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Exchange Rate Volatility and Its Impact on the Transaction Costs of Covered Interest Rate Parity

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Abstract:

This paper provides empirical evidence on the linkage between foreign exchange market volatility and daily 90-day covered interest rate parity conditions of the three major exchange rates against the US$. Markov regime shifting models were utilized to generate time series of volatility regime probabilities and these were used to explain the first and second moments of the daily deviations from and the transaction cost bands around the covered parity conditions. We find a significant positive relationship between the deviations and the regime probabilities, indicating an increasing probability of higher volatility state being associated with rising deviations (both first and second moments) from the parity condition. Similar positive relationship is found for the transaction bands. Rising (Falling) probabilities of high (low) volatility regimes increased the first and second moments of the bands. Furthermore, we find a higher volatility state combined with a US$ depreciation is associated with significantly higher volatility in the daily deviations than an appreciation. Also, US$ depreciation is associated with widening transaction bands. This suggests that the level of market uncertainty was higher when the US$ was depreciating.

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1. Introduction:

Short-term interest rate differentials between two countries, in theory, convey information regarding markets' expectations concerning future exchange rate movements. This linkage between foreign exchange and money markets, via arbitrage, has been shown not to hold in its uncovered form (uncovered interest rate parity, UIP) but is often assumed to be a valid empirical regularity in its covered form (covered interest rate parity, CIP) once various market imperfections are taken into account[1]. An enormous extant literature on forward premium (*inter alia* Hansen and Hodrick, 1980, Mark, 1988, Hodrick, 1989, Backus et al., 1993, Levich and Thomas, 1993, Stulz, 1994, Bansal et al., 1995, Bekaert, 1996) suggests that persistent deviations from the theoretical condition of UIP are deemed to be attributed to the failure of either or both of the two conditions underlying UIP, namely risk neutrality and rationality of expectations of market participants. However, despite some limited success in resolving the forward premium puzzle, on balance a general conclusion is that it remains a serious challenge and an anomaly in the literature of currency exchange. In parallel with the research on the forward risk premium briefly touched on above there exists a different strand of research that focuses on the empirical validity of the equilibrium conditions implied by CIP. Despite the empirical support in the Eurocurrency markets (Taylor, 1987, and Clinton, 1988), violations of CIP between national markets (significant deviations of forward exchange rates from the CIP conditions) are observed which are attributed to transactions costs (Frenkel and Levich, 1975, 1977, 1981), political risks (Aliber, 1973), tax differentials (Levi, 1977), and capital market imperfections (Blenman, 1991). In addition, Balke and Wohar (1998) show non-linear dynamics of persistence of CIP deviations

[1] These include differential tax rates between nations, transactions costs, risk premium, etc and they create a band around the exact CIP line within which no profitable arbitrage is possible.

where deviations outside of the transaction cost bands were less persistent compared to those within the bands. While most of the arbitrage profits are small there are also large deviations from CIP from their sample. Peele and Taylor (2002) investigate covered interest arbitrage in the interwar foreign exchange market, using weekly US$-UKP rates during the 1920s. Specifically their analysis supports the Keynes-Einzig conjecture that the neutral band is of the order of one percentage point on an annual basis and the deviations are moderately persistent even outside this band. Overall deviations from the exact CIP conditions are often attributed to transactions costs in line with much of the published work (see, inter alia, Demsetz, 1968, Frenkel and Levich, 1977, Taylor, 1987, 1989). In particular, in the Eurocurrency markets, where most of the market imperfections that hinder the covered interest arbitrage between national money/foreign exchange markets identified above are absent, deviations from the exact CIP are mostly attributable to transaction costs. In other words, no arbitrage bands around the exact CIP conditions are determined by transaction costs of covered arbitrage. The transaction costs, measured as bid-ask spreads, can also be influenced by risk considerations in the foreign exchange market. For example, an expected rise in the level of foreign exchange volatility would induce wider spreads to compensate the liquidity providers for the information (adverse selection) costs. Assuming that in the highly competitive Eurocurrency markets (in major currencies) a significant part of the transaction costs of covered arbitrage (and thus deviations from the exact CIP conditions) may then be attributable to this compensation for the information costs.

