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BY

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Currency Forecast Errors at Times of Low Interest Rates: Evidence from Survey Data on the Yen/Dollar Exchange Rate*

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Abstract:

Using survey expectations data and Markov-switching models, this paper evaluates the characteristics and evolution of investors' forecast errors about the yen/dollar exchange rate. Since our model is derived from the uncovered interest rate parity (UIRP) condition and our data cover a period of low interest rates, this study is also related to the forward premium puzzle and the currency carry trade strategy. We obtain the following results. First, with the same forecast horizon, exchange rate forecasts are homogeneous among different industry types, but within the same industry, exchange rate forecasts differ if the forecast time horizon is different. In particular, investors tend to undervalue the future exchange rate for long term forecast horizons; however, in the short run they tend to overvalue the future exchange rate. Second, while forecast errors are found to be partly driven by interest rate spreads, evidence against the UIRP is provided regardless of the forecasting time horizon; the forward premium puzzle becomes more significant in shorter term forecasting errors. Consistent with this finding, our coefficients on interest rate spreads provide indirect evidence of the yen carry trade over only a short term forecast horizon. Furthermore, the carry trade seems to be active when there is a clear indication that the interest rate will be low in the future.

JEL classification: F3

Keyword: Currency forecast errors, uncovered interest parity, forward premium puzzle, carry trade, Markov-switching model

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1. Introduction

Using survey data on currency forecasts, we investigate the characteristics and evolution of forecast errors for the yen/dollar exchange rate. Since economic theory suggests that the current exchange rate is partly determined by investors' expectations, a considerable amount of research has been carried out to verify the role of expectations in the exchange rate determination process. For example, there is now a large literature that uses aggregate survey data, in the form of the mean or median, to measure exchange rate expectations in order to explore the unbiasedness and expectational formation process of the expected change in the exchange rate (see MacDonald (2000) for a survey). Such data has also been used to shed light on the so-called forward premium puzzle (see, for example, Froot and Frankel (1989)) and disaggregate survey data has indicated that there is significant heterogeneity in the forecasting behavior of individual survey participants in terms of their expectations formation (see, for example, Ito (1990) MacDonald and Marsh (1996), Ruelke et al (2010)).

Since our forecast error specification is derived from the uncovered interest rate parity condition, this study is closely related to the so-called forward premium puzzle. The forward premium puzzle arises in a simple projection equation in which the change in the exchange rate is regressed onto the forward premium and the estimated coefficient on the latter is empirically usually closer to minus one than plus one (see, for example, Fama (1984)). Given covered interest parity is essentially an identity (since commercial banks essentially price the forward premium from the interest differential) this result implies a strong violation of uncovered interest parity and is usually interpreted as some form of expectational failure, evidence of time varying risk premia or both.

One important recent explanation for the forward premium puzzle is the existence of carry trade strategies that can produce the negative relationship between the exchange rate change and the interest rate spread. The currency carry trade strategy is usually implemented when investors in a low interest rate country purchase foreign assets by selling domestic assets. This results in an increase in demand for the foreign currency, and this in turn produces a depreciation of the home currency. Therefore, this strategy attempts to exploit interest rate spreads across countries in an optimal way.

Against the above background, this paper tries to explain exchange rate forecast errors for the JPY/USD exchange rate. Since the Bank of Japan (BoJ) has for some time implemented an extremely relaxed monetary policy, which has guided nominal short-term interest rates to stay around zero percent since 1995, the currency carry trade has often been used to explain movements (yen devaluation) in this rate. While the US has followed a similar monetary policy, known as QE, in order to boost her economy,[1] Japan has a longer history of such extraordinary monetary policy and her interest rate has stayed lower than the US rate. This was symbolized in April 2013 when the yield on the 10 year Japanese government bond recorded 0.315%--historically the lowest rate in human history. Thus there has been a clear and consistent gap between interest rates in these countries.

The novelty of this paper is twofold. First, expectations data on the foreign exchange rate from a survey data set are used, and therefore unlike most previous studies, we do not need to assume investors' rationality. Second, in the absence of statistical data which can capture the currency carry trade activities (see next section), they are inferred from the Markov-switching regime model with time-varying transition probabilities (MS-TVTP) (Filardo (1994) and Diebold et al (1994)) which enables us to determine regimes using exogenous variables of our choice.

2. Currency forecast errors and the UIRP

Our theoretical model for forecast errors is based on the uncovered interest rate parity (UIRP) condition which predicts that arbitrage will equalize returns on investment at home and abroad under the assumption of risk neutrality. The forward premium puzzle and the currency carry trade, which have been discussed over decades, can be analyzed within this framework.

In a two-country world, the UIRP can be summarized using a bilateral nominal exchange rate, S, as:

$$\log(S^{e,t+j})_t - \log(S)_t = (i-i^*)_t \tag{1}$$

where $S^{e,t+j}$ is the forecast exchange rate for the jth period ahead (j>0) which is projected at time t, and i is an interest rate. An asterisk refers to a foreign variable. The UIRP suggests a one-to-one relationship between the exchange rate change and the

[1] The QE is an abbreviation for quantitative easing, a terminology named after the Japanese QE policy from 2001 to 2006. A series of QE operations has been implemented in the US known as QE1 (2008-2010), QE2 (2010-2011) and QE3 (2012-).

interest rate differential. However, previous studies suggest that one percent increases in the interest rate differential do not bring about a one percent deprecation in the home exchange rate. Furthermore, many studies report that increases in the interest rate differential resulted in currency appreciation (Fama (1984)). This is called the forward premium puzzle.

Similarly, the forward premium puzzle can be studied using the covered interest rate parity (CIRP) condition:

$$\log(F^j)_t - \log(S)_t = (i-i^*)_t, \tag{2}$$

where F^j is the jth period forward exchange rate.

Similar to (1), the forward premium puzzle is said to be present in this equation if increases in the interest rate differential do not result in equi-proportional changes in the forward premium ($\log(F^j)_t$ - $\log(S)_t$). Alternatively, combining (1) with (2) and assuming rational expectations so that $(S^{e,t+j})_t = (S)_{t+j} + u_{t+j}$, where u is a random error with a zero mean and a constant variance:

$$\log(F)_t - \log(S)_t = \log(S)_{t+j} - \log(S)_t + u_{t+j.} \tag{3}$$

Research on the forward premium puzzle is also conducted using Eq. 3 where the assumption of rationality is invoked in the absence of survey expectations data. Since this paper will analyze the characteristics and evolution of expectation errors, we consider a variant of Eq. 1. Our model for expectation errors can be obtained by extracting $\log(S)_{t+j}$ from both sides of Eq. 1:

$$\log((S^{e,t+j})_t/(S)_{t+j}) = -\Delta\log(S)_{t+j} + (i-i^*)_{t.} \tag{4}$$

where Δ is the difference operator. For the estimation, we shall base our analysis on the following statistical model:

$$\log((S^{e,t+j})_t/(S)_{t+j}) = a - \theta\Delta\log(S)_{t+j} + \beta(i-i^*)_t + e_{t,} \quad e_t \sim N(0,\sigma^2), \tag{5}$$

or

$$\Delta\log(S)_{t+j} = a - \theta\log((S^{e,t+j})_t/(S)_{t+j}) + \beta(i-i^*)_t + e_{t,} \quad e_t \sim N(0,\sigma^2). \tag{6}$$

where β is a parameter of interest; $\beta < 1$ confirms the forward premium puzzle, and $\beta < 0$ becomes indirect evidence of the significant level of carry trade activities.

These equations enable us to analyze both the forward premium puzzle and currency carry trade since interest rates are included in this specification. In the case of the Japanese yen, it has been argued that currency carry trade started taking place in the period 2005-2007, exploiting the low interest rate policies in Japan (Curcuru et al (2010), Kawai and Takagi (2009), Hattori and Shin (2009)).[2] Specifically, during this period investors were borrowing in yen in order to purchase US and Australian assets, which produced a yen depreciation (Curcuru et al (2010)). Furthermore, the carry trade strategy seems to have been led by foreign banks operating in Japan (Hattori and Shin (2009)) but more aggressively by the Japanese public sector rather than domestic private financial companies (Ronaldo and Soderlind (2010)). More recently, under new Prime Minister Abe and new BoJ governor Kuroda, further aggressive expansionary monetary policy was announced and a yen depreciation followed (spring 2013), and investors were again said to have employed a currency carry trade strategy.

