In this section, we take the perspective of an individual currency trader, and examine whether this trader gains more by diversifying a carry trade across different currencies. We consider equally weighted carry trade strategies where the Yen, Franc and Dollar positions give equal weight at each point in time to all the currencies for which b_t is not equal to zero.

Table 3 reports performance statistics of carry trade returns for all currencies. They are based on one period ahead forecast of exchange rates with rolling window samples beginning in December 1979 to December 1998, and continuing until December 2011. The out of sample forecasts include the fall of 2007 where crash episodes or peso events took place, so that forecasting analysis provides a realistic assessment of the type of returns that could have made at that time.

The results are based on an equally weighted portfolio of the six currencies against the Japanese Yen and the Swiss Franc and five currencies against the US Dollar.

Performance statistics include the annualized return, Sharpe Ratio, return skewness, kurtosis and maximum drawdown. All carry trading strategies have positive mean returns ranging from 1% to 7% annually[6]. Models with fundamentals perform better than naive model or momentum strategy. More importantly models with a Markov Switching dynamic factor and macro-fundamentals give the highest return for the Yen and Dollar trades. With the MS-Factor augmented Taylor Rule model, annual returns rose to 5% and 7% for Yen and Dollar trades, respectively. The mean return is low in Franc trades and the model with Taylor Rule fundamentals performs slightly better than most of other models, but much better than the naive trading strategy.

The most striking measure of the return per unit of risk is the Sharpe ratio. It is the ratio of mean excess return per unit of volatility. The Sharpe ratios of carry trade strategies are usually low, since, although the mean excess returns for carry trade strategies are moderate, the volatility for those returns is high. We see that carry trade strategies with MS-Factor augmented Taylor rule have larger Sharpe ratios than other models in the simulation, implying carry trades with those models are more profitable on average than the naive model. The Taylor rule fundamentals model in Swiss Franc has a lower standard deviation which in turn increases the Sharpe ratio of the Franc trades. Although the simulated models resulted in carry trade returns with larger Sharpe ratios than the naive model, Sharpe ratios are still low for an investor. Usually investors prefer to buy an asset for which Sharpe ratio is higher than one.

While the Sharpe ratio suggests whether the carry trade strategies have low or

[6] We did not include a transaction cost in the analysis. Some studies use a 10 basis point round-trip transaction cost for trading in currency markets.

high risk return profiles, it does not account for either the crash risk or downside risk. The maximum drawdown measures the largest possible loss, whereas skewness measures the possibility of large losses or gains during market crashes. From Table 3, for the naive model, all currency carry trade returns have negative skewness, high kurtosis and high maximum drawdown, which means that carry trade returns with all currencies have a crash risk and fat tails. Although the payoffs to naive model are negatively skewed and have fat tails, we should consider the statistical significance of skewness and kurtosis[7]. Since we have an equal number of observations for all carry trades, the SES (Standard Error of Skewness) is calculated as 0.19 and SEK (Standard Error of Kurtosis) as 0.39. The sample is very likely negatively skewed (fat tails) if the absolute value of Skewness (Kurtosis) is more than the double of SES (SEK). For the naive model, the returns of Yen and Dollar trades are negatively skewed and these numbers are statistically significant, suggesting the trades have a crash risk. All currency carry trades have fat tails, implying that large losses in carry trades based on solely on interest rate differentials will be fast.

The results for the Japanese Yen show that the negative skewness is improved when traders use Taylor rule fundamentals in exchange rate forecasting. Table 3 (Panel A) reports that naive Yen carry trade has a terrible skewness of -1.28. We find that MS-factor augmented Taylor rule fundamentals model impressively improves the skewness of the returns. For Dollar carry trades, Table 3 Panel C, the return

[7] Standard errors of skewness and Kurtosis are calculated respectively as $SES = \sqrt{\frac{6}{N}}$, $SEK = 2SES\sqrt{\frac{N^2-1}{(N-3)(N+5)}}$ where N is the number of observations.

skewness in the naive model becomes a positive significant number with the MS-factor augmented Taylor rule model (Model 8). On the other hand, the payoffs in Swiss Franc trades do not have a significant probability of large losses in a case of market crash. Carry trade returns are negatively skewed in all models but this skewness is not significant in most cases.

The naive model for all currency carry trades have a maximum drawdown ranging from 28% to 37%. The reason for such a large downside risk is simple: There are several episodes of target currency collapses during the simulation period. Every crash in a target currency against the funding currency significantly increases the downside risk in the carry trade. We find that Taylor rule model, and MS-factor augmented Taylor rule model impressively reduce the downside risk. In Yen and Dollar trades, maximum drawdown is reduced to 11% (Model 8). In Franc trades similar improvement in the downside risk can be seen with Taylor rule model (Model 5); maximum drawdown decreased to 10%.

2.6.6 Financial Crisis of 2007

Recent literature emphasizes the importance of market wide distress in carry trading strategies. Carry traders experience significant losses during periods of market distress, which is the main reason why the returns of carry trades are negatively skewed. As is obvious from Table 3, MS-factor augmented Taylor rule fundamentals as a trading strategy has better performance in mean returns, risk adjusted returns and in terms of downside risk for the whole sample period, so we would like to examine whether our MS-factor augmented Taylor rule model will perform better when the market crashes. To do this, we will evaluate the performance statistics of carry trades during the financial crisis.

The 2008-2009 financial crisis is a telling example of a severe period of market stress or tail event. Carry traders had a high probability of crash risk in this period. The performance statistics of portfolios in this period are presented in Table 4. The performance statistics of our benchmark model is terrible during the financial crisis period starting in 2007. The naive model has mean returns that are negative for the Yen and Franc trades, positive but lower than normal times for the Dollar trades. The payoffs to both Yen trades and Dollar trades are negatively skewed and the risk for carry trading is high. The standard errors rose 2 to 3% during that period. The mean returns of macro fundamental models are positive and higher than our benchmark model of random walk. The MS-factor augmented Taylor rule model performs well in mean returns, in terms of downside risk and risk adjusted returns for Yen trades. However, we cannot find improvement in the performance of Franc trades when we consider Taylor rule fundamentals in a MS-factor augmented framework. For Franc trades, Taylor rule fundamentals as a trading strategy seem to be the best candidate for a profitable trade during this financial turmoil.

The most striking result from Table 4 is that our proposed MS-factor augmented Taylor rule Model performs better than the random walk and other models in the simulation for Dollar trades. Although the financial crises was clearly not a good period for the carry trade investors (Table 4, Panel C), our proposed strategy has mean returns of 9% annually and has a Sharpe Ratio greater than one. Therefore we claim that our strategy predicts the movement of exchange rates during the financial crises better than other strategies. Thus, traders can make profitable carry trades even during the market distress using our proposed strategy.

2.7 Conclusion

This paper provides evidence of enhancing carry trade returns when factor augmented Taylor rule models are used as a trading strategy with an equally-weighted portfolio of individual currency trades. Our factor is derived from the excess returns of currency trading and is subject to regime switches depending on expansions and contractions in the economy. We design alternative carry trading strategies with macro-fundamentals and document that these alternative macro-fundamental trading strategies better than a naive strategy. Moreover, the MS-factor augmented Taylor rule fundamentals model performs better than our benchmark model of the random walk in terms of mean returns, downside risk and risk adjusted returns for Dollar and Yen trades. The statistically significant crash risk of Yen carry trades are reduced to an insignificant level, and the negative skewness is improved to a positive level in Dollar carry trades. The best trading strategy for Franc trades is where Taylor rule fundamentals are used to forecast exchange rates.

While we provide better performed returns with the MS-factor augmented Taylor rule model, our analysis finds profitable payoffs to Dollar trades when we consider the recent financial crisis of 2008-2009. During the crisis, the mean returns and adjusted risk returns are negative for Yen and Franc for our benchmark model of a random walk. The equally weighted portfolios of the Japanese Yen and the US dollar have negative skewness and fat tails for most of the macro-fundamental carry trading strategies in simulation due to the financial turmoil of 2007. The MS-factor model with Taylor Rule fundamentals in exchange rate forecasting does well, since strategies using this model increase the mean returns of dollar trades by 2% and raise the Sharpe Ratio above one. The negative skewness became positive and the largest possible drop of returns decreased to 9%.