In this paper we aim to establish a time varying relationship between the foreign exchange market volatility and the transaction cost considerations in the covered interest rate parity conditions. We measure transaction costs in two ways, i) deviations from the exact CIP conditions and ii) vertical distance between the upper and lower bounds around the exact CIP conditions. The underlying motivation for using the first measure of transaction costs is the

premise that rising levels of foreign exchange volatility due to market turbulence would give rise to wider bid ask spreads of market makers to compensate for the information costs, and this would result in higher incidences of daily deviations. In addition, there is a potential for asymmetry of volatility impact depending on whether the volatility is associated with domestic/foreign currency depreciation/appreciation. To this end we examine the empirical relationship between the daily deviations from the exact CIP conditions and the nature of the foreign exchange market volatilities. In particular, we investigate disaggregate effects of various levels of spot exchange rate volatility (low, mid and high levels) and the high and low volatility associated with US$ appreciation/depreciation on the daily deviations from the CIP conditions. This is accomplished by constructing various volatility states as required and investigating the explanatory powers of the generated (times series of) state probabilities from Markov regime switching models. In addition, we examine the time varying nature of the transaction cost bands around the CIP conditions. Transaction costs will vary across time depending on the level and the nature of volatility in each of the component markets. We investigate the empirical relationship between this time varying nature of the transaction bands and the time varying foreign exchange market volatility states.

The major findings of this paper are that i) there is a significant positive relationship between the daily CIP deviations and the exchange rate volatility regime probabilities in all three exchange rates we considered (US$ against the German Mark, the Pound Sterling and the Yen) which indicates that an increasing probability of higher volatility (and decreasing probability of lower volatility) state is associated with rising deviations in both the first and the second moments, ii) there is evidence that the combination of a higher volatility and a US$ depreciation is associated with significantly higher volatilities of deviations from the daily CIP than when the US$ was appreciating, iii) in general, high volatility regime probabilities are associated with widening and more volatile transaction bands, and vice versa,

and iv) a US$ appreciation (especially with lower volatility regime) resulted in a narrowing bands whereas a US$ depreciation (and high volatility regime) significantly raised the first and second moments of the bands.

The rest of the paper is organized as follows: In section 2, data and modeling issues are discussed. We employ EGARCH models to address the statistical characteristics of the deviations from and the transaction cost bands around the exact CIP conditions, and the Markov regime shifting models are estimated to generate various volatility state probabilities in the foreign exchange markets which we use to help explain the first and second moments of daily deviations. Section 3 discusses the empirical results and the conclusions are presented in section 4.

2. Modeling Approaches

2.1 Foreign Exchange Volatilities

The exchange rates under investigation are the US dollar (US$) against the three most traded currencies of the German Mark (DEM), the Japanese Yen (Yen) and the Pound Sterling (UKP). The daily closing bid, ask and mid-point (5pm GMT, London market) rates of the spot and three month forward rates for the three currencies against the US$ were obtained from Datastream (sourced from Barclays Bank International) for the period 2nd January 1986 to 31st December 1998. The interest rates used were also obtained from Datastream (sourced from Financial Times) and they are the London market close (5pm GMT) bid, ask and mid-point of three month euro interest rates in the three currencies observed at daily interval. The choice of the end point of the sample was due to the Euro denomination of the DEM from January 1999. The exchange rates are defined as the US$

price of the other currencies (number of units of the US$ per unit of foreign currency). The daily returns of exchange rates (mid-point) are calculated as continuously compounding returns, $R_t = \log(S_t / S_{t-1}) \times 100$, where S_t = US$/DEM, US$/YEN and US$/UKP. Figure 1 contains the plots of the daily returns and return volatilities (squared returns) of the three exchange rates. In addition to the usual volatility clustering, there are a few episodes of higher volatility for all three exchange rates. These are the EMS crisis in the October 1992 which is clearly shown in the US$/UKP and (to a less extent) US$/DEM volatilities; the 'tequila crisis' of December 1994 which is clearly visible in all three exchange rates; the Asian currency crisis of July 1997; and a highly visible hike in the US$/Yen volatilities which represents the beginning of the Japanese banking crisis of November 1997 which led to the Japan Premium (1997 – 2000) in the interbank money markets for Japanese banks.

2.2 Covered Interest Rate Parity

The covered interest rate parity (CIP) condition states the returns from investing in two money markets over a holding period, *n*, after the currency conversion in both the spot and forward markets are completed must be the same in order to discourage arbitrage. The exact CIP condition, ignoring transactions costs and other capital market imperfections, is written as:

$$\frac{(i_t - i_t^*)}{(1 + i_t^*)} = \frac{(F_{t+n/t} - S_t)}{S_t} \tag{1}$$

Where i_t and i_t^* are mid-point interest rates for the holding period *t* to *t+n* (three months) at home (the U.S. in this study) and foreign countries (Germany, U.K. and Japan), respectively[2];

[2] The 90 day interest rates are quoted per annum and these were converted to correspond to the holding period: $i_{p.90d} = (1 + i_{p.a}/4) - 1$.