Despite such a popular explanation about temporary yen depreciation, however, it is difficult to find evidence of the currency carry trade directly from economic and financial statistics which are disseminated to the public. Therefore, Brunnermeier et al (2009) and Curcuru et al (2010) discuss carry trade activities using the currency futures positions of countries, while other researchers rely on the balance sheet information of banks (Hattori and Shin (2009), Ronaldo and Soderlind (2010), Habib and Stracca (2011)).

3. Data

In this paper, we have access to data on exchange rate expectations for the JPY/USD and focus on this currency particularly since it has been the focus of carry trade and quantitative easing type monetary policies, noted above. The data are monthly and run from 1993M7-2012M4, and we utilize data on exchange rates and interest rates. The spot exchange rate is downloaded from Datastream and exhibits fluctuations ranging from 76 to 145 yen during this sample period (Figure 1). The yen depreciation from the mid- to end-1990s seems to reflect prolonged economic recession along with the BoJ's expansionary policy which led short term interest rates to around 0% in 1995. Since the

[2] Furthermore, Clarida et al (2009) argue that the yen had been a funding currency for the carry trade during most of their sample period (1991-2009).

turn of the century, there has been a tendency for yen appreciation, and this trend in recent periods has been reinforced by a number of financial crises overseas (e.g., the sub-prime loan problem, the Lehman Shock and the European sovereign debt crisis). Interest rates (LIBOR) are also downloaded from DataStream and we note that Japanese interest rates are generally lower than the US interest rate during most of the period,[3] which is one necessary condition for the yen currency carry trade to be implemented.

The forecasts of the JPY/USD exchange rate are purchased from the Japan Center for International Finance (JCIF). The data are available for several industries (All industries (All), Banking sector (Bank), Export sector (Export), Import sector (Import) and Securities companies (Stock)) and for three time forecasting horizons (j=1, 3 and 6 months). Forecast data to which we have access are country and industry averages that are compiled on the basis of interviews to around 30 investors in key industries located in Japan. These interviews have been conducted twice a month except August when the interview is conducted once a month (end of period), and thus our analysis is based on the second interview of the month. Unfortunately, information from individual responses is not available due to confidentiality issues.

JCIF data has also been exploited by Ito (1990) who had access to the responses of individual participants for the period 1985-1987. Ito demonstrates the existence of heterogeneity in exchange rate forecasts, and his sectoral analysis suggests that the forecasts from the export industry have a bias toward yen depreciation, while those from the import industries tend toward yen appreciation.

Otherwise, all papers (Froot and Ito (1989) and Ito (1994)) analyzed the industry average of foreign exchange forecasts. Froot and Ito (1989) studied if there is consistency between short and long term forecasts between 1985 and 1987 when Japan experienced a sharp yen appreciation after the Plaza Meeting. The forecasts from different time forecasting periods are considered consistent when compound short-term forecasts yield the same level of the exchange rate as long-term forecasts. Then they concluded that exchange rate forecasts are inconsistent, and actually short-term forecasts are over-acting to economic shocks. A similar analysis is also conducted by Ito (1994) for the period 1985-1993, but to our knowledge, since then, virtually no academic research has explored this data set.

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3 The Japanese interest rate is always lower than US rate from 1993M9 onwards.

4. Forecast errors

Prior to the formal analysis, we shall describe forecast errors using the industry specific forecast data provided by the JCIF. Forecast errors are defined here as $(s^{e,t+j}_{t} - s_{t+j})*100$ where s is the log of the exchange rate, and the date of the spot exchange rate is consistent with the timing of the interviews and is drawn from daily data. Figure 2 plots the histogram of forecast errors and shows heterogeneity in forecast errors among different forecast time horizons. More specifically, the average of forecast errors is close to zero for all time horizons, but is slightly higher as the forecasting time horizon increases. Since the positive forecast errors suggest that forecast rates are higher than the actual rates, this implies that investors have perceived further depreciation of the yen than actual changes when making long-run (j=3, 6) projections. Second, long forecast errors have a fatter distribution than the 1 month ahead forecast errors. This indicates that short-term forecasts are more accurate and investors are more prone to making mistakes when projecting longer term forecasts.

Table 1 provides summary statistics of forecast errors from different industries and time horizons. Consistent with Figure 2, there are some discrepancies in forecast errors over different sample periods. In particular, the average value of errors is negative for 1 month ahead forecasts, but becomes positive for 3 and 6 month-ahead forecasts. Thus investors' expectations about the exchange rate appear to have a bias toward yen appreciation over the short term horizon, but this bias tends to change toward yen depreciation along with the forecasting period. These results are consistent with the current view that an over-valued yen will continue in the near future due to a number of crises triggered overseas (i.e., the safe heaven argument), but the yen should be depreciated further over the long time horizon in line with Japan's fragile economic recovery. Finally, this table confirms that forecast errors increase along with the forecast time horizons. The absolute mean value of forecast errors is largest when 6 month ahead forecasts are made. This shows the increasing difficulty in accurately predicting exchange rates over longer time horizons.

In order to investigate commonality in forecast errors, Table 2 examines whether the average and variance of forecast errors are identical among different industries for the same forecast time horizon, j. The null hypothesis of the equalization of the average is tested by the Anova and Welch tests, and is accepted by these tests. The equalization of the variance is examined by three tests (Bartlett, Levene, and Brown-Forsythe tests), and again the null of homogeneity in variances cannot be rejected. Therefore, it seems that investors in different industries have a similar view of the prospects of the Japanese economy, especially the exchange rate, when the forecasting time span is identical.

Table 3 conducts a similar analysis, but this time examines if the mean and variance of forecast errors are identical among different forecast time horizons. The results generally provide evidence of heterogeneous forecast errors over time. The null of equality is rejected for both the average and variance. Therefore, like Table 1 and Figure 2, this table shows that the distribution of forecast errors changes significantly along with forecast time periods.

As a final preliminary analysis, we analyze the heterogeneity in forecast errors using a simple Markov-switching (MS) model. Here, rather than emphasizing their heterogeneity in terms of industry type and forecast period, we are interested in whether forecast errors are time specific. More specifically, we analyze if investors are over- or under-estimating the exchange rate in particular time periods. This should be an interesting exercise since both countries have undergone several economic and financial crises which may result in asymmetry in exchange rate forecasts.

For this analysis, we use an MS model which was originally developed by Hamilton (1989) and was applied to analyze US business cycles. Since then, many researchers have implemented his statistical approach in different economic fields. Among exchange rate studies, Engel and Hamilton (1990) and Kaminsky (1993) have used the MS model and attempted to explain the dynamics of the USD exchange rate while taking into account the effect of the peso problem.

Following the standard MS literature, the probability of regime R at time t+1 can be written as follows:

$$\mathrm{p}(\mathrm{R}_{t+1} = \mathrm{j} | \mathrm{R}_t = \mathrm{i}) = \mathrm{p}_{\mathrm{ij}}$$

where i and j are integers reflecting regime type. This equation states that the probability of the future regime (R_{t+1}) becomes equal to j, which is dependent on the past value of the state being i.

In this paper, we follow the conventional practice of assuming two regimes; this assumption reduces the computational burden and is intuitively easier to provide economic justification for the regime type. For a two regime model, i, j $\in$ 1,2, the probability of each regime can be summarized as.

$$\mathrm{p} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

By definition, the probability of all occurrence sums to one: $\sum_{j=1}^{2} p_{ij} = 1$. In this paper we consider a two-regime model with regime-specific parameters and volatility, and the model will be estimated by a feasible sequential quadratic programming method (Lawrence and Tits 2001).

$$error_t = \alpha_{R_t} + u_t \qquad u_t \backsim N(0, \sigma_{R_t}^2)$$

where *error* is the forecast error observed at time *t*, and regime type is shown as R_t (R_t = 1 or 2). This model allows heterogeneity in the mean (α_{R_t}) and variance ($\sigma_1^2 < \sigma_2^2$), and in this simple setting the mean can be interpreted as the average forecast error in each regime.