Overall, our results are consistent with the view that returns to carry trade have high mean returns and low Sharpe Ratios with a possibility of crash risk. This crash risk is reduced when models with Taylor rule fundamentals are used as trading strategies throughout the sample period. As well, there is profitable carry trading when Taylor rule fundamentals are used in MS-factor augmented framework for Yen and Dollar trades. This could be the outcome of the predictive power of Taylor rule fundamentals in exchange rate movements and the inclusion of an estimated regime switching factor derived from risk premium into the forecasting equation of exchange rates. Finally, our result that trading strategies with MS-factor augmented Taylor rule fundamentals have better performance in mean and risk adjusted returns would be helpful to the practitioner, since these trading strategies are more profitable than naive carry trade strategy.

Appendices

Appendix A

STATE SPACE REPRESENTATION OF THE EMPIRICAL MODEL

$(1) Measurement Equation:$

$$\begin{vmatrix} Y_{1t} \\ Y_{2t} \\ Y_{3t} \\ Y_{4t} \\ Y_{5t} \\ Y_{6t} \end{vmatrix} = \begin{vmatrix} \lambda_1 & 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_2 & 0 & 1 & 0 & 0 & 0 & 0 \\ \lambda_3 & 0 & 0 & 1 & 0 & 0 & 0 \\ \lambda_4 & 0 & 0 & 0 & 1 & 0 & 0 \\ \lambda_5 & 0 & 0 & 0 & 0 & 1 & 0 \\ \lambda_6 & 0 & 0 & 0 & 0 & 0 & 1 \end{vmatrix} \times \begin{vmatrix} F_t \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \end{vmatrix} \quad \text{(A.1)}$$

$(2) Transition Equation:$

$$\begin{vmatrix} F_t \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \end{vmatrix} = \begin{vmatrix} \alpha_{1t}S_t + \alpha_{2t} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{vmatrix} + \begin{vmatrix} \phi & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \gamma_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \gamma_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \gamma_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \gamma_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \gamma_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \gamma_6 \end{vmatrix} \times \begin{vmatrix} F_{t-1} \\ \varepsilon_{1t-1} \\ \varepsilon_{2t-1} \\ \varepsilon_{3t-1} \\ \varepsilon_{4t-1} \\ \varepsilon_{5t-1} \\ \varepsilon_{6t-1} \end{vmatrix} + \begin{vmatrix} v_t \\ \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \\ \epsilon_{5t} \\ \epsilon_{6t} \end{vmatrix} \quad \text{(A.2)}$$

Different specifications for each funding currencies are examined. For example, the best model for the Japanese Yen is a common factor as a regime switching mean with an autoregressive idiosyncratic term. Thus, the AR(1) parameter of the model is zero:

$$F_t = \mu_{st} + v_t \quad \text{(A.3)}$$

Although equation (A.3) is a tight assumption, restricting the AR parameter of the common factor, it decreases the likelihood value making the transition probabilities highly significant. The likelihood ratio test is used to test whether there is a difference between the restricted and unrestricted model. The test results favors for no difference.

In vector notation, the measurement and transition equation will be written as:

$$Y_t = HB_t + \omega_t \quad \text{(A.4)}$$

$$B_t = \alpha_{st} + ZB_{t-1} + u_t \quad \text{(A.5)}$$

$$\begin{pmatrix} \omega_t \\ v_t \end{pmatrix} \sim N\left(0, \quad \begin{pmatrix} R_t & 0 \\ 0 & Q_t \end{pmatrix} \right) \tag{A.6}$$

Appendix B

THE ALGORITHM FOR ESTIMATING THE MS-DYNAMIC FACTOR

The filter for the state space model with Markov switching in the Appendix A is the combination of the Kalman Filter and the Hamilton Filter with appropriate approximations. Given the state space representation by the equations A.3 and A.4, the Markov switching dynamic factor is estimated by following these steps:

1. Run the Kalman Filter:

$$\beta_{t|t-1}^{(i,j)} = \alpha_j + Z_j \beta_{t-1|t-1}^{i} \tag{B.1}$$

$$P_{t|t-1}^{(i,j)} = Z_j P_{t-1|t-1}^{i} Z_j' + Q \tag{B.2}$$

$$\eta_{t|t-1}^{(i,j)} = Y_t - H_j \beta_{t|t-1}^{(i,j)} \tag{B.3}$$

$$f_{t|t-1}^{(i,j)} = H_j P_{t|t-1}^{(i,j)} H_j' + R \tag{B.4}$$

$$\beta_{t|t}^{(i,j)} = \beta_{t|t-1}^{(i,j)} + P_{t|t-1}^{(i,j)} H_j' [f_{t|t-1}^{(i,j)}]^{-1} \eta_{t|t-1}^{(i,j)} \tag{B.5}$$

$$P_{t|t}^{(i,j)} = (I - P_{t|t-1}^{(i,j)} H_j' [f_{t|t-1}^{(i,j)}]^{-1} H_j) \eta_{t|t-1}^{(i,j)} \tag{B.6}$$

where $\beta_{t-1|t-1}^{i}$ is an inference on β_{t-1} up to time $t-1$, given $S_{t-1} = i$; $\beta_{t|t-1}^{(i,j)}$ is an inference on β_t up to time $t-1$, given $S_t = j$ and $S_{t-1} = i$; $P_{t|t-1}^{(i,j)}$ is the mean square error matrix of $\beta_{t|t-1}^{(i,j)}$ conditional on $S_t = j$ and $S_{t-1} = i$; $\eta_{t|t-1}^{(i,j)}$ is the conditional forecast error of Y_t based on infromation up to time $t-1$, given $S_t = j$ and $S_{t-1} = i$ and $f_{t|t-1}^{(i,j)}$ is the conditional variance of forecast error $\eta_{t|t-1}^{(i,j)}$.

2. Run the Hamilton Filter and calculate $Pr[S_t, S_{t-1}|\psi_t]$ and $Pr[S_t|\psi_t]$, given that ψ_t denote the vector of observations available as of time t.

3. Approximations: Using the probability terms in step 2, collapse GXG posteriors in equations B.5 and B.5 into $Gx1$ using the following equations:

$$\beta_{t|t}^{j} = \frac{\sum_{i=1}^{G} Pr[S_{t-1} = i, S_t = j|\psi_t] \beta_{t|t}^{(i,j)}}{Pr[S_t = i|\psi_t]} \tag{B.7}$$

$$P_{t|t}^{j} = \frac{\sum_{i=1}^{G} Pr[S_{t-1} = i, S_t = j|\psi_t][P_{t|t}^{(i,j)} + (\beta_{t|t}^{j} - \beta_{t|t}^{(i,j)})(\beta_{t|t}^{j} - \beta_{t|t}^{(i,j)})']}{Pr[S_t = i|\psi_t]} \tag{B.8}$$

The conditional mean and the conditional variance of the AR(1) process is used as the initial values to start the Kalman Filter. For the Hamilton Filter, the steady state probabilities are used as initial values for the state probabilities. The parameters and and probabilities are estimated by the approximate likelihood function:

$$LL = ln[f(Y_1, Y_2, ..., Y_T)] = \sum_{t=1}^{T} ln(f(Y_t|\psi_{t-1}) \tag{B.9}$$