$F_{t+n/t}$ is the mid-point forward exchange rate for delivery at time $t+n$ (three months) and formed at time t; S_t is the mid-point spot exchange rate defined as units of domestic currency (the US$) per unit of foreign currency (DEM, YEN, and UKP). The right hand side of (1) is the forward premium (FP_t) and the left hand side is the interest rate differentials ($IDiff_t$). The deviations from the CIP are then defined as $Deviation_t = FP_t - IDiff_t$ and a positive (negative) deviation might imply a possible outward (inward) money market arbitrage opportunity for domestic residents. Realistically, however, almost all of the deviations from the exact CIP using time synchronized Eurocurrency interest rates and interbank foreign exchange market rates can be accounted for by transaction costs, and as such the only credible interpretation of the time varying deviations is the time varying transaction costs. Thus, the sign of the deviations may not have a meaningful interpretation other than measuring the time variations of transaction costs of CIP.

In addition to the CIP deviations, we construct transaction cost bands around the CIP conditions. Due to the presence of transaction costs, among others, deviations from the exact CIP conditions will not lead to arbitrage activities if the deviations are within the bands. The time variation of the first and second moments of the transaction cost bands will be dependent on, amongst others, the level of foreign exchange volatilities. The upper bound of the band is defined as no inward arbitrage condition (NIAC) shown in (2) below.

$$\frac{F_a}{S_b} - \frac{(1+i_b)}{(1+i_a^*)} \geq 0 \tag{2}$$

The lower bound is defined by no outward arbitrage condition (NOAC) as in (3) below.

$$\frac{F_b}{S_a} - \frac{(1+i_a)}{(1+i_b^*)} \leq 0 \tag{3}$$

The transaction cost band is then defined as the difference between NIAC and NOAC.

$$Transaction\ Cost\ Band = \left(\frac{F_a}{S_b} - \frac{(1+i_b)}{(1+i_a^*)} \right) - \left(\frac{F_b}{S_a} - \frac{(1+i_a)}{(1+i_b^*)} \right) \quad (4)$$

Where the subscripts *b* and *a* denote *bid* and *ask*, respectively.

Figure 2 shows the plots of the daily deviations from the 90-day CIP conditions for the three bilateral cases. The daily deviations show no obvious pattern and appear to be stationary around zero. This indicates that deviations in either side tend not to persist. Figure 3 depicts the times series plots of the transaction bands around the daily 90-day CIP conditions for the three exchange rates. In all cases the band fluctuates around 0.24. The YEN bands are relatively stable around the flat trend line, whereas the DEM and UKP bands are more volatile. Although there are only four large spikes in the UKP transaction bands, which represent over 20 times the size of the trend line, the DEM bands show more frequent surges between 1991 and 1993. The summary statistics of the daily time series are reported in Table 1. Although the mean is essentially zero, positive skewness and significant excess kurtosis are observed in all cases, which is a typical feature of high frequency financial time series. The deviations and the transaction bands are shown to be serially correlated in all cases and the squared series are also highly serially correlated in the cases of the DEM and the YEN, suggesting a time varying volatility of the deviations and the transaction cost bands.

2.3 *Empirical Modelling of the Transaction Costs of CIP*

The investigation of the disaggregated influences of the volatility states of the foreign exchange markets on the time varying transaction costs starts with the modelling of the time varying nature of the transaction costs. The deviations and the transaction cost bands exhibit all the characteristics of high frequency financial time series, namely, serial correlations in

the second moments, skewness, and excess kurtosis. The GARCH family of models has been shown to be effective in explaining the typical characteristics of high frequency time series. We adopt a parsimonious EGARCH(1,1) model[3] to explain the patterns of the daily transaction cost movements and use Markov regime probabilities as exogenous variables[4] in both the conditional mean and variance equations as shown below:

$$Deviation_t,\ and\ TCostBand_t = \alpha_c + \delta_i^m \cdot P_{i,t} + \varepsilon_t + \sum_{j=1}^{q} \varepsilon_{t-j} \qquad (5)$$

$$\varepsilon_t = z_t \sqrt{h_t} \sim (0, h_t),\ z_t \sim iid(0,1)$$

$$\ln h_t = \beta_c + \delta_i^v \cdot P_{i,t} + \beta_{\varepsilon 1} \cdot \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_{\varepsilon 2} \cdot \left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right) + \beta_h \cdot \ln h_{t-1} \qquad (6)$$

Where

h_t is the conditional variance of the residuals ε_t in (5).
q is the number of lags of moving average terms included in (5) to achieve white noize residuals.
P_i is the time series of state probability for each mean/volatility regime,
i = 1, 2 and 3 for the three regime state probabilities (model 1 in section 2.4 below) where three regimes are low, mid and high volatility regimes, $\sum_{i=1}^{3} p_i = 1$, and
i = 1, 2, 3 and 4 for the four regime state probabilities (model 2 in section 2.4 below) where the regimes are the four combinations resulting from two states (high and low) in both the mean and the volatility of exchange rate returns, $\sum_{i=1}^{4} p_i = 1$. They are
regime 1: low mean (US$ appreciation) and low volatility,
regime 2: high mean (US$ depreciation) and low volatility,
regime 3: low mean (US$ appreciation) and high volatility,
regime 4: high mean (US$ depreciation) and high volatility.