The results from the two-regime MS model for each industry and forecasting time horizon are summarized in Table 4. The regime-specific constant terms suggest that forecast errors are, on average, positive for Regime 2, indicating that investors have forecasted further depreciation than what actually occurred. Since the exchange rate volatility is generally higher in Regime 2, this table implies a strong expectation bias towards yen depreciation when the foreign exchange market is chaotic. In contrast, the constant term is often negative when the market is relatively calm (Regime 1), and this sign suggests that the yen depreciated further than the expected value in tranquil periods. Furthermore, the probability for these regimes (p_{.|.} in Table 4) implies that a tranquil period lasts longer than a volatile one particularly at a short term horizon, which can be also confirmed in Figure 3. Finally, we find more support for this two-regime model than for a linear model; the Likelihood Ratio (LR) test for parameter equalization among regimes is strongly rejected in favor of a two-regime model.

5. Forward Premium Puzzle

Since our statistical specifications are derived from the UIRP condition, the topic of our study is closely related to the forward premium puzzle. In this regard, this section analyzes the relationship between the exchange rate and interest rates and studies whether the forward premium puzzle indeed exists in the JPY/USD exchange rate.

However, unlike previous studies, a variant of the UIRP is used here in order to include explicitly forecast errors in the statistical specification. Therefore, we shall not rely on the investors' rationality assumption, but shall use the forecast values of the exchange rate. The treatment of these variables means that our study departs from the existing literature.

5.1. OLS Estimates

Initially, we estimate Eq 5 using OLS for All since forecast errors from different industries are found to be homogenous in the same forecasting time framework. Table 5 summarizes the results, with standard errors robust to heteroskedasticity and autocorrelation, and suggests that the forward premium puzzle indeed exists, in particular, in short term forecast errors. The parameter of the interest rate differential (β) is well below the theoretical value of unity in all cases, and the negativity of this parameter is observed when j = 1. Indeed, as the forecasting time horizon increases, this parameter turns out to be significantly positive and becomes more consistent with UIRP underlining the dominance of economic fundamentals over changes in the long term exchange rate.[4] As an alternative specification, we examine an equation in which actual exchange rate changes are treated as an endogenous variable (i.e., Eq 6) since we do not have a firm view on causality between forecast errors and actual exchange rate changes. However, our result remains generally unchanged even in the model of exchange rate changes; the forward premium puzzle is more significant in short term assets.

With respect to other parameters, forecast errors and exchange rate changes in Eqs 5 and 6, respectively, are correctly signed and are close to the theoretical value of minus one. While this parameter differs statistically from the theoretical value in most cases, its proximity suggests that investors make quite accurate forecasts of the exchange rate on average although they are not perfectly correct.

Furthermore, in order to clarify causality between forecast errors and exchange rate changes, we carry out the Granger noncausality test in a panel data context. With the null hypothesis of noncausality, Table 6 suggests that unidirectional causality exists between these variables but depends on forecasting time spans. For 1 and 3 month ahead forecasts, there is evidence that the actual exchange rate has caused forecast errors. In other words, large expectation errors occur when there are wide fluctuations in actual exchange rates, consistent with a model specification Eq 5. In contrast, for 6

[4] This point is consistent with Chinn and Meredith (2004) although they do not use forecast data.

month forecasts, the direction of causality is reversed and it is forecast errors that resulted in changes in exchange rates (i.e., Eq 6). It follows that investors' expectations are driving forces of the actual exchange rate when j = 6.

5.2. Bayesian Model Averaging Results

While in the past the OLS has been the most frequently used estimation technique, it attempts to find optimal point estimates for parameters under a prior assumption that the model specification is congruent with data; in other words, all statistical tests were conducted with a particular specification. Therefore, in order to check the robustness of our findings, we study the presence of the forward premium puzzle by means of the Bayesian Model Averaging (BMA) which examines the relevance of parameters in different model specifications. Thus, the BMA addresses parameter and model uncertainty and is used to choose the best model. Over recent decades, the BMA has drawn considerable interest from applied researchers since it can deal with complicated models with a number of explanatory variables, and has been applied to a wide range of economic analyses, in particular in order to seek the relevant economic variables to explain economic growth (e.g., Fernandez et al (2001)).

The main feature of the BMA is that model uncertainty is analyzed by considering all combinations of explanatory variables (X). This means that if there are k explanatory variables (excluding the constant), it analyzes 2^k models for y and constructs the weighted average of posterior model probabilities (PMP) based on Bayes' theorem.

$$p(\mathrm{M}_s|y,X) = \frac{p(y|\mathrm{M}_s,X)p(\mathrm{M}_s)}{p(y|X)} \propto p(y|\mathrm{M}_s,X)p(\mathrm{M}_s)$$

where model M_s depends on a composition of parameters (s, s=1,…2^k). $p(y|X)$ represents the integrated likelihood and is constant over models. This equation states that the PMP is proportional to the marginal likelihood $p(y|\mathrm{M}_s,X)$ times a prior model probabilities $p(\mathrm{M}_s)$.

Furthermore, using the PMP as a weight and considering all combinations of explanatory variables, the posterior distribution for the parameter can be calculated as;

$$p(\beta|y,X) = \sum_{j=1}^{2^k} p(\beta|\mathrm{M}_s,y,X)\, p(\mathrm{M}_s|y,X)$$

Thus parameter uncertainty is captured by $p(\beta|\mathrm{M}_s,y,X)$ as in the standard Bayesian approach and model uncertainty by the PMP term. Since we do not have any information about these parameters, this paper follows the most orthodox assumption, namely Zellner's g prior, to calculate the marginal likelihood for M_s. In other words, the improper priors are imposed on the intercept and variance, i.e., $p(\mathrm{Intercept}_s) \propto 1$ and $p(\sigma) \propto \sigma^{-1}$, and β is assumed to possess the following property:

$$\beta | g \sim \mathrm{N}(0, \sigma^2 g (X'X)^{-1}).$$

The g determines the uncertainty about β; a small g indicates a small variance and thus less uncertainty. We follow the Unit Information Prior (g-UIP) and set $g = N$, where N is the number of observations. Furthermore, the prior model probabilities for each model are set as $p(\mathrm{M}_s) = 1/2^k$ (Fernadez et al (2001), Koop (2006)), assigning the same weight to a set of models under investigation.[5] Since the number of covariates is not large, all models are evaluated here.

Table 7 summarizes the results based on Eq 5 from the BMA and shows generally consistent results with OLS results in Table 5; in other words, the relationship between the exchange rate and interest rate can be explained more consistently with the UIRP for long term forecasts. More specifically, the exchange rate change is reported to be the most significant explanatory variable. A high value of the posterior inclusion probability (PIP)—the sum of PMP from models containing a particular variable—suggests a high likelihood of this variable to be included in the model. In contrast, the importance of interest rates is specific to models and forecasting time periods. Indeed, the interest rates are found to be closely associated with 6 month ahead forecast errors, but less so with 1 and 3 month ahead errors.

With respect to the sign of these covariates, interest rates are negative (see Post Mean; the average of parameters from all models) for 1 month forecast errors, suggesting the presence of the forward premium puzzle. But this parameter is positive in 3 and 6 month ahead forecast errors, consistent with the UIRP. These results are in line with the conventional view that movements in the longer rate are more governed by economic fundamentals compared to the short-term rate which contains lots of noise components. As regards actual exchange rate changes, in contrast to interest rates, they always enter forecast error equations with a negative parameter. These parameter signs are correct and can be seen in all models (see Sign certainty for being positive), and they remain unchanged even when actual exchange rate changes are used as an endogenous variable; i.e., Eq 6.

[5] The results are consistent even when g is chosen from a different criterion.