Tab. 2.1: BASIC STATISTICS

	Australia	Canada	Euro Zone	UK	New Zealand	USA
Panel A: Japanese Yen is the Funding Currency						
Δe	-0.003	-0.002	0.000	-0.004	-0.004	-0.002
	(0.033)	(0.030)	(0.039)	(0.029)	(0.030)	(0.027)
$i^\star - i$	0.005	0.003	0.004	0.006	0.005	0.002
	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)
$\Delta y^\star_{gap} - y_{gap}$	-0.005	-0.005	-0.003	-0.009	-0.000	-0.008
	(0.071)	(0.076)	(0.040)	(0.075)	(0.083)	(0.088)
$\pi^\star - \pi$	0.005	0.003	0.004	0.006	0.005	0.002
	(0.033)	(0.030)	(0.039)	(0.029)	(0.030)	(0.027)
Panel B: Swiss Franc is the Funding Currency						
Δe	-0.003	-0.003	-0.000	-0.004	-0.004	-0.002
	(0.033)	(0.030)	(0.033)	(0.023)	(0.031)	(0.029)
$i^\star - i$	0.005	0.003	0.004	0.005	0.003	0.002
	(0.004)	(0.002)	(0.003)	(0.006)	(0.004)	(0.002)
$\Delta y^\star_{gap} - y_{gap}$	-0.003	-0.003	-0.000	-0.007	0.002	-0.006
	(0.043)	(0.053)	(0.038)	(0.049)	(0.076)	(0.061)
$\pi^\star - \pi$	0.004	0.001	0.000	0.003	0.003	0.001
	(0.032)	(0.023)	(0.013)	(0.041)	(0.048)	(0.023)
Panel C: US Dollar is the Funding Currency						
Δe	-0.001	-0.000	0.003	-0.001	-0.001	–
	(0.026)	(0.014)	(0.040)	(0.024)	(0.027)	
$i^\star - i$	0.02	0.000	-0.001	0.001	0.004	–
	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	
$\Delta y^\star_{gap} - y_{gap}$	0.003	0.003	0.005	-0.001	0.008	–
	(0.046)	(0.049)	(0.074)	(0.038)	(0.068)	
$\pi^\star - \pi$	0.001	0.000	-0.001	0.001	0.002	–
	(0.027)	(0.015)	(0.021)	(0.032)	(0.039)	

[1] The numbers in the paranthesis are the standard deviations. An asterisk indicates values for the target currency.Δe is the percentage change in the exchange rate
[2] The interest rate is the money market rate. The interest rate data of new Zealand is available from 1979:09 to 2011:12. The output gap is calculated from 1980:01 to2011:12
[3] The CPI and industrial production data for New Zealand and Australia are only available in quarterly frequency. They are turned into monthly frequency by quadratic matching in E-views6.

Tab. 2.2: APPROXIMATE MLE ESTIMATES OF THE MS-FACTOR MODEL

		JAPAN	SWITZERLAND	USA
Likelihood Value		-750.71	-851.55	-1137.16
f_t	p	0.95	0.88	0.96
		(0.02)	(0.06)	(0.05)
	q	0.43	0.27	0.97
		(0.13)	(0.05)	(0.04)
	ϕ	–	0.17	0.36
			(0.06)	(0.07)
	μ_0	-2.61	-1.30	-0.16
		(0.40)	(0.34)	(0.19)
	$\mu_{\mathbf{1}}$	2.81	1.59	$0.39^{\star\star}$
		(0.37)	(0.34)	(0.23)
Factor Loadings	$\lambda_{\mathbf{1}}$	0.67	0.66	0.75
		(0.04)	(0.05)	(0.04)
	$\lambda_{\mathbf{2}}$	0.77	0.79	0.53
		(0.04)	(0.05)	(0.05)
	$\lambda_{\mathbf{3}}$	0.31	0.20	0.37
		(0.04)	(0.04)	(0.05)
	$\lambda_{\mathbf{4}}$	0.57	0.49	0.43
		(0.04)	(0.05)	(0.05)
	$\lambda_{\mathbf{5}}$	0.61	0.61	0.74
		(0.04)	(0.05)	(0.04)
	$\lambda_{\mathbf{6}}$	0.71	0.73	–
		(0.04)	(0.05)	

[1] The sample period is 1975:01 to 2011:12. Total number of observations are 444 for the Japanese Yen and US Dollar.
[2] The Swiss sample starts from 1975:12.
[3] The standard errors of parameters are given in the parenthesis.
[4] $\star\star$ indicates significance at 10% level.

Tab. 2.3: PERFORMANCE STATISTICS OF CARRY TRADE RETURNS

	Naive (Model1)	Moment. (Model2)	PPP Signal (Model3)	VECM (Model4)	Taylor Rule (Model5)	Moment + Taylor Rule (Model6)	Factor + Taylor Rule (Model7)	MS-Factor + Taylor Rule (Model8)
Panel A: Japanese Yen is the Funding Currency								
Mean Return	0.02	0.03	0.03	0.04	0.03	0.02	0.04	0.05
Standard Error	0.10	0.05	0.09	0.05	0.06	0.07	0.06	0.07
Sharpe Ratio	0.21	0.55	0.28	0.80	0.59	0.32	0.66	0.64
Skewness	-1.28	-0.73	-1.38	0.06	0.14	-1.21	0.20	-0.24
Kurtosis	5.59	2.46	6.18	3.05	1.22	6.61	2.15	2.22
Max. Drawdown	0.37	0.15	0.35	0.09	0.15	0.28	0.12	0.15
Panel B: Swiss Franc is the Funding Currency								
Mean Return	0.01	0.03	0.02	0.02	0.03	0.03	0.03	0.03
Standard Error	0.07	0.04	0.05	0.04	0.04	0.04	0.04	0.04
Sharpe Ratio	0.19	0.72	0.30	0.41	0.80	0.71	0.69	0.64
Skewness	-0.08	-0.39	-0.63	-0.78	-0.29	-0.29	-0.28	-0.99
Kurtosis	3.02	0.61	1.30	1.90	0.30	0.04	0.67	3.79
Max. Drawdown	0.28	0.11	0.19	0.18	0.10	0.12	0.11	0.16
Panel C: US Dollar is the Funding Currency								
Mean Return	0.04	0.03	0.02	0.05	0.04	0.04	0.05	0.06
Standard Error	0.08	0.05	0.05	0.06	0.05	0.06	0.06	0.07
Sharpe Ratio	0.55	0.55	0.32	0.78	0.71	0.65	0.96	0.98
Skewness	-1.07	0.04	-1.34	-0.05	-0.11	-0.74	0.46	0.40
Kurtosis	5.06	0.88	6.11	1.38	0.99	5.24	0.76	1.25
Max. Drawdown	0.28	0.13	0.21	0.14	0.13	0.21	0.11	0.11

[1] The sample period is from 1999:01 to 2011:12. The total number of observations is 156.
[2] The Sharpe Ratio is the mean returns divided by standard deviations.
[3] All returns are annualized.
[4] Equally weighted portfolio is calculated as giving equal weight to each currency trade in time (Funding currencies are: the Australian Dollar, Canadian Dollar, UK Pound, Euro,New Zealand Dollar, US Dollar for Panel A and B).

Tab. 2.4: PERFORMANCE STATISTICS OF CARRY TRADE RETURNS-Financial Crisis of 2007

	Naive (Model1)	Moment. (Model2)	PPP Signal (Model3)	VECM (Model4)	Taylor Rule (Model5)	Moment + Taylor Rule (Model6)	Factor + Taylor Rule (Model7)	MS-Factor + Taylor Rule (Model8)
Panel A: Japanese Yen is the Funding Currency								
Mean Return	-0.05	-0.01	-0.04	0.02	0.01	-0.01	0.02	0.03
Standard Error	0.13	0.06	0.11	0.07	0.07	0.09	0.07	0.09
Sharpe Ratio	-0.37	-0.18	-0.34	0.28	0.08	-0.07	0.21	0.30
Skewness	-1.26	-0.76	-1.53	-0.15	0.05	-1.45	-0.24	-0.24
Kurtosis	3.68	1.79	4.78	0.99	0.13	4.66	0.91	0.95
Max. Drawdown	0.37	0.15	0.35	0.09	0.15	0.28	0.12	0.15
Panel B: Swiss Franc is the Funding Currency								
Mean Return	-0.02	0.01	-0.01	-0.01	0.01	0.01	0.01	0.00
Standard Error	0.09	0.05	0.06	0.05	0.04	0.04	0.04	0.05
Sharpe Ratio	-0.23	0.15	-0.19	-0.32	0.29	0.19	0.27	0.05
Skewness	0.23	-0.55	-0.72	-0.76	-0.32	-0.15	-0.29	-1.28
Kurtosis	2.32	-0.02	1.16	0.89	-0.12	-0.02	0.59	2.75
Max. Drawdown	0.28	0.11	0.19	0.18	0.10	0.12	0.11	0.16
Panel C: US Dollar is the Funding Currency								
Mean Return	0.02	0.04	0.01	0.04	0.04	0.04	0.07	0.09
Standard Error	0.10	0.06	0.07	0.07	0.06	0.08	0.07	0.08
Sharpe Ratio	0.21	0.59	0.13	0.61	0.65	0.52	1.11	1.18
Skewness	-1.27	-0.40	-1.65	-0.32	-0.65	-0.96	0.03	0.03
Kurtosis	3.04	0.62	5.42	0.79	1.71	3.15	0.46	0.77
Max. Drawdown	0.28	0.12	0.21	0.14	0.13	0.21	0.08	0.09