The Markov regime probabilities, P_i's, are generated time series of probabilities of foreign exchange market belonging to regime i, and as such they sum to one. Thus, they are used one

[3] Parsimonious GARCH(1,1) models are shown to be adequate in modeling most of the high frequency financial time series. See Bollerslev, et. al, 1992 for an extensive survey of empirical papers.

[4] The construction of the Markov regime probabilities used in (5) and (6) are explained in section 2.4.

at a time in a separate regression run for each regime. EGARCH models allow exogenous variables to have a negative coefficient in the conditional variance equation in addition to modelling asymmetric effects of positive and negative innovations on the conditional variance. Depending on the volatility regime the foreign exchange market was in on a particular day, the conditional volatility may be expected to be either higher or lower in response to the movements in the regime probabilities. A higher conditional volatility of daily deviations and transaction cost bands would be associated with a higher level of uncertainty in the market represented by either a rising probability of a higher volatility state or a decreasing probability of a lower volatility state. Conversely, a lower conditional volatility would be observed in the face of a falling probability of a high volatility state and a rising probability of a low volatility state. Thus, the coefficient for the regime probabilities in the conditional variance equation, δ_i^v, is expected to be positive (negative) for high (low) volatility states.

Table 2 reports the estimation results of the base EGARCH(1,1) models (without the exogenous variables) for the daily deviations and the transaction cost bands for each of the three exchange rates. The estimated coefficients are significant at least at 10% in all cases except for the $\beta_{\varepsilon 1}$ in the YEN transaction cost band estimation. The constant in the mean equation is negative for the DEM deviations while it is positive for the others, and the constant in the variance equation is negative in all cases. The effects of lagged innovations on the conditional volatility are shown in $\beta_{\varepsilon 1}$ and $\beta_{\varepsilon 2}$. The former picks up the sign effect where a negative sign suggests a bigger impact of negative innovations, and the latter shows the size effect where larger innovations, irrespective of sign, have bigger impacts on the conditional volatility. For the deviations the negative sign effect is present for the DEM and the UKP suggesting that negative deviations from the CIP conditions the day before contributed to a higher current conditional volatility. Unexpected negative deviations (that is, negative

innovations) from the CIP conditions imply an unexpected rise in the costs of inward money market (from the viewpoint of a U.S. arbitrageur) arbitrage transactions[5]. In the case of the YEN, however, the opposite result is observed. Unexpected positive deviations, representing an unexpected rise in the costs of outward arbitrage transactions tend to raise next day's conditional volatility. The size effect coefficient, $\beta_{\varepsilon 2}$, is positive in all three deviation models suggesting an elevated conditional volatility in response to a bigger deviation in either direction. For the transaction cost bands, the negative asymmetric effect is found only for the DEM. The size effect is positive in all cases suggesting that an unexpected change in the band raised the conditional volatility the next day.

Significant first and second moment serial correlations found in the daily deviations reported in Table 1 are eliminated, in general, in the standardized residuals from the models of the deviations. The highly significant second moment serial correlation in the DEM is caused by two outliers[6]. The remaining first moment serial correlation in the UKP is only marginally significant at 10%. The standardized residuals from the transaction cost band estimation are free from remaining serial dependence in the first and second moments. In

[5] For those deviations that represent potential arbitrage opportunities (deviations over and above the transaction costs would account for), the expected rate of depreciation of the US$ against these two currencies is lower than the respective interest rate differentials on a covered basis. This is due to perceived higher returns in the US money market due to a higher U.S. interest rate relative to the exchange rate expectations and/or stronger US$ beyond what the current interest rate differentials would allow. In either case, it may be argued that a higher interest rate and stronger US$ environment would adversely affect the domestic U.S. economy and its external balance position, possibly leading to a more uncertain economic environment. This would result in a higher level of uncertainly in both the foreign exchange and money markets leading to a higher than otherwise conditional volatility of daily CIP deviations.

[6] These are 17 June 1986 and 30 July 1990 and without these the test statistic becomes 11.179 with the p-value of 0.941. The UKP and the Yen deviations, however, do not show extreme values on these two dates.

short, the EGARCH(1,1) models effectively addressed the characteristics of the daily deviations and the transaction cost bands identified in Table 1.