In short, our model derived from the UIRP yields similar empirical results to those reported in previous studies using the conventional UIRP. For example, the forward premium puzzle is more often observed in short maturity assets (Chinn and Meredith (2004)) and in developed countries with high capital income (Bansal and Dahlquist (2000)). Recent studies from the market microstructure literature (e.g., Evans and Lyons (2002), Burnside et al. (2009)) have provided an economic reason for the puzzle by showing improvements in the performance of interest parity conditions once private information is incorporated in the model. It follows that since interest parity conditions are derived from public information alone, the misspecification bias (and thus private information) may play a more important role in the dynamics of exchange rates of developed countries.[6]

6. Evidence from the Markov-Switching Model with Time Varying Transition Probabilities

Given that there is evidence of nonlinearity in forecast errors (Table 4), this section re-examines their relationship with actual exchange rate changes and interest differentials (i.e., Eqs 5 and 6) using the MS model with time-varying transition probabilities (MS-TVTP). This model has several advantages over the conventional MS model. Unlike the standard MS model used in Table 4, we relax the assumption of constant transition probabilities and specify regimes to be a function of exogenous variables of our choice. This extra information associated with regimes helps us to make an assessment of the abovementioned economic relationship with forecast errors in a more meaningful way than the conventional model where an endogenous variable determines regimes. As shall be discussed shortly, in this paper we specify economic variables that are relevant to capturing the unique characteristics of the carry trade activities which are unobservable given the data available to the public. Furthermore, since it is possible to change the choice of variables to explain regimes, we can check the robustness of our findings. In short, the MS-TVTP is useful to better understand the timing of the occurrence of the puzzle and the evolution of forecast errors by clarifying the economic conditions of the regimes.

The MS-TVTP has been proposed by Filado (1994) and Diebold et al (1994), and like the standard MS model, their model has often been applied to many areas of

[6] While consideration of private information is an important and interesting area, we leave it for future study since we do not have access to order flow data which have often been used in previous studies in order to capture private information.

economic research; for example, US business cycles (Durland and McCurdy (1994)), the asymmetric effects of monetary policy (Lo and Piger (2005)) and oil prices (Raymond and Rich (1997)), and the currency crisis in the European Monetary System (Engel and Hakkio (1996), Peria (2002)) among exchange rate literature. However, while there are clearly attractive features in the MS-TVTP, its application to economic and financial data is rather limited.

The model can be expressed by allowing transition probabilities to vary over time maintaining the notations used in the previous section, the probabilities of regimes, p(*R*), can be re-written as:

$$\mathrm{p}(R_{t+1} = \mathrm{j} | R_t = \mathrm{i}) = p_{ij,t+1}$$

For a two regime MS-TVTP, there are four transition probabilities to be obtained:

$$\mathrm{p(t)} = \begin{bmatrix} p_{11,t} & p_{12,t} \\ p_{21,t} & p_{22,t} \end{bmatrix}$$

where $\sum_{j=1}^{2} p_{ij} = 1$ for all *i*. Each time-varying transition probability will be expressed as a function of exogenous variables (*Z*) in the immediately previous period and their parameters δ, and can be written as:

$$p_{11,t} = \frac{\exp(Z_{1,t-1}\delta_1)}{1 + \exp(Z_{1,t-1}\delta_1)}$$

$$p_{22,t} = \frac{\exp(Z_{2,t-1}\delta_2)}{1 + \exp(Z_{2,t-1}\delta_2)}$$

$$p_{12,t} = 1 - \frac{\exp(Z_{1,t-1}\delta_1)}{1 + \exp(Z_{1,t-1}\delta_1)}$$

$$p_{21,t} = 1 - \frac{\exp(Z_{2,t-1}\delta_2)}{1 + \exp(Z_{2,t-1}\delta_2)}$$

This data transformation to a multinominal logit specification ensures that *p* ranges from 0 to 1 (Filardo (1994), Diebold et al. (1994)). We consider two types of specifications for *Z*. Initially, we have chosen lagged forecast errors in absolute terms as a proxy for *Z*. The choice of this variable is related to the underlying motivations for the currency carry trade; the stability of the foreign exchange market is one important condition for the successful implementation of this strategy. More specifically, low exchange rate volatility implies low price risk associated with the exchange rate which is the major source of risk when interest rate movements are minimal (Bhansali (2007)). It follows that the carry trade becomes active when exchange rate volatility is small and the interest rate spread is perceived to exist persistently. Alternatively, we consider the financial crisis index as a determinant of regimes since this indicator also measures the level of market stability. This variable is demeaned so that it is easier for us to interpret the parameters. Specifying regimes as a function of exogenous economic variables allows us to estimate the timing and the duration of the carry trade, which is useful in the absence of statistical data which directly measure carry trade activities.

In short, we consider the following specifications, based on Eqs 5 and 6, where the intercept and the interest rate spread which is of most interest to us, are assumed to be regime specific.

$$error_t = \alpha_{R_t} + \beta_{R_t}\left(i_{t-j} - i^*_{t-j}\right) + \theta \Delta s_t + u_t \qquad u_t \backsim N(0, \sigma^2) \tag{7}$$

$$\Delta s_t = \alpha_{R_t} + \beta_{R_t}\left(i_{t-j} - i^*_{t-j}\right) + \theta error_t + u_t \qquad u_t \backsim N(0, \sigma^2) \tag{8}$$

This model makes further assumptions. First, it also assumes homogenous variance between regimes since heterogeneous volatility is expected to be captured by Z (the lagged forecast errors and the lagged crisis index in absolute terms) which is designed to affect time-varying transition probabilities. Furthermore, two regimes (R = 1, 2) are assumed since they are probably the most obvious choices, i.e., over- and under-forecasting of the exchange rate, and this assumption helps minimize computation time. As regards estimation methodologies, the Kalman filter iteration could be used for estimation, but the number of parameters is large. Thus we follow Kim (1994) who has proposed an approximation method for parameter estimation and smooth probabilities.[7] We expect β to have a different size in different regimes; in particular, the negative sign of this parameter is regarded as evidence of significant carry trade activities.

Table 8 summarizes the results from the forecast error equation with TVTP using the lagged forecast errors (the upper half) and the lagged crisis index (the bottom half). As the causality test results suggest, this specification is more relevant to short term assets (j = 1,3) although all (j = 1, 3, 6) results are reported. Then we can infer that a consistent and strong relationship exists between forecast errors and exchange rate changes. As the UIRP suggests, forecast errors are reported to be negatively and significantly associated with actual exchange rates, and this result is robust to forecasting time periods.

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[7] Alternatively, one could estimate them by the ME or Bayesian methods. See Filardo (1994) regarding the deficiencies of these estimation methods.

In contrast to exchange rate changes, the results for interest rates are specific to forecasting periods as well as regime. Consistent with the interpretation of Filardo (1994), in our model, Regime 1 refers to the tranquil period, and Regime 2 to the crisis period. With this interpretation of regimes, we observe evidence of the carry trade effect (i.e., a negative parameter on the interest rate differential) in short term forecast errors (j = 1, 3) during crisis periods in Table 8. This is a result inconsistent with the UIRP but has been reported by previous studies (e.g., Fama (1984)). Needless to say, since the parameters of interest rates are below unity, the forward premium puzzle is still present.

Considering the direction of causality between forecast errors and exchange rate changes, it is more appropriate to evaluate the effect of interest rates with a longer forecasting period (j = 6) in the equation of exchange rate changes. While this specification does not provide an explanation of the dynamics of forecast errors, we can evaluate the relationship between actual exchange rate changes and interest rates. Table 9 shows the results and reports no evidence of the carry trade for j = 6. The interest rate spread turns out to be statistically insignificant at times of normality but is significantly positive when the market is in crisis. This is in line with previous findings that the UIRP tends to hold more in longer maturity assets (Chinn and Meredith (2004)) and in developing countries (Bansal and Dahlquist (2000)) whose economy exhibits more fluctuations.