[1] The sample period is from 2007:01 to 2011:12.The total number of observations is 61.
[2] The Sharpe Ratio is the mean returns divided by standard deviations.
[3] All returns are annualized.
[4] Equally weighted portfolio is calculated as giving equal weight to each currency trade in time (Funding currencies are: the Australian Dollar, Canadian Dollar, UK Pound, Euro,New Zealand Dollar, US Dollar for Panel A and B).

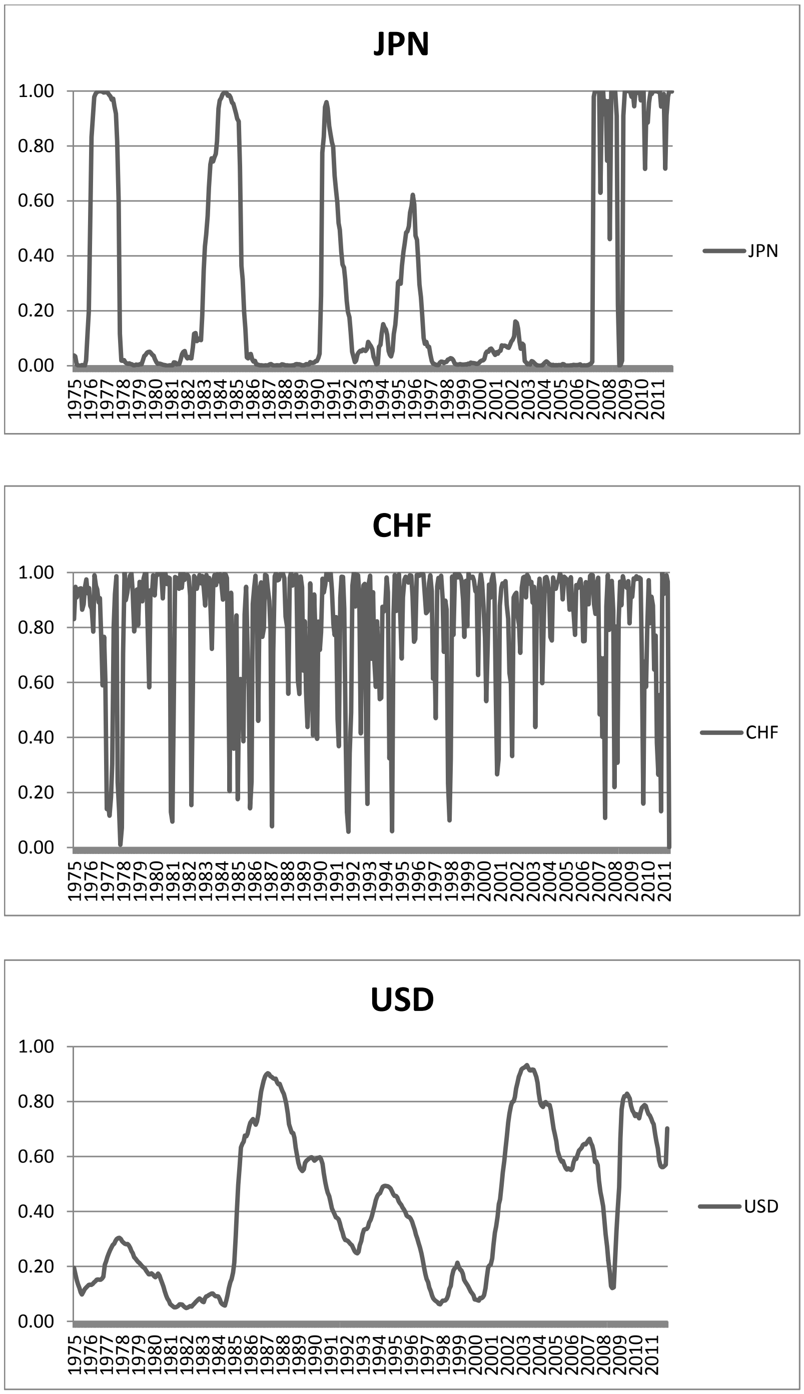


Fig. 2.1: The Smoothed Probabilities of the Expansion State

3. RISK PREMIUM FACTOR AND EXCHANGE RATE FORECASTING

Abstract: We estimate a dynamic factor from the risk premium of carry trading of bilateral US Dollar against 15 OECD countries and use that factor to augment the macro fundamentals suggested by the Taylor rule, monetary and purchasing power parity models. Meese and Rogoff [1983] show that economic models of exchange rates do not outperform the random walk forecast. We find evidence of short term predictability of bilateral exchange rates between 1991 and 2012 with factor augmented macro fundamentals.

3.1 Introduction

The past few years have seen an academic interest in exchange rate forecasting with factor models. Engel et al. [2012] use factor augmented macro fundamentals in exchange rate determination. McGrevy et al. [2012] perform a factor analysis on a 23 nominal exchange rates where the factors are derived from exchange rates themselves. They claim that although these factors are significant and important after controlling macro fundamental determinant of exchange rates, they do not attach an economic meaning to the factors. The authors identify Euro/Dollar, Swiss-Franc/Dollar and Yen/Dollar exchange rates as empirical counterparts of common factors.

An important distinction between these papers and this empirical research is the source of the derived factor. In this empirical study, we extract the factor from the risk premium of currency trading. Our starting point is the idea of incorporating large co-movements among the risk premium of different currencies into exchange rate determination. Engel and West [2006] suggest that the risk premium, a short run deviation from rational expectations, may contain important information in exchange rate determination. In our empirical study, we extract the factor from the risk premium, suggesting that co-movements in the risk premium are important in explaining exchange rate movements.

Our results indicate that the factor has strong predictive power in exchange rate determination in the short run. For instance, an out of sample forecasting exercise for the late sample (1999 to 2012) results in a Theil's U-statistic value that lies below 1 for 90 percent of the currencies at the one month horizon (Table 3, factor augmented

Taylor rule model). Rossi [2005] shows that a persistent factor, one highly correlated with the variables has strong predictive power. Table 1 shows that our factor is highly, and significantly correlated with the change in the exchange rate. This is probably the reason that the factor has strong predictive power in exchange rate determination.

Even though Meese and Rogoff [1983] show that economic models of exchange rates do not outperform the random walk forecast, many studies show the predictive ability of macro fundamentals for currency movements. Fundamental based models performed well in exchange rate forecasting during the 1980s and 1990s, however, their predictive ability declined with the availability of new data on exchange rates from the 1990s and 2000s. Earlier research focused on purchasing power parity (PPP) and the monetary approach in exchange rate forecasting. Recent studies have been successfull in the prediction of exchange rate movements using the endogenity of monetary policy with interest rate feedback rules, such as Taylor rules [Molodtsova and Papell, 2009].

We incorporate these macro fundamental models in the present paper, augment with the risk premium factor and compare with the benchmark model of random walk. We have three different factor augmented macro fundamental models: the Taylor rule model, the monetary model and the PPP model. The sample period is divided into three different periods in order to analyze forecasts of exchange rates in different periods: the early sample (1991-1999), the late sample (1999-2012) and the long sample (1991-2012).