2.4 *Markov Regime Shifting Models of Exchange Rate Volatility*

The aim of investigating the daily deviations and the transaction cost bands in this paper is twofold: to model the general patterns of the first and second moments of these transaction cost considerations of the CIP; and to ascertain the roles of expected volatility states of the foreign exchange markets as determinants of the transaction costs in the CIP arbitrage activities. In particular, we aim to derive time series (at daily frequency) that represent various aspects of foreign exchange market volatilities that are useful in modeling the daily movements of transaction costs of the CIP. In this paper we adopt two different approaches to generate time series proxies for the volatility regimes in the foreign exchange markets. Both models depend on the Markov regime switching process, which drives the unobserved state at any time. The resulting times series are the probabilities of the foreign exchange market being in a particular volatility state (high, medium or low volatility; high/low volatility with US$ appreciation/depreciation) at a given time *t*.

Model 1:

It has been suggested in the literature that the observed heteroscedasticity in the asset return process may be modelled as a pure Markov switching variance process. The observed variance clustering is thought to be due to different regimes with different variances present in the data generating process. Examples of such approach include Turner, Starz and Nelson (1989) and Kim, Nelson and Starz (1998). In order to generate the conditional variance of the

exchange rate return, we consider the following specification for the demeaned return series. The return, r_t, generated in period *t* by holding spot currency, is computed by log differences.

$$r_t \sim N(0, \sigma_t^2) \tag{7}$$

$$\sigma_t^{\,2} = \sigma_1^{\,2} ST_{1,t} + \sigma_2^{\,2} ST_{2,t} + \sigma_3^2 ST_{3,t} \tag{8}$$

$ST_{k,t} = 1$ if $ST_t = k$, and $ST_{k,t} = 0$, otherwise; $k = 1,\ 2,\ 3$.

$$\Pr\left[ST_t = j \,|\, ST_{t-1} = i\right] = p_{ij}, \quad i, j = 1, 2, 3, \qquad \text{and} \tag{9}$$

$$\sum_{j=1}^{3} p_{ij} = 1, \qquad \sigma_1^{\,2} < \sigma_2^{\,2} < \sigma_3^2. \tag{10}$$

In the above specification, ST_t is an unobserved state variable, which evolves according to a first order Markov process with transition probabilities described in equation (9). Equation (10) shows that state 1 corresponds to the low-volatility state, state 2 corresponds to the medium-volatility and state 3 corresponds to the high-volatility state. So each of the three states correspond to one of the three volatility regimes that are specified for the first model for conditional variance. The conditional variance would be given by the following expression:

$$E(\sigma_t^2 \,|\, \Psi_t) = \hat{\sigma}_1^2 E[ST_t = 1 \,|\, \Psi_t] + \hat{\sigma}_2^2 E[ST_t = 2 \,|\, \Psi_t] + \hat{\sigma}_3^2 E[ST_t = 3 \,|\, \Psi_t]$$

where $\hat{\sigma}_i^2$ is the estimate of volatility for state i , and Ψ_t is the information at time t. This has an immediate interpretation in line with the GARCH conditional variance. In a GARCH model, conditional on information at *t-1* the variance at *t* is determined with probability of one. In Markov switching model it is the expectation of the states determine the volatility expectation.

Since the return generating process is conditionally normal, it is straightforward to write the conditional density function of the joint process given the state ST_t. We then multiply the conditional densities for different states by the corresponding probabilities of the states and sum them to obtain the likelihood function. It is this likelihood function we maximize numerically with respect to the parameters of the model. The algorithm is described in detail in Hamilton (1994, chapter 22) and Kim and Nelson (1999, chapter 4). The parameter vector in this case is, $\Theta \equiv \left(p_{11}, p_{12}, p_{21}, p_{22}, p_{31}, p_{32}, \sigma_1^2, \sigma_2^2, \sigma_3^2\right)$. As a by-product of this algorithm we also get the filtered probabilities of the state, i.e. the probability of a particular state occurring given the information up to that point in time. These are the time series of volatility regime probabilities that represent the market participants' view of the state of volatility in the foreign exchange markets and so they would play an important role in modelling the first and second moments of daily CIP deviations. It is expected that higher foreign exchange market volatility would encourage a higher forward risk premium and so this might lead to more incidences of departure from the CIP conditions. Thus, an increasing probability of high (low) volatility state materialising would lead to a higher (lower) conditional volatility of the daily deviations. This implies a positive (negative) coefficient for the regime probability in the conditional variance equation in (6). The effects of the mid volatility regime probabilities on the conditional variance of the deviations, however, are less than clear cut and so are the *a priori* expectations of the role of the regime probabilities in the conditional mean of the daily deviations. The regime probabilities are used separately so as to avoid multicollinearity issues as they are constructed to sum to unity.