A robustness check is also conducted using the crisis index for Japan (VXJ) for Z to determine transition probabilities. The VXJ is available from 1998 and is compiled following the statistical methodology used for the US crisis index (known as the CBOE volatility index).[8] The VXJ is an appropriate measure since our forecast data are collected from Japanese residents, and reflects economic and financial uncertainty in Japan. Therefore, the market volatility is measured by increases in this index. Although the VXJ is derived from the option prices of equities, this index is used as a proxy for volatility in the foreign exchange market since foreign exchange rate crises are highly correlated with stock market volatility. Generally, our results remain unchanged although this definition of Z is used. Our results using this index for All confirm the significant carry trade activity in Regime 2 for j = 1, 3, and this effect ceases over the long term forecast horizon (Tables 8 and 9).

[8] This data set is compiled by the University of Osaka. To our knowledge no study has exploited the VXJ.

In order to complement our interpretations above, Tables 8 and 9 also present δ_1 and δ_2, parameters for Z used to calculate transition probabilities for Regimes 1 and 2, respectively. The δ_1 is reported to be positive and δ_2 to be negative, an opposite sign indicating transition probabilities (p_{11} and p_{22}) moving in an opposite direction. Given the definition of our variables in Z, the economy is regarded as being in a crisis in a previous period when $Z > 0$. In such a case, the positive sign for Regime 1 indicates increases in the likelihood of being in Regime 1 for the next period; at the same time, reducing the probability for Regime 2 as the negative sign for Regime 2 suggests. The same logic applies to a case where Z is negative. Tables 8 and 9 show that our parameters do not always have a correct sign or statistical significance; however, they are not contracted to each other in terms of identifying regime type.

The smoothed probabilities for Regime 2 (i.e., the crisis period) are plotted in Figure 4 for j = 1 for brevity, and as discussed, we can draw a conclusion from these parameters and graphs that Regime 1 corresponds to the tranquil period and Regime 2 to crisis times. According to Figure 4, the foreign exchange rate market is more likely to have experienced a tranquil period, and the opportunity for the carry trade is very limited (Table 10). But such opportunities arose when expansionary monetary policy lead the Japanese interest rate to around zero percent (after 1995) and a clear commitment to keeping low interest rates was observed. The increase in this probability around 2003 is consistent with the timing of the long term government bond yield dropping to a historically low level (0.43%) at that time.[9] Similarly, evidence of the carry trade around 2006 is in line with many previous studies (Clarida et al (2009), Hattori and Shin (2009), Kawai and Takagi (2009), Curcuru et al (2010)).

Interestingly, Figure 4 and our model specification imply that the commitment of the Bank of Japan (BOJ) to low (zero) interest rates has triggered the currency carry trade. This interpretation is consistent with Bhansali (2007) who argues that profits are likely to result from interest rate spreads in this strategy. However, unlike his prediction, the carry trade seems to have taken place at times of high exchange rate volatility. Therefore, profit opportunities from interest rate differentials seem to offset exchange rate uncertainty when making investment decisions. After all, a stronger commitment of

[9] The Japanese government bond set a new record of 0.315% in April 2013. Prior to 2003, the lowest level of the long term rate was recorded in Italy (1.125%) in 1619.

any central banks to boost their economy is usually more clearly observed at times of financial crises.

The evaluation of forecast errors can thus be summarized by the explanations above for Table 8. In short, the interest rate differential and exchange rate changes are the driving forces of short forecast errors (j = 1, 3). Furthermore, there is a tendency for investors to become conservative in terms of forecasting yen deprecation at times when the yen is actually depreciating. In contrast, their expectations become aggressive toward yen depreciation at times when the yen is actually appreciating. As regards interest rates, they are statistically insignificant when the market is tranquil; however, interest rates become significant (although negatively associated with forecast errors) when the market is chaotic. Therefore, the introduction of nonlinearity in the economic relationship clarifies the timing of the strengthening of the relationship between forecast errors and interest rates. Unfortunately, our model cannot tell much about the evolution of long term forecast errors (j = 6) because of a causality issue; however, there is an interesting insight into the role of investors' expectations in formation of the exchange rate implying the stabilization of investors' expectations would lead to that of the actual exchange rate.

7. Conclusion

In this paper we take exchange rate survey data generated by the Japan Center for International Finance (JCIF) to analyse investor's forecast errors about the yen/ dollar exchange rate. The data are available for several industries, including the banking sector, the export sector, the import sector and securities companies and over three time forecasting horizons (j=1, 3 and 6 months). Our econometric framework exploits the uncovered interest parity condition and we use a number of different econometric modeling methods. We demonstrate that for a specific forecast horizon, exchange rate forecasts are homogenous among different industry types, but for a given industry forecasts differ for different over different forecast horizons. Specifically, investors tend to undervalue the future exchange rate at long term forecast horizons and overvalue the exchange rate at short horizons. In addition, we find a bias in investors' forecasts toward yen depreciation is strengthened when uncertainty increases in the foreign exchange markets.

We also report evidence that forecast errors are partly driven by interest rate spreads and our non-linear modeling clarifies the timing of the strengthening of the relationship between forecast errors and interest rates. Not surprisingly, we report evidence against UIRP regardless of the forecasting horizon, but the so-called forward premium puzzle is more significant at shorter forecasting horizons. Consistent with this finding, our coefficients on interest rate spreads provide indirect evidence of the yen carry trade over only a short term forecast horizon.

However, unlike the conventional belief (Bhansali (2007)), the investors' decision for the carry trade is driven not so much by exchange rate stability but largely by the perceived stronger commitment of the Bank of Japan to maintain a low interest rate. Since accommodative policies have often been implemented during financial crises when there is a high level of uncertainty about the future exchange rate, the negative effect of exchange rate volatility seems to have been offset by the positive effect of a clearer prospect about a low interest rate in Japan. In other words, a persistent and low interest rate seems to be the major driving force of the carry trade strategy.

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Table 1. Summary Statistics for Forecast Errors

1 month	All	Bank	Export	Import	Stock
Mean	-0.175	-0.216	-0.121	-0.234	-0.114
Median	-0.389	-0.226	-0.459	-0.463	-0.338
Maximum	14.609	14.249	14.081	14.472	15.855
Minimum	-11.885	-12.672	-12.174	-11.061	-12.174
Std. Dev.	3.333	3.349	3.413	3.383	3.450
Skewness	0.179	0.086	0.272	0.264	0.127
Kurtosis	5.099	5.049	4.936	4.625	5.302
Obs	225.000	225.000	225.000	225.000	225.000
3 months					
Mean	0.364	0.224	0.497	0.320	0.489
Median	-0.213	-0.414	-0.344	-0.283	0.241
Maximum	18.607	18.377	20.198	18.469	20.253
Minimum	-16.884	-17.960	-15.492	-16.037	-17.707
Std. Dev.	5.809	5.812	5.869	5.888	6.018
Skewness	0.416	0.351	0.505	0.420	0.370
Kurtosis	3.816	3.717	3.716	3.758	3.963
Obs	223.000	223.000	223.000	223.000	223.000
6 months					
Mean	1.210	0.943	1.230	1.177	1.588
Median	1.376	0.727	1.475	0.973	1.878
Maximum	20.712	19.653	21.145	20.951	23.109
Minimum	-17.945	-18.886	-16.769	-17.890	-18.670
Std. Dev.	7.797	7.929	7.899	7.874	7.868
Skewness	0.023	0.001	0.103	0.041	-0.014
Kurtosis	2.674	2.716	2.527	2.677	2.753
Obs	220.000	220.000	220.000	220.000	220.000

Note: Forecast errors obtained with taking log. Full sample.

Table 2. Mean and Variance Equality for Forecast Errors in Different Industries

Mean	d.f.	Stat	Prob	Variance	d.f.	Stat	Prob
1 month							
Anova F-test	(3, 896)	0.076	0.973	Bartlett	3.000	0.217	0.975
Welch F-test	(3, 498)	0.076	0.973	Levene	(3, 896)	0.036	0.991
				Brown-Forsythe	(3, 896)	0.026	0.994
3 months							
Anova F-test	(3, 888)	0.114	0.952	Bartlett	3.000	0.288	0.962
Welch F-test	(3, 493)	0.115	0.951	Levene	(3, 888)	0.031	0.993
				Brown-Forsythe	(3, 888)	0.042	0.988
6 months				Bartlett	3.000	0.016	0.999
Anova F-test	(3, 876)	0.251	0.861	Levene	(3, 876)	0.021	0.996
Welch F-test	(3, 487)	0.251	0.861	Brown-Forsythe	(3, 876)	0.021	0.996

Note: Forecast errors in log form. Full sample. The Welch test takes into account unequal variances among samples.