The data set consists of monthly data on bilateral US dollar exchange rates with OECD countries between the years 1973 and 2012. Our results indicate that factor augmented macro fundamentals perform better than benchmark model having Theil's U-statistics value lower than 1 for 80 to 90 percent of currencies at one month horizon for the late sample and for 60 to 88 percent of currencies for the long sample.

The paper is organized as follows. We review the related literature in section 2. In section 3, we explain the construction of the factor. In section 4, we describe the empirical models. In section 5, we explain the data and the forecast evaluation. Section 6 includes the empirical results. Section 7 concludes.

3.2 Related Literature

It is difficult to tie exchange rates to macro economic fundamentals such as money supply, price levels, interest rates and output. The behavior of exchange rates is approximated well by the random walk model, although economic theory states that exchange rates are determined by macro fundamentals. The random walk forecast states that the best prediction of today's exchange rate is its previous level. In the literature, Meese and Rogoff [1983] show that economic models of exchange rates do not outperform the random walk forecast. Cheung et al. [2005] find that none of the macro fundamental models used in 1990s such as the PPP fundamentals model, the sticky price monetary model, the productivity differential model, the uncovered interest rate parity and the composite model of fundamentals can be successfully used by examining five developed countries' currency markets.

In the mid-90s, some authors reported empirical evidence that monetary and PPP fundamentals may contain predictive power for exchange movements in the long run [Mark, 1995, Chinn and Meese, 1995]. These findings are confirmed by Mark and Sul [2001]. Although it is successful to use monetary fundamentals in exchange rate determination in the long run, the results are not robust Cheung et al. [2005].

Earlier research focuses on monetary and PPP fundamentals, later research focuses on Taylor rule fundamentals. The Taylor Rule approach predicts exchange rate movements using expected inflation and the output gaps of the home and foreign countries instead of macro economic fundamentals. The main idea is that if monetary policy is conducted by the nominal interest rate which is set by central banks in accordance with a Taylor rule type of reaction function, then the market expectations regarding these fundamentals can be quite different. This expectation formation will have an effect on exchange rate determination. Starting with Engel and West [2005], some authors emphasize and use Taylor rule fundamentals in exchange rate determination [Engel and West, 2006, Engel et al., 2007, Mark, 2009]. Molodtsova and Papell [2009] use the variables that enter the Taylor rule to evaluate the exchange rate forecast. Molodtsova and Papell [2009] find that, by assessing the out of sample performance of 12 currencies, the predictability of these models with Taylor rule fundamentals is stronger for 8 out of 12 currencies.

Engel et al. [2007] mention that the exchange rates themselves have an unobservable common component which may contain useful information for prediction. Engel et al. [2012] derive factors from a cross section of exchange rates and then use these estimated factors in the forecast equation of exchange rates. Using quarterly data from 1973 to 2007, factor augmented macro fundamentals model of exchange rate forecasts tends to improve on the forecasts of a random walk model in mean square error for their late sample, starting from 1999 and ending at 2007, although the factors themselves are not statistically significant. Using monthly data from 1999 to 2010, McGrevy et al. [2012] perform a factor analysis on a panel of 23 nominal exchange rates. They extract factors from the exchange rates themselves. The authors identify the Euro/Dollar, the Swiss-Franc/Dollar and the Yen/Dollar exchange rates as the empirical counterparts to these common factors. They find that the exchange rate factor augmented PPP Model has significant in sample and out of sample predictive power. Lustig et al. [2011] extract common factors from the excess currency returns associated with the carry trade. They claim that the global risk factor is the dominant factor. However they do not use this factor for explaining the variation in exchange rates. Verdelhan [2011] uses these common risk factors that are extracted from excess returns from carry trades to explain the variations in bilateral exchange rates. However, Verdelhan [2011] does not use factors in exchange rate forecasting.

In this paper, we examine whether the risk premium factor can increase the predictive power of macro fundamentals. We utilize the monetary, PPP and Taylor rule models of exchange rate forecasting and augment these models with the risk premium factor. Our proposed forecasting equation will utilize the information that is derived from the risk premium and the macro fundamentals of exchange rate forecasting.

3.3 Factor Construction

Dynamic factor models are frequently used in economics and finance. Prominent examples include multi-factor models of the term structure of interest rates, dating business cycles and the capital asset pricing model. The basic idea is to get information from the estimated factors for predicting the future developments in the variables. These factors are the summary of the information contained in a large set of predictors. Thus, factor analysis is purely a statistical method in which unobservable characteristics account for the variation and co-variation across the observed variables.

A drawback of factor models is lack of the economic and financial meaning, since the factors are unobservable. Engel and West [2005] claim that there are unobserved fundamentals, stemming from risk premium, and money demand shocks, as well as observed fundamentals (macro economic models) in exchange rate determination. Engel and West [2007] suggest that the risk premium, a short run deviation from rational expectations, may contain important information in exchange rate determination. In our empirical study, we extract the factors from the risk premium, believing that movements in the risk premium are important in explaining exchange rate movements.

The risk premium from currency trading is modeled as the combination of a single unobserved component, which is the common factor for the observable variable (the risk premium), and an idiosyncratic component. The empirical analysis is done by using the logs of first differences of the spot exchange rates, and the interest rate differentials of the countries. The sum of these two macro economic data is defined as the observable variable displaying comovements with the aggregate economic conditions.

The model is:

$$y_{i,t} = i^{\star}_{i,t} - i_{i,t} + \Delta e_{i,t+1} \qquad \text{for } i = 1,2,...,n \tag{3.1}$$

$$y_{i,t} = \lambda_i f_t + \varepsilon_{i,t} \qquad \text{for } i = 1,2,...,n \tag{3.2}$$

$$f_t = \mu + \phi f_{t-1} + v_t \tag{3.3}$$

$$\varepsilon_{i,t} = \gamma_i \varepsilon_{i,t-1} + \xi_{i,t} \qquad \text{for } i = 1,2,...,n \tag{3.4}$$

The assumptions of the model are:

$$v_t \sim i.i.d.\ N(0,1)$$

$$\xi_{i,t} \sim i.i.d.\ N(0,\Sigma)$$

$Y_{i,t}$ is the excess return, the parameters λ_i are the factor loadings, and f_t is the common factor. The idiosyncratic term $\varepsilon_{i,t}$ is serially uncorrelated at all leads and lags, $\xi_{i,t}$ is the measurement error.

The state space representation for the dynamic factor (3.1) - (3.4) with the AR(1) process for the factor and the AR(1) process for the disturbance term is explained in Appendix C.

The AR(1) factor and AR(1) error terms are used for modeling the risk premium of the bilateral exchange rates. We can write the measurement equation and the transition equation in vector notation as:

$$Y_t = HB_t \tag{3.5}$$

$$B_t = \alpha + ZB_{t-1} + u_t \tag{3.6}$$

Several different specifications of the model are estimated, including an AR(1) and an AR(2) factor with an AR(1) and an AR(2) idiosyncratic terms for the observables. Combinations of these models are also tested. However, highly parameterized models with higher dynamic orders have coefficients that are not significant at the 5 percent significance level. The likelihood ratio test is used to choose among the alternative specifications of the model.

The dynamic factor model is estimated by maximizing its likelihood function with Kalman Filter. The procedure to estimate the model starts with calculating recursively one step ahead predictions and updating equations of the dynamic factor, given the parameters of the model and starting values. As a by-product of the filter the conditional density of the observable variables is calculated. This conditional density will then be used to estimate the unknown parameters of the model. These parameter estimates will be substituted into the Kalman Filter again. This process will be repeated until the estimates of parameters converge. The maximum likelihood estimators and the sample data are then used in the final application of the filter to draw inferences about the dynamic factor. The estimation procedure is discussed in detail in the Appendix D.