Figure 4 shows the plots of the estimated (filtered) regime probabilities for the three currencies. The US$/DEM rate was mostly in the mid-level volatility state throughout the sample period although there is a clear sign of increasing incidences of lower level volatility state at the expense of the higher level state since the mid-1990s. The US$/UKP and

US$/Yen rates show a similar pattern of decreasing incidences of the higher level volatility states, but the mid level volatility state seemed to have been more relevant instead of the lower level volatility state.

Model 2:

As the second approach to generate the conditional variance we adopt the model successfully applied by Bollen, Gray and Whaley (2000) and here we simply outline the essential elements of that approach. The return r_t in period t is assumed to have the following structure:

$$r_t = \mu_{ST1,t} + e_t \tag{11}$$

where, ST1 is the first order, two state Markov switching process that drives the mean return and has following transition probability:

$$\Pi_\mu \equiv \begin{bmatrix} p_\mu & 1-p_\mu \\ 1-q_\mu & q_\mu \end{bmatrix} \tag{12}$$

Depending on the state governed by S1 the mean return could be either $\mu_1(ST1=1)$ or $\mu_2(ST1=2)$. The error term e_t in equation (11) is characterized by $N(0,\sigma^2_{ST2,t})$, where the variance is also driven by another first order, two state independent Markov switching process, S2. Thus, the variance could be either $\sigma_1^2(ST2=1)$ or $\sigma_2^2(ST2=2)$, depending on the state. This, in turn, has the following transition probability:

$$\Pi_\sigma \equiv \begin{bmatrix} p_\sigma & 1-p_\sigma \\ 1-q_\sigma & q_\sigma \end{bmatrix} \tag{13}$$

It is clear from equation (11) that the model for the return generating process is conditionally normal and the parameters of the distribution depend on the state under consideration. But the nature of the two independent Markov switching processes suggests that we have four

different states to consider. These are $\{ST1,ST2\} \equiv \{(1,1),(2,1),(1,2),(2,2)\}$. That is, there are four separate regimes that need to be considered, these are Regime 1 = low mean (US$ appreciation) state and low volatility state, Regime 2 = high mean (US$ depreciation) and low volatility, Regime 3 = low mean and high volatility, and Regime 4 = high mean and high volatility. With the help of equations (12) and (13), the overall transition probability of the combined process can be written as:

$$\begin{bmatrix} \Pi_{\mu}.p_{\sigma} & \Pi_{\mu}.(1-p_{\sigma}) \\ \Pi_{\mu}.(1-q_{\sigma}) & \Pi_{\mu}.q_{\sigma} \end{bmatrix} \tag{14}$$

As before, since the return generating process is conditionally normal, it is straightforward to write the conditional density function of the joint process given a state pair $\{ST1,ST2\}$. We then multiply the conditional densities for different states by the corresponding probabilities of the states and sum them to obtain the likelihood function. The conditional variance in this case also is defined in a similar way as in the previous model and is expressed as,

$$E(\sigma_t^2 \mid \Psi_t) = \hat{\sigma}_1^2 E[ST1_t = 1, ST2_t = 1 \mid \Psi_t] + \hat{\sigma}_1^2 E[ST1_t = 2, ST2_t = 1 \mid \Psi_t] + \hat{\sigma}_2^2 E[ST1_t = 1, ST2_t = 2 \mid \Psi_t] + \hat{\sigma}_2^2 E[ST1_t = 2, ST2_t = 2 \mid \Psi_t]$$

The approach to maximization of the likelihood function is similar to that described earlier. The unknown parameters of the model are, however, $\Theta \equiv \left(\mu_1, \sigma_1^2, \mu_2, \sigma_2^2, p_{\mu}, q_{\mu}, p_{\sigma}, q_{\sigma}\right)$. The time series of the generated filtered regime probabilities are then used as exogenous variables in (5) and (6). As for the model 1 above, higher volatility regimes (3 and 4) are expected to have positive coefficients in the conditional variance equation (6). In addition, within the higher volatility environments, the relative magnitude of the estimated coefficient of the regime 3 and 4 probabilities would further reveal the disaggregated impact of the higher volatility with a US$ appreciation/depreciation.

Figure 5 shows the plots of the estimated time series of these regime probabilities. In the cases of the US$/DEM and the US$/UKP, there is a clear sign of the increasing

incidences and persistence of the lower volatility regimes (1 and 2) and lower incidences of higher volatility regimes since the early to mid 1990s. Interestingly, the lower return regimes (1 and 3) which indicates a US$ appreciation, became more relevant. To a less extent, the US$/YEN returns show a similar pattern.