Table 3. Mean and Variance Equality for Forecast Errors in Different Time Horizons

	d.f.	Stat	Prob		d.f.	Stat	Prob
All							
Anova F-test	(2, 665)	3.094	0.046	Bartlett	2.000	144.443	0.000
Welch F-test	(2, 391)	3.222	0.041	Levene	(2, 665)	58.103	0.000
				Brown-Forsythe	(2, 665)	57.330	0.000
Bank							
Anova F-test	(2, 665)	2.127	0.120	Bartlett	2.000	148.523	0.000
Welch F-test	(2, 391)	2.184	0.114	Levene	(2, 665)	60.382	0.000
				Brown-Forsythe	(2, 665)	59.090	0.000
Export							
Anova F-test	(2, 665)	2.828	0.060	Bartlett	2.000	141.255	0.000
Welch F-test	(2, 393)	3.138	0.045	Levene	(2, 665)	61.071	0.000
				Brown-Forsythe	(2, 665)	59.160	0.000
Import							
Anova F-test	(2, 665)	3.128	0.044	Bartlett	2.000	142.926	0.000
Welch F-test	(2, 392)	3.270	0.039	Levene	(2, 665)	56.607	0.000
				Brown-Forsythe	(2, 665)	55.834	0.000
Stock							
Anova F-test	(2, 665)	4.533	0.011	Bartlett	2.000	136.506	0.000
Welch F-test	(2, 393)	4.595	0.011	Levene	(2, 665)	54.151	0.000
				Brown-Forsythe	(2, 665)	53.654	0.000

Note: Forecast errors in log form. Full sample. The Welch test takes into account unequal variances among samples.

Table 4. Markov-Switching Model for Forecast Errors

	Coef	SE	Prob	Coef	SE	Prob	Coef	SE	Prob
All	1 month			3 months			6 months		
Const(1)	-0.269	0.232	0.248	-3.370	0.473	0.000	-5.269	0.700	0.000
Const(2)	0.420	1.400	0.764	4.934	0.691	0.000	6.284	0.750	0.000
sigma(1)	2.656	0.211	0.000	3.561	0.268	0.000	4.999	0.381	0.000
sigma(2)	6.003	1.296	0.000	4.609	0.365	0.000	5.450	0.406	0.000
p_{1|1}	0.908	0.072	0.000	0.878	0.033	0.000	0.948	0.030	0.000
p_{1|2}	0.585	0.327	0.075	0.151	0.047	0.002	0.045	0.027	0.104
LR test	16.821		0.002	66.782		0.000	122.770		0.000
Bank									
Const(1)	-0.245	0.230	0.286	-3.058	0.519	0.000	-4.643	0.608	0.000
Const(2)	-0.032	1.351	0.981	5.552	0.858	0.000	7.213	0.661	0.000
sigma(1)	2.666	0.220	0.000	3.746	0.280	0.000	5.279	0.370	0.000
sigma(2)	6.040	1.334	0.000	4.423	0.402	0.000	5.216	0.401	0.000
p_{1|1}	0.891	0.078	0.000	0.886	0.033	0.000	0.942	0.026	0.000
p_{1|2}	0.682	0.235	0.004	0.188	0.054	0.001	0.070	0.029	0.015
LR test	15.978		0.003	65.256		0.000	115.870		0.000
Export									
Const(1)	-0.378	0.241	0.119	-3.151	0.441	0.000	-5.597	0.561	0.000
Const(2)	1.339	1.321	0.312	5.476	0.727	0.000	6.612	0.557	0.000
sigma(1)	2.694	0.199	0.000	3.468	0.259	0.000	4.631	0.358	0.000
sigma(2)	5.807	1.100	0.000	4.660	0.387	0.000	5.335	0.358	0.000
p_{1|1}	0.933	0.055	0.000	0.889	0.031	0.000	0.952	0.024	0.000
p_{1|2}	0.384	0.233	0.102	0.154	0.046	0.001	0.041	0.020	0.040
LR test	19.312		0.001	77.679		0.000	146.630		0.000
Import									
Const(1)	-0.451	0.234	0.055	-3.235	0.521	0.000	-5.567	0.589	0.000
Const(2)	0.754	1.048	0.473	5.167	0.799	0.000	6.362	0.566	0.000
sigma(1)	2.704	0.191	0.000	3.701	0.274	0.000	4.860	0.369	0.000
sigma(2)	5.358	0.900	0.000	4.708	0.380	0.000	5.399	0.361	0.000
p_{1|1}	0.951	0.037	0.000	0.885	0.032	0.000	0.952	0.024	0.000
p_{1|2}	0.225	0.161	0.164	0.158	0.052	0.002	0.043	0.020	0.031
LR test	15.489		0.004	66.563		0.000	131.790		0.000
Stock									
Const(1)	-0.162	0.250	0.518	-3.527	0.467	0.000	-5.467	1.008	0.000
Const(2)	0.022	0.801	0.978	4.853	0.648	0.000	6.347	0.762	0.000
sigma(1)	2.664	0.247	0.000	3.819	0.281	0.000	4.994	0.500	0.000
sigma(2)	5.022	0.783	0.000	4.775	0.366	0.000	5.490	0.389	0.000
p_{1|1}	0.962	0.032	0.000	0.872	0.035	0.000	0.916	0.039	0.000
p_{1|2}	0.108	0.104	0.297	0.141	0.044	0.001	0.058	0.027	0.033
LR test	16.716		0.002	57.159		0.000	111.420		0.000

Note: The Const is the constant, and the endogenous variable is forecast errors. The numbers in parentheses represent regime type. p_{n|m} is a probability of a regime shifting from m to n. The LR test examines the nonlinearity of the model.

Table 5. Variants of the UIRP

	1 month			3 months			6 months		
Variable	Coef	SE	P-value	Coef	SE	P-value	Coef	SE	P-value
Endog:	Error	Eq. 5							
Const	-0.575	0.290	0.049	0.230	0.397	0.563	2.222	0.480	0.000
(i-i*)	-0.092	0.068	0.177	0.067	0.104	0.525	0.555	0.124	0.000
△Log(S)	-0.962	0.041	0.000	-0.960	0.033	0.000	-0.904	0.030	0.000
Endog:	△Log(S)	Eq. 6							
Const	-0.587	0.245	0.017	0.063	0.399	0.875	1.920	0.567	0.001
(i-i*)	-0.102	0.057	0.073	0.023	0.099	0.815	0.475	0.132	0.000
Error	-0.866	0.037	0.000	-0.948	0.025	0.000	-1.019	0.030	0.000

The OLS estimation is based on Eqs 5 and 6. The HAC standard errors are reported with the Newey-West approach.

Table 6. Granger non-causality tests (p-values)

Null hypothesis	1 month	3 months	6 months
△Log(S) $\nrightarrow$ Error	0.009	0.007	0.375
Error $\nrightarrow$ △Log(S)	0.368	0.615	0.000

Note: The tests are conducted in the bivariate panel data context with a lag length of one.

Table 7. Bayesian Model Averaging for Model Comparison

		PIP	Post Mean	Post SD	Sign certainty
Eq 5					
1 month	ΔLog(S)	1.000	-0.909	0.028	0.000
	(i-i*)	0.309	-0.017	0.029	0.000
3 months	ΔLog(S)	1.000	-0.950	0.020	0.000
	(i-i*)	0.111	0.003	0.010	1.000
6 months	ΔLog(S)	1.000	-0.914	0.019	0.000
	(i-i*)	1.000	0.136	0.019	1.000
Eq 6					
1 month	Error	1.000	-0.862	0.026	0.000
	(i-i*)	0.489	-0.000	0.001	0.000
3 months	Error	1.000	-0.942	0.020	0.000
	(i-i*)	0.067	0.000	0.000	1.000
6 months	Error	1.000	-1.011	0.021	0.000
	(i-i*)	1.000	0.004	0.001	1.000

Note: PIP is the posterior inclusion probability. Based on Eqs 5 and 6. Sign certainty measures the likelihood of parameters to be positive.