3.4 Empirical Models

We use macro fundamental models with one factor. Maximum likelihood estimation produces a time series for $\hat{f}_t$ and factor loadings $(\hat{\lambda}_i)$ for $i = 1, 2, 3, ..., n$, where n is the number of bileteral exchange rates. In its simplest specification, $\hat{F}_{i,t} = \hat{\lambda}_i \hat{f}_t$. We use OLS to estimate and forecast the exchange rates. Our forecasting equation is of the form:

$$e_{i,t+1} - e_{i,t} = \theta_i + \gamma \hat{F}_{i,t} + \beta z_{i,t} + \eta_{i,t+1} \qquad \text{for } i = 1, 2, ..., n \tag{3.7}$$

where $e_{i,t}$ is the log level of 14 bilateral exchange rates of OECD countries and the European Unioun, $\hat{F}_{i,t}$ is risk premium factor and $z_{i,t}$ is different specification of macro fundamentals. The variable $e_{i,t}$ is the log of the US Dollar (domestic currency) in units of one of OECD countries' currency (foreign currency), such that an increase in $e_{i,t}$ is a depreciation of the domestic currency.

3.4.1 Factor Augmented Monetary Model (Model 1)

A change in the logarithm of the nominal exchange rate is represented as a function of its deviation from its fundamental value [Mark, 1995]. The monetary approach determines the fundamental value of exchange rate as a relative price of the two currencies:

$$e_{t+1} - e_t = \theta + \gamma \hat{F}_t + \beta z_t + \eta_{t+1} \tag{3.8}$$

$$z_t = h_t - e_t \tag{3.9}$$

$$h_t = m_t - m_t^\star - k(y_t - y_t^\star) \tag{3.10}$$

where m_t and y_t are logs of the money supply and industrial production respectively, k is the fixed value of income elasticity and is equal to 1. An asterisk indicates the domestic country's variables.

3.4.2 Factor Augmented PPP Model (Model 2)

Purchasing Power Parity holds in the long run as many studies have shown. Under PPP fundamentals, the exchange rate forecasting equation includes the price differences of the two countries. The PPP fundamentals model presumes convergence of price levels:

$$e_{t+1} - e_t = \theta + \gamma \hat{F}_t + \beta z_t + \eta_{t+1} \tag{3.11}$$

$$z_t = h_t - e_t \tag{3.12}$$

$$h_t = p_t - p_t^\star \tag{3.13}$$

where p_t is the log of the price level.

3.4.3 Factor Augmented Taylor Rule Model (Model 3)

The Taylor rule model builds on the view that interest rates rather than money supplies are the instruments of monetary policy. Following Molodtsova and Papell [2009], we will use Taylor rule fundamentals for exchange rate determination. The interest rate differentials between the foreign country and the domestic country will be replaced by the Taylor rule fundamentals:

$$e_{t+1} - e_t = \theta + \gamma \hat{F}_t + \beta_\pi(\pi_t - \pi_t^\star) + \beta_g(\hat{y}_t - \hat{y}_t^\star) + \eta_{t+1} \tag{3.14}$$

where π_t and $\hat{y}_t$ are the inflation and output gaps respectively.

3.5 Data and Forecast Evaluation

We use monthly data 1971:01 to 2012:09, with the out of sample period beginning in 1991:01. The primary data source is the IMF International Financial Statistics, supplemented by the OECD Main Economic Indicator database when necessary. Exchange rates are end-of-month values of the US dollar vs. Euro and the currencies of 14 OECD countries: Australia, Canada, Denmark, Finland, France, Germany, Japan, Italy, Korea, the Netherlands, Norway, Sweden, Switzerland, and the United Kingdom. The seasonally adjusted Industrial Production Index is used to proxy for countries' GDP, since GDP data is only available at quarterly frequency[1] . The inflation rate is calculated from the Consumer Price Index, and is the annual rate measured as the 12 month difference of the CPI [2]. The money market rate is used for the monthly interest rate, which central banks set every period. M1 is used to measure the money supply for most of the countries[3] . We use M0 for the U.K. and

[1] The industrial production series for Australia and Switzerland and the CPI series for Australia is only available at quarterly frequency. They are transformed into monthly frequency data with the quadratic-match average option in E-views 6.0

[2] The Taylor Rule estimation for U.S depends on forward looking nature of policymaking. Therefore, using ex-post realized values of inflation, such as in CGG or Greenbook forecast such as in Orphanides [2001] will be appropriate. However, ex-post data and central bank forecasts are not available for other countries; we will use actual inflation rates.

[3] Monetary aggregates for Sweden and Finland are not available during the sample period.

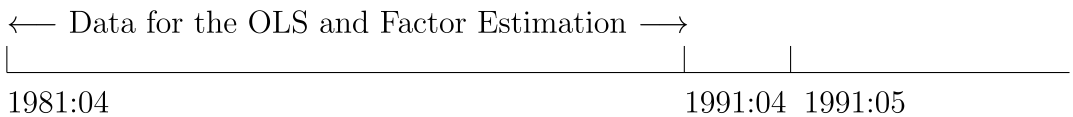
M2 for Italy and Netherlands, because M1 data is not available for these countries. Using M2 as a measure of the money supply provides similar results. German exchange rates and macro fundamentals are substituted for those of the Euro Zone before January, 1999.

The output gap calculations are based on potential output. The output gap is calculated as percentage deviations of actual output from a quadratic time trend, since there is no assumption about which definition of output is used by central banks. We use quasi-real time data in the output gap estimation. The quasi-real time estimate is constructed in two steps. The first step begins with taking the final vintage of the output series using the observations up to, and including $t-1$ computing the quasi-real time estimate for period t. Then, in each period, the sample period is extended by one observation and OLS is used for de-trending. In the second step, the first available estimate of the output gap at each point in time that is constructed in the first step is collected. The final sequence of the output gap series is the quasi-real time estimation of the output gap data[4] .

We illustrate a forecasting exercise for the long sample to explain how our mechanic works. The out of sample performance starts in May 1991. We first estimate the unobservable factor and factor loadings. After obtaining the sequence of factor and factor loadings, we estimate the coefficients of the models using OLS, with the

[4] Policy makers estimate output gaps using the data available to them at the time they are making decision. However, real time data is not available for most of the countries throughout the period that we are studying. Orphanides and Simon van [2002] find the correlation between real time and the quas- real time output gap is high. Thus, using quasi-real time output gap will be appropriate. The output gap for the first series is calculated from 1971:1 to 1980:1. True real time data is not available for most of the countries throughout the period that we are studying. The output gap for the first series is calculated from 1971:1 to 1981:04.

factor as an explanatory variable. As depicted in (3.15) , we use data from 1981:04 through 1991:04 to estimate factors and factor loadings and construct ($F_{i,t}$) for all currencies.



(3.15)

The forecasting equation is the conditional expectation form equation (3.7) for $i = 1, , n$:

$$\hat{e}_{i,t+1} - \hat{e}_{i,t} = E_t(\beta_i + \beta_F \hat{F}_{i,t} + \beta_z z_{i,t}) \qquad t = 1991 : 05, ..., 2012 : 09 \tag{3.16}$$

The out of sample forecast is done by estimating each equation by OLS in a rolling regression framework. Each model is initially estimated using the first 120 data points to generate the one period ahead forecast. Then the first data point is dropped, an additional data point is added at the end of sample and the model is reestimated. A one month ahead forecast is generated at each step. The sample size, that is used to estimate factors and the OLS regression in each rolling window, stays the same.

Our sample period is divided into three different subsamples in order to analyze the behavior of exchange rate in different time periods. The "Long sample" includes 9 non-Euro currencies: Australia, Canada, Denmark, Japan, Korea, Norway, Sweden, Switzerland, and the United Kingdom. We report "long sample" forecasting statistics between 1991 and 2012. For all 14 currencies, "early sample" forecasting statistics are reported between 1991 and 1998. For the 9 non-Euro currencies and the Euro, "late sample" forecasting statistics are reported between 1999 and 2012. There are 223, 165, 93 months of forecasts in the long , late and early sample respectively.

Forecast performance is measured by root mean squared prediction error (RMSPE). From these Theil's U-statistic, that is the ratio of the RMSPE from each of the models to the RMSPE from a random walk model, is calculated. A value less than one means our proposed models have smaller RMSPE than a random walk.

A U-statistic of 1 indicates that the RMSPEs from the factor augmented macro fundamentals model and from the random walk model are the same. Sample U-statistics strictly less than 1 imply that our models beat the benchmark model of random walk.