Table 3 reports the estimation results for the two Markov regime-shifting models. The upper panel of Table 3 displays the parameters for the three-variance regime model of the mean adjusted daily returns of the spot exchange rates. The variance parameters for the three different regimes show substantial variations for all three exchange rates. The interpretation of the transition probabilities in this model has to focus on the variance regimes only since the mean returns are not identified in this model. The parameter p_{11} indicates that the Japanese Yen has the highest propensity to stay in the low variance state once it enters that state. Similarly, $p_{33} \equiv (1 - p_{31} - p_{32})$ is high for all the three currencies indicating the probability of staying in the high variance state. Also, the level of the variance in the highest variance state is greater than the level of the high variance in the four-regime model described below.

The lower panel of Table 3 relates to the four-regime model that is characterized by the fact that two independent Markov switching processes drive the mean and the variances of the daily returns of spot exchange rates. The mean returns μ_1, μ_2 indicate appreciation and depreciation of the US$ with respect to the three currencies analyzed. The transition probabilities P_μ and Q_μ help us infer the persistence of these two different regimes. The high values of P_μ for all the three currencies relative to Q_μ indicate that that the probability of encountering the appreciating dollar period is very high during the sample period analyzed. Similarly the probability of encountering depreciating dollar period is quite low. The two estimated variance parameters suggest different levels of variances in the two regimes. The

higher variance is about four to five times higher than the variance in the low-variance regime. This is consistent with the finding in Bollen, Gray and Whaley (2000). The transition probabilities for the variance regimes suggest that all three currencies have high propensity to stay in a particular variance regime once it is in that regime. In fact, Bollen, Gray and Whaley (2000) explore this particular finding in their article in the context of currency option pricing.

3. Empirical Results:

Table 4 reports the EGARCH(1,1) model estimation results for the daily CIP deviations with the regime probability variables as regressors in the conditional mean and variance equations. Only the coefficients for the regime probabilities are reported as the generic EGARCH(1,1) coefficients are fundamentally the same as the ones for the base models reported in Table 2.

The estimations utilizing the three state regime probabilities are reported in the first half of Table 4. For the three state regime probabilities, the effects of the state probabilities on the conditional mean of the deviations are not present except for the low volatility state for the DEM and the YEN. The response of the conditional volatility to the regime probabilities is highly significant in all cases except for the mid volatility state probability for the UKP. The low volatility state probability significantly reduced the conditional variance of the deviations in all cases implying that if a trading day is more likely to be in a low volatility state, perhaps due to a lower level of information uncertainty in the markets, the need for the imposition of an adverse selection related information charges in the money and foreign exchange markets is reduced and this would lead to a lower volatility of deviations from the CIP conditions. The mid volatility state probability is also showing a volatility dampening

effect for the DEM and the YEN. The high volatility state probability, on the other hand, is contributing to a higher conditional volatility in all cases. The positive sign for the coefficient, δ_3, in all cases suggests a higher conditional variance in response to a rise in the probability of high volatility in the foreign exchange market. A higher level of uncertainty, and thus a rising likelihood of the foreign exchange markets being in the high volatility state, would create an environment of rising adverse selection component in the transaction costs and this in turn would result in a higher level of conditional volatility of daily deviations from the CIP conditions.

The estimation results for the four regime probabilities are shown in the bottom half of Table 4. It is possible now to further investigate the disaggregated sources of impact on the first and second moments of the daily deviations. Regime one is associated with the low return (US$ appreciation) and low volatility state. The coefficient estimated in the mean equation is positive and significant for the DEM, whereas a significant negative coefficient is shown for the YEN. Positive coefficients are also observed for regime three (low return and high volatility) where two of the three are significant at 1%. The positive coefficient for the low return regimes (one and three) suggests that rising probabilities of the lower return (US$ appreciation) regimes resulted in positive deviations being observed. This might be due to the falling forward premium that is more than offset by the falling interest rate differential that is greater in magnitude, and this resulted in positive deviations on the whole. On the contrary, the high return (US$ depreciation) regimes of two and four show a negative coefficient in all cases except for the YEN in the regime two. This implies negative deviations in response to rising probabilities of US$ depreciation, and this suggests that higher probabilities of US$ depreciation leading to higher forward premium is more than offset by rising interest rate differential.