Table 8. Markov-Switching Model with Time-varying Transition Probabilities for Forecast Errors

	1 month			3 months			6 months		
	Coef	SE	Prob	Coef	SE	Prob	Coef	SE	Prob
Const(1)	***-0.189***	***0.088***	***0.032***	***0.845***	***0.215***	***0.000***	0.340	0.520	0.512
(i-i*)(1)	0.003	0.019	0.897	0.014	0.075	0.855	***0.370***	***0.114***	***0.001***
Const(2)	***-9.008***	***0.560***	***0.000***	***-2.531***	***0.477***	***0.000***	***3.351***	***0.314***	***0.000***
(i-i*)(2)	***-1.938***	***0.138***	***0.000***	***-0.309***	***0.101***	***0.002***	***0.465***	***0.086***	***0.000***
△Log(S)	***-1.041***	***0.023***	***0.000***	***-0.966***	***0.017***	***0.000***	***-0.883***	***0.018***	***0.000***
LOG(SIGMA)	-0.080	0.050	0.108	***0.290***	***0.053***	***0.000***	***0.405***	***0.056***	***0.000***
P1-|Error|(δ_1)	***1.221***	***0.209***	***0.000***	***1.540***	***0.427***	***0.000***	***0.579***	***0.201***	***0.004***
P2-|Error| (δ_2)	-0.064	0.195	0.743	***-0.660***	***0.208***	***0.002***	***-0.477***	***0.139***	***0.001***
Const(1)	-0.214	0.133	0.107	***0.856***	***0.295***	***0.004***	***3.048***	***0.324***	***0.000***
(i-i*)(1)	-0.005	0.039	0.903	***0.011***	***0.105***	***0.920***	***0.392***	***0.115***	***0.001***
Const(2)	***-9.115***	***0.609***	***0.000***	***-2.321***	***0.627***	***0.000***	0.662	0.389	0.089
(i-i*)(2)	***-2.073***	***0.170***	***0.000***	-0.253	0.135	0.061	***0.438***	***0.102***	***0.000***
△Log(S)	***-1.039***	***0.029***	***0.000***	***-0.977***	***0.026***	***0.000***	***-0.875***	***0.022***	***0.000***
LOG(SIGMA)	-0.005	0.053	0.925	***0.391***	***0.064***	***0.000***	***0.514***	***0.058***	***0.000***
P1-|VXJ| (δ_1)	***22.724***	***5.214***	***0.000***	***19.779***	***6.424***	***0.002***	36.519	21.971	0.097
P2-|VXJ| (δ_2)	10.877	12.378	0.380	***-10.733***	***3.726***	***0.004***	***-46.932***	***10.825***	***0.000***

Note: The estimation is based on Eq. 7. P1 and P2 are explanatory variables in transition matrix. The absolute value of lagged forecast errors is used for them. VXJ=Volatility index for Japan. The number in parentheses shows regime type.

Table 9. Markov-Switching Model with Time-varying Transition Probabilities for Actual Exchange Rate Changes

All	1 month			3 months			6 months		
	Coef	SE	Prob	Coef	SE	Prob	Coef	SE	Prob
Const(1)	-0.178	0.112	0.112	***0.885***	***0.225***	***0.000***	***3.023***	***0.315***	***0.000***
(i-i*)(1)	-0.006	0.033	0.845	0.131	0.072	0.068	***0.447***	***0.087***	***0.000***
Const(2)	***-8.509***	***0.485***	***0.000***	***-2.930***	***0.546***	***0.000***	-1.167	0.766	0.127
(i-i*)(2)	***-1.838***	***0.125***	***0.000***	***-0.352***	***0.153***	***0.022***	0.070	0.161	0.665
Log(Error)	***-0.874***	***0.018***	***0.000***	***-0.956***	***0.018***	***0.000***	***-1.043***	***0.020***	***0.000***
LOG(SIGMA)	***-0.177***	***0.050***	***0.000***	***0.316***	***0.055***	***0.000***	***0.449***	***0.058***	***0.000***
P1-|Error|(δ_1)	***1.188***	***0.196***	***0.000***	***1.842***	***0.566***	***0.001***	***0.463***	***0.110***	***0.000***
P2-|Error| (δ_2)	0.036	0.181	0.842	***-0.432***	***0.203***	***0.033***	***-0.389***	***0.115***	***0.001***
Const(1)	-0.200	0.125	0.110	0.382	0.198	0.054	***2.698***	***0.333***	***0.000***
(i-i*)(1)	-0.011	0.037	0.761	0.105	0.058	0.072	***0.571***	***0.097***	***0.000***
Const(2)	***-8.538***	***0.539***	***0.000***	***-8.323***	***0.892***	***0.000***	***-1.641***	***0.296***	***0.000***
(i-i*)(2)	***-1.859***	***0.172***	***0.000***	***-1.456***	***0.319***	***0.000***	-0.001	0.011	0.919
Log(Error)	***-0.859***	***0.023***	***0.000***	***-0.914***	***0.022***	***0.000***	***-0.987***	***0.023***	***0.000***
LOG(SIGMA)	-0.095	0.058	0.101	***0.316***	***0.060***	***0.000***	***0.550***	***0.063***	***0.000***
P1-|VXJ| (δ_1)	***22.507***	***5.916***	***0.000***	***29.784***	***7.890***	***0.000***	***25.894***	***10.104***	***0.010***
P2-|VXJ| (δ_2)	14.800	14.454	0.306	19.630	35.135	0.576	***-8.065***	***2.865***	***0.005***

Note: Based on Eq. 8.

Table 10. The Average of Transition Probabilities

	i(row)＼j(column)	1	2	1	2	1	2
Table 8	Z(Error) 1	0.873	0.127	0.938	0.062	0.887	0.113
	2	0.459	0.541	0.144	0.856	0.134	0.866
	Z(VXJ) 1	0.897	0.103	0.883	0.117	0.935	0.065
	2	0.815	0.185	0.187	0.813	0.049	0.951
Table 9	Z(Error) 1	0.870	0.130	0.949	0.051	0.862	0.138
	2	0.523	0.477	0.201	0.799	0.160	0.840
	Z(VXJ) 1	0.897	0.103	0.920	0.080	0.908	0.092
	2	0.853	0.147	0.883	0.117	0.226	0.774