3.6 Empirical Results

We use monthly exchange and interest rate data for calculating risk premium of currency trading. The parameter estimates and factor loadings are estimated from the dynamic factor. The estimates obtained through numerical maximization of the conditional log likelihood function are presented in Table 1.

For the largest sample used (1981-2012), factor loadings suggest that the excess returns of Denmark, Norway and Switzerland have the highest coefficients, suggesting the observations are the most sensitive returns to the factor. Overall, all factor loadings are highly significant, implying the risk premium for all currencies is highly sensitive to the risk premium factor. The same results are true for the early and late samples. Denmark, the Netherlands, Sweden and Switzerland have the highest factor loadings for the early sample. The Danish Krone has the highest parameter estimates for all samples, and all of the excess returns have significant factor loadings except for South Korea and Australia in the early sample.

Table 2 reports some forecasting results. The results are based on one month ahead forecast of exchange rates with rolling window samples beginning in April 1981 to April 1991, and continuing until September 2012. We present the Theil's U statistics of the individual currencies for each different sample period. Theil's U is the root mean square prediction error (RMSPE) of the candidate model divided by the RMSPE of the random walk model [5]. U-statistic values below 1 indicate superior forecast accuracy of the candidate model.

In the long sample, factor augmented macro fundamental models dominate the benchmark model of the random walk. 89 percent of currencies have U statistics below 1 with factor augmented PPP model. The values of 0.92 and 0.99 for the U-statistics imply a reduction in RMSPE relative to a no-change forecast about 7 and 1 percent. The PPP model reduces the RMSPE of the British Pound and the Swidish Krone by 8 and 7 percent, repectively. The Taylor rule model and the monetary rule model have U-statistics less than 1 for over 55 percent of the forecasts, although they perform relatively worse than the PPP model.

In the late sample, factor augmented models perform the best, except for Japanese Yen. Our predictions fared poorly for the Japanese Yen, which generally has one of

[5] Theil's U-statistics are biased along the argument of Clark and West [2007] in the sense that if the random walk is true, we expect Theil's U to be greater than 1. Hence, a U-statistic of 1 is actually evidence in favor of predictability.

the highest U-statistics in each sample and model. The best improvement in the prediction of currencies comes from the factor augmented Taylor rule model. The RMSPE of the benchmark model is reduced by 12 percent for the Bristish Pound. Overall, factor augmented macro fundamental models perform well in the late sample. The U-statistics values are lower than 1 for 90 percent of the currencies for both the Taylor rule and PPP models, and for 80 percent of the currencies for the monetary model.

The U-statistics of the early sample are not as good as the other sample periods. The factor augmented monetary model seems to perform better than other macro fundamental model in this period. The factor augmented monetary model dominate the random walk model in 11 of 14 cases.

Results with the long and late samples are promising. We find evidence of short term predictiability of exchange rates with factor augmented macro fundamentals especially in the late sample. In the late sample, the lowest U-statistics come with the factor augmented Taylor rule model. Factor augmented PPP models perform relatively better than other models in the long sample.

Some statistics related to the estimated risk premium factor and macro fundamentals for the long sample from 1981 to 2012 are presented in Table 1. Panel A reports the correlation between the factor and macro variables. Panel B reports the correlation betweenthe time $t-1$ factor and time t variables. Table 3 shows that the factor is correlated with the exchange rate changes. This is probably the reason that the factor has strong predictive power in exchange rates.

3.7 Conclusion

In this paper, we show that a common factor obtained by statistical methods from the excess return of currency trading improves exchange rate forecasting with macro fundamentals. A brief examination shows that the unobservable factor contains very useful information for forecasting future exchange rates. The factor extracted from the risk premium is correlated with future exchange rates. Since we do not have a fully working model of exchange rate for prediction, the factor augmented macro fundamentals model may be a candidate model for exchange rate forecasting.

The factor augmented PPP model dominates the random walk in 8 of 9 cases in the long sample and in 9 of 10 cases in the late sample. U-statistics of the factor augmented Taylor rule model value lower than 1 for 90 percent of the currencies in the late sample and 55 percent of the currencies in the long sample. In the early sample, the results of the factor augmented monetary model seem to be relatively better than other macrofundamentals. Overall, factor augmented macro fundamentals perform better than random walk model in more than 55 percent of the cases and periods.

A drawback of the factor model is lack ofits economic and financial meaning, since the factors are unobservable. Although the factor is correlated to future exchange rates, it would be desirable to correlate factors with the risk or the volatility index of the markets. Different forecasting techniques should also be included in order to analyze the forecast results clearly. It would be also desirable to compare our models with models other than random walk. Such extensions are priorities for future work.

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Appendices

Appendix C

STATE SPACE REPRESENTATION OF THE EMPIRICAL MODEL

$(1) Measurement Equation:$

$$\begin{vmatrix} Y_{1t} \\ Y_{2t} \\ Y_{3t} \\ Y_{4t} \\ Y_{5t} \\ Y_{6t} \\ Y_{7t} \\ Y_{8t} \\ Y_{9t} \end{vmatrix} = \begin{vmatrix} \lambda_1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \lambda_2 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \lambda_3 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \lambda_4 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_5 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \lambda_6 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \lambda_7 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ \lambda_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \lambda_9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{vmatrix} \times \begin{vmatrix} F_t \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \\ \varepsilon_{8t} \\ \varepsilon_{9t} \end{vmatrix} \tag{C.1}$$

$(2) Transition Equation:$

$$\begin{vmatrix} F_t \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \\ \varepsilon_{8t} \\ \varepsilon_{9t} \end{vmatrix} = \begin{vmatrix} \alpha_t \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{vmatrix} + \begin{vmatrix} \phi & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \gamma_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \gamma_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \gamma_3 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \gamma_4 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \gamma_5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \gamma_6 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_7 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_8 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_9 \end{vmatrix} \times \begin{vmatrix} F_{t-1} \\ \varepsilon_{1t-1} \\ \varepsilon_{2t-1} \\ \varepsilon_{3t-1} \\ \varepsilon_{4t-1} \\ \varepsilon_{5t-1} \\ \varepsilon_{6t-1} \\ \varepsilon_{7t-1} \\ \varepsilon_{8t-1} \\ \varepsilon_{9t-1} \end{vmatrix} + \begin{vmatrix} v_t \\ \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \\ \epsilon_{5t} \\ \epsilon_{6t} \\ \epsilon_{7t} \\ \epsilon_{8t} \\ \epsilon_{9t} \end{vmatrix} \tag{C.2}$$

In vector notation, the measurement and transition equation will be written as:

$$Y_t = HB_t + \omega_t \tag{C.3}$$

$$B_t = \alpha_t + ZB_{t-1} + u_t \tag{C.4}$$

$$\begin{pmatrix} \omega_t \\ v_t \end{pmatrix} \sim N\left(0, \begin{pmatrix} R_t & 0 \\ 0 & Q_t \end{pmatrix} \right) \tag{C.5}$$

Appendix D

THE ALGORITHM FOR ESTIMATING THE DYNAMIC FACTOR

The filter for the state space model in the Appendix A is the Kalman Filter and Maximum Likelihood Estimation. Given the state space representation by the equations C.3 and C.4, the dynamic factor is estimated by following these steps:

1. Set the initial parameter values : $\beta_{0|0}$ and $P_{0|0}$

2. Calculate the conditional expectation of log-likelihood function. Run the Kalman Filter to estimate factors given the initial parameter values:

$$\beta_{t|t-1} = \alpha + Z\beta_{t-1|t-1} \tag{D.1}$$

$$P_{t|t-1} = ZP_{t-1|t-1}Z^{'} + Q \tag{D.2}$$

$$\eta_{t|t-1} = Y_t - H\beta_{t|t-1} \tag{D.3}$$

$$f_{t|t-1} = HP_{t|t-1}H^{'} + R \tag{D.4}$$

$$\beta_{t|t} = \beta_{t|t-1} + P_{t|t-1}H^{'}[f_{t|t-1}]^{-1}\eta_{t|t-1} \tag{D.5}$$

$$P_{t|t} = (I - P_{t|t-1}H^{'}[f_{t|t-1}]^{-1}H)P_{t|t-1} \tag{D.6}$$

where $\beta_{t-1|t-1}$ is an inference on β_{t-1} up to time $t-1$; $\beta_{t|t-1}$ is an inference on β_t up to time; $P_{t|t-1}$ is the mean square error matrix of $\beta_{t|t-1}$; $\eta_{t|t-1}$ is the conditional forecast error of Y_t based on infromation up to time $t-1$ and $f_{t|t-1}$ is the conditional variance of forecast error $\eta_{t|t-1}$.

3. MLE: Maximize the log-likelihood function to obtain the new parameter estimates:

$$LL(\theta) = (-1/2)(\sum_{t=1}^{T} ln(2\pi f_{t|t-1} + \sum_{t=1}^{T} \eta^{'}_{t|t-1} f^{-1}_{t|t-1} \eta_{t|t-1}) \tag{D.7}$$

4. Repeat steps 2 and 3 until the convergence is satisfied.

Tab. 3.1: BASIC STATISTICS

Panel A: Correlations with factor									
	AUS	CAN	DNK	JPN	NOR	SWE	CHE	KOR	GBR
Δs	-0.24	-0.26	-0.33	-0.15	-0.37	-0.39	-0.27	-0.24	-0.37
$i - i^*$	-0.07	0.00	0.10	-0.04	0.01	0.13	-0.03	0.09	-0.02
$\pi - \pi^*$	-0.13	-0.05	-0.03	-0.07	-0.02	0.01	-0.04	-0.01	-0.05
$p - p^*$	-0.12	0.03	-0.02	0.09	-0.08	-0.01	0.09	-0.08	0.01
$m - m^*$	-0.08	-0.20	-0.02	0.13	0.02	-0.12	0.03	0.02	0.07
$\hat{y} - \hat{y^*}$	-0.06	-0.03	0.03	-0.03	0.06	-0.04	-0.05	-0.13	-0.07
Panel B: Correlations with factor (-1)									
Δs	-0.07	-0.05	-0.00	0.03	-0.08	-0.09	0.02	-0.03	-0.04
$i - i^*$	-0.04	-0.02	0.11	-0.04	-0.01	0.07	-0.05	0.12	-0.03
$\pi - \pi^*$	-0.11	-0.01	0.01	-0.03	0.01	0.05	0.03	0.01	0.01
$p - p^*$	-0.12	0.03	-0.01	0.10	-0.07	-0.00	0.10	-0.07	0.02
$m - m^*$	-0.11	-0.20	-0.02	0.15	0.02	-0.12	0.03	0.02	0.07
$\hat{y} - \hat{y^*}$	-0.07	-0.06	0.04	-0.06	0.02	-0.05	-0.07	-0.15	-0.07

[1] The sample period is from 1991:04 to 2012:09. The total number of observations is 223.
[2] Δs is the percentage change in the exchange rate (An increase in the exchage rate implies depreciation of the domestic currency).
[3] The interest rate is the money market rate. $\star$ refers to US values.
[4] The output gap is calculated from 1981:04 to2012:09.
[5] The CPI and industrial production data for Australia are only available in quarterly frequency. They are turned into monthly frequency by quadratic matching in E-views6.

Tab. 3.2: MLE ESTIMATES OF DYNAMIC FACTOR MODEL

		Long Sample	Early Sample	Late Sample
Likelihood Value		-427.75	770.83	-520.39
f_t	ϕ	0.34	0.34	0.34
		(0.05)	(0.07)	(0.05)
	μ	-0.001	0.001	0.001
		(0.05)	(0.05)	(0.05)
Factor Loadings	$\lambda_{\mathbf{AUS}}$	0.19	0.06*	0.19
		(0.04)	(0.05)	(0.04)
	$\lambda_{\mathbf{CAN}}$	0.35	0.17	0.34
		(0.05)	(0.07)	(0.05)
	$\lambda_{\mathbf{DNK}}$	0.91	0.92	0.91
		(0.04)	(0.05)	(0.04)
	$\lambda_{\mathbf{FIN}}$	–	0.76	–
			(0.05)	
	$\lambda_{\mathbf{FRA}}$	–	0.921	–
			(0.05)	
	$\lambda_{\mathbf{DEU}}$	–	0.94	–
			(0.05)	
	$\lambda_{\mathbf{JPN}}$	0.49	0.58	0.50
		(0.05)	(0.06)	(0.05)
	$\lambda_{\mathbf{ITA}}$	–	0.78	–
			(0.05)	

[1] The sample period is from 1981:04 to 2012:09. Total number of observation is 378.
[2] Early sample period is from 1981:04 ends at 1998:12.
[3] The standard errors of parameters are given in the parenthesis. $*$ indicates insignificance.

Tab. 3.2 (Continued): MLE ESTIMATES OF DYNAMIC FACTOR MODEL

		Long Sample	Early Sample	Late Sample
Likelihood Value		-427.75	770.83	-520.39
f_t	ϕ	0.34	0.34	0.34
		(0.05)	(0.07)	(0.05)
	μ	-0.001	0.001	0.001
		(0.05)	(0.05)	(0.05)
Factor Loadings	$\lambda_{\mathbf{NLD}}$	–	0.93	–
			(0.05)	
	$\lambda_{\mathbf{NOR}}$	0.82	0.82	0.82
		(0.04)	(0.05)	(0.04)
	$\lambda_{\mathbf{SWE}}$	0.75	0.66	0.76
		(0.04)	(0.05)	(0.04)
	$\lambda_{\mathbf{CHE}}$	0.86	0.88	0.86
		(0.04)	(0.05)	(0.04)
	$\lambda_{\mathbf{KOR}}$	0.22	0.10*	0.22
		(0.04)	(0.06)	(0.05)
	$\lambda_{\mathbf{GBR}}$	0.71	0.67	0.70
		(0.04)	(0.05)	(0.04)
	$\lambda_{\mathbf{EUN}}$	–	–	0.58
				(0.04)

[1] The sample period is from 1981:04 to 2012:09. Total number of observation is 378.
[2] Early sample period is from 1981:04 ends at 1998:12.
[3] The standard errors of parameters are given in the parenthesis. $*$ indicates insignificance.

Tab. 3.3: FORECAST EVALUATION- THEIL'S U TEST STATISTICS

	LONG SAMPLE			**EARLY SAMPLE**			**LATE SAMPLE**		
	Money Model	PPP Model	Taylor Model	Money Model	PPP Model	Taylor Model	Money Model	PPP Model	Taylor Model
AUS	0.99	0.99	1.00	1.02	1.01	1.00	0.98	0.97	0.97
CAN	0.97	0.97	0.97	1.00	1.05	0.97	0.97	0.96	0.98
DNK	0.96	0.96	0.96	0.94	0.94	0.95	0.96	0.93	0.93
FIN	–	–	–	–	1.99	0.95	–	–	–
FRA	–	–	–	0.98	0.97	0.96	–	–	–
DEU	–	–	–	0.96	0.96	1.00	–	–	–
JPN	1.01	1.01	1.02	0.95	0.97	1.01	1.08	1.05	1.04
ITA	–	–	–	0.95	0.93	0.91	–	–	–
NLD	–	–	–	0.92	0.94	1.01	–	–	–
NOR	0.98	0.95	0.97	0.93	0.93	0.95	1.03	0.93	0.95
SWE	–	0.93	0.98	–	0.91	0.99	–	0.93	0.92
CHE	1.01	0.98	1.00	1.02	0.96	1.01	0.98	0.97	0.96
KOR	0.98	0.98	1.02	0.99	1.00	1.04	0.96	0.95	0.94
GBR	0.97	0.97	0.92	1.02	0.97	1.06	0.91	0.89	0.88
EUN	–	–	–	–	–	–	0.97	0.98	0.95

[1] The long sample period is from 1991:04 to 2012:09. The late sample period is from 1999:01 to 2012:09.
[2] The early sample period is from 1991:04 to 1998:12
[3] M1 is not available for Sweden and Finland.