Figure 1. The Spot and Forecast JPY/USD exchange rate

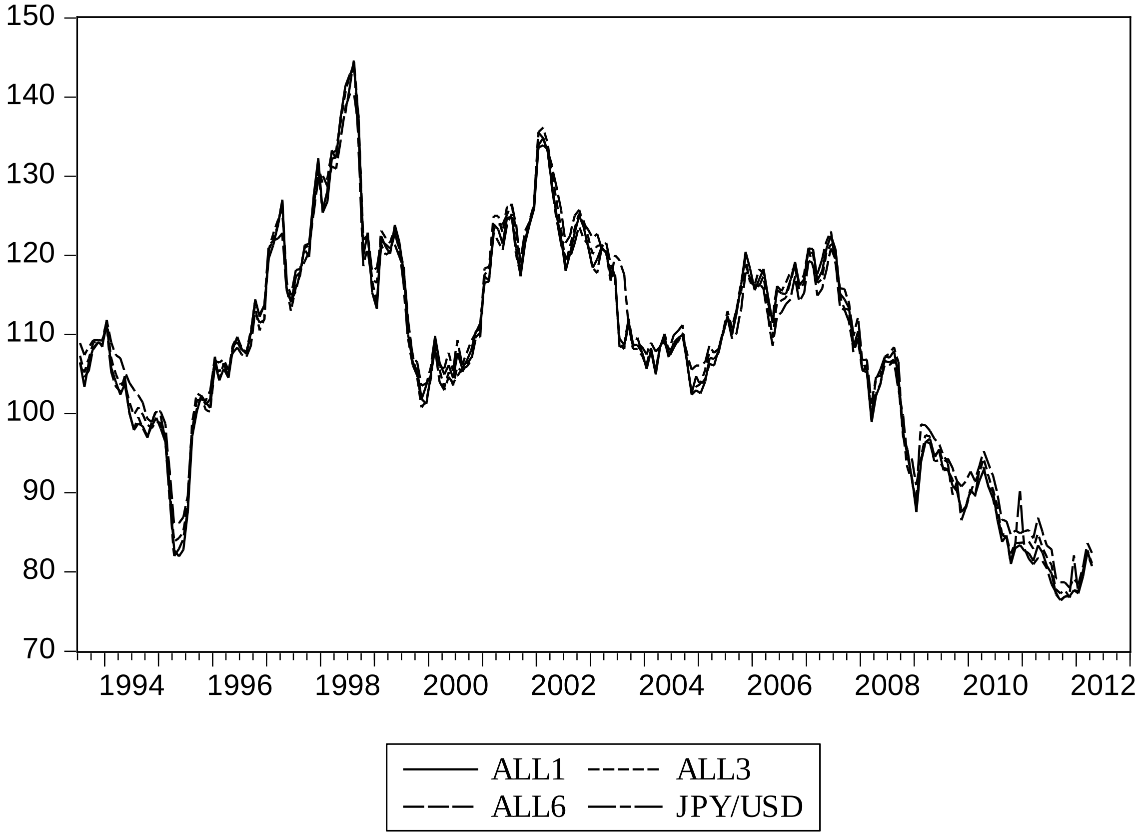

Figure 2. Histogram of Forecast Errors

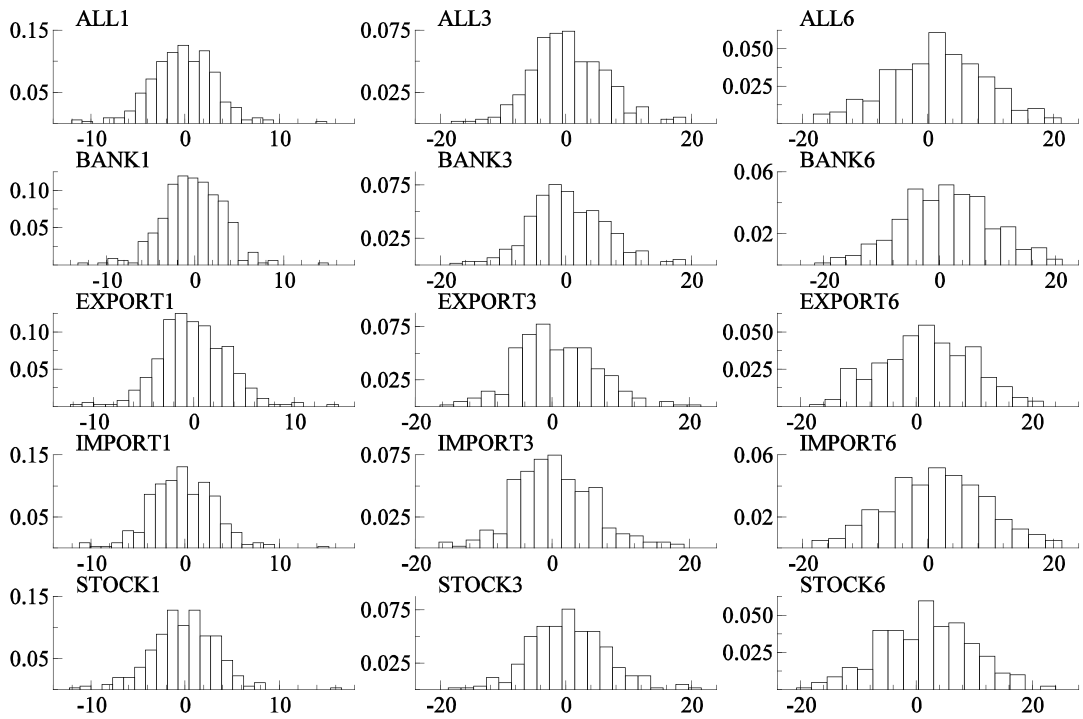

Figure 3. MS Model for One Month Ahead Forecast Errors (Regime 2: Volatile Period)

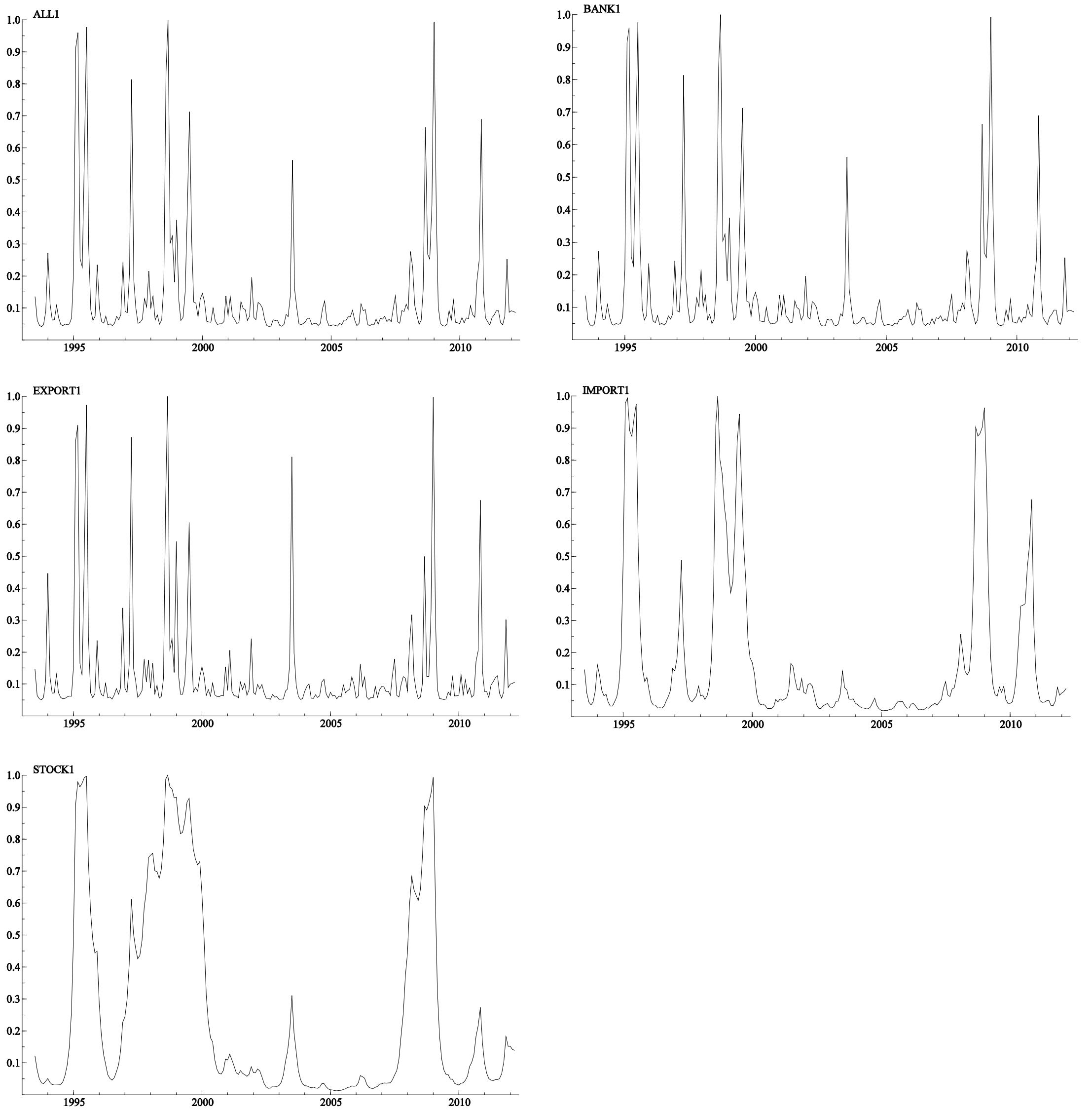

Figure 4. Smoothed Transition Probabilities for MS-TVTP models for One Month Forecast Errors