As for the conditional variance equations, it is shown that, in general, the low volatility regime (one and two) probabilities are associated with a falling conditional variance of deviations as shown by the negative and significant coefficients except for the regime 2 for the DEM, which is positive and significant. In addition, the higher volatility regime (three and four) probabilities lead to high conditional variance as shown by the positive and significant coefficient in all cases. This suggests that under a high volatility environment, foreign currency investments entail greater foreign exchange risk exposures for the providers of forward contracts. This would lead to higher transaction costs in the forward contracts and so higher conditional variance of the daily deviations from the CIP conditions would result. The opposite rationale applies for the two low volatility regimes (one and two). In addition, it is observed that within the high volatility regimes, the combination of a higher return (i.e. US$ depreciation) and high volatility (regime 4) is shown to have a larger impact on the conditional volatility than the low return and high volatility (regime 3) combination as evidenced by the regime 4 coefficient which is considerably larger, by a factor of 3 to 4, than the regime 3 counterpart in all cases. This implies that high foreign exchange market volatility when the US$ was depreciating against the major currencies created more uncertain trading environment than when the high volatility was associated with a US$ appreciation.

Table 5 reports the estimation results using the transaction cost bands around the exact CIP conditions. The top panel presents the three regime probability estimations. The low volatility regime probabilities were associated with a significant drop in the first and second moments of the transaction band for the DEM and the YEN. Interestingly, a wider band for the UKP is associated with lower US$/UKP volatility. A significantly lower band is observed in all cases although the volatility of the band was higher for the DEM and UKP in response to mid-level volatility. The higher volatility regime raised both the first and second moments of the YEN transaction band. Interestingly, although the UKP band was also

significantly raised, its conditional volatility was lowered. In short, the transaction bands tended to fall when low and mid volatilities were expected, and rose when the high volatility regime probabilities rose. As for the volatility of the bands, they tended to be lower for the low volatility regime and higher for the mid- and high volatility regimes.

The lower panel of Table 5 presents the four regime estimations. Regimes one and three represent the combination of a US$ appreciation and low/high exchange rate volatility, respectively. The transaction band was significantly lower in all cases for the regime one and for the YEN and the UKP for the regime three. The reverse is observable for the regime two and four probabilities where evidence suggests a rise in the transaction band in response to US$ depreciation. This suggests that the environments where the US$ depreciates are associated with higher transaction cost bands, and this might be due to the role of the US$ as an anchor currency for international transactions. As the US$ loses value, the volatility of international financial transactions denominated in it may rise leading ultimately to a higher cost environment in the CIP transactions. The high volatility regimes (three and four) led, in general, to a higher transaction band volatility which is as expected. The low volatility regime results, however, are mixed. Whereas the DEM bands show significantly lower volatility regardless of the exchange rate movements, only the combination of US$ appreciation (depreciation) and low exchange rate volatility had a significant negative (positive) impact on the YEN cost bands. The reverse is true for the UKP. In fact, the UKP band volatility is determined purely by the first moment of the US$/UKP exchange rate. Regardless of the volatility state, depreciating (appreciating) US$ caused a significant fall (rise) in the volatility of the UKP cost bands.

4. Concluding Remarks

Empirical linkages between exchange rate volatilities and the time varying nature of daily covered interest rate parity conditions have been investigated in this paper. The time series of different volatility regime probabilities were used as explanatory variables to explain the first and second moments of daily deviations from CIP conditions and the transaction cost bands around the CIP conditions for the three currencies, the DEM, the YEN and the UKP against the US$. We find significant explanatory power of these regime probabilities and the results of the estimations indicate that the higher is the probability of the foreign exchange market belonging to a higher volatility state, the higher is the conditional volatility of daily CIP deviations. We conjecture that this positive linkage is due to the heightened need to price in the extra risk in the forward contracts (in the form of a wider bid ask spread) to mark a higher volatility state of the market. This view is consistent with the evidence of widening transaction cost bands in response to rising (falling) probability of high (low) volatility regime. It was also noticed that the combination of higher volatility and the US$ depreciation led to the highest rise in the conditional volatility of the deviations. Also, widening transaction band was associated with US$ depreciation and high volatility. This suggests a US$ depreciation is associated with higher level of uncertainty in the foreign exchange market necessitating higher spreads for market makers, and this could explain the widening and more volatile transaction bands as well as higher volatility of CIP deviations.

Our contribution to the literature is the empirical confirmation of the hypothesis that there exists a positive relationship between spot foreign exchange market volatility and the risk premium/transaction cost considerations in the market from a research angle that has not been implemented previously. In particular, the volatility regime probabilities were shown to be an important factor in explaining the daily CIP deviations and the time varying nature of the transaction cost bands around the CIP conditions.

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Figure 1: Daily Returns and Volatilities (squared returns) of USD Exchange Rates 2-Jan-1986 to 30-Dec-1998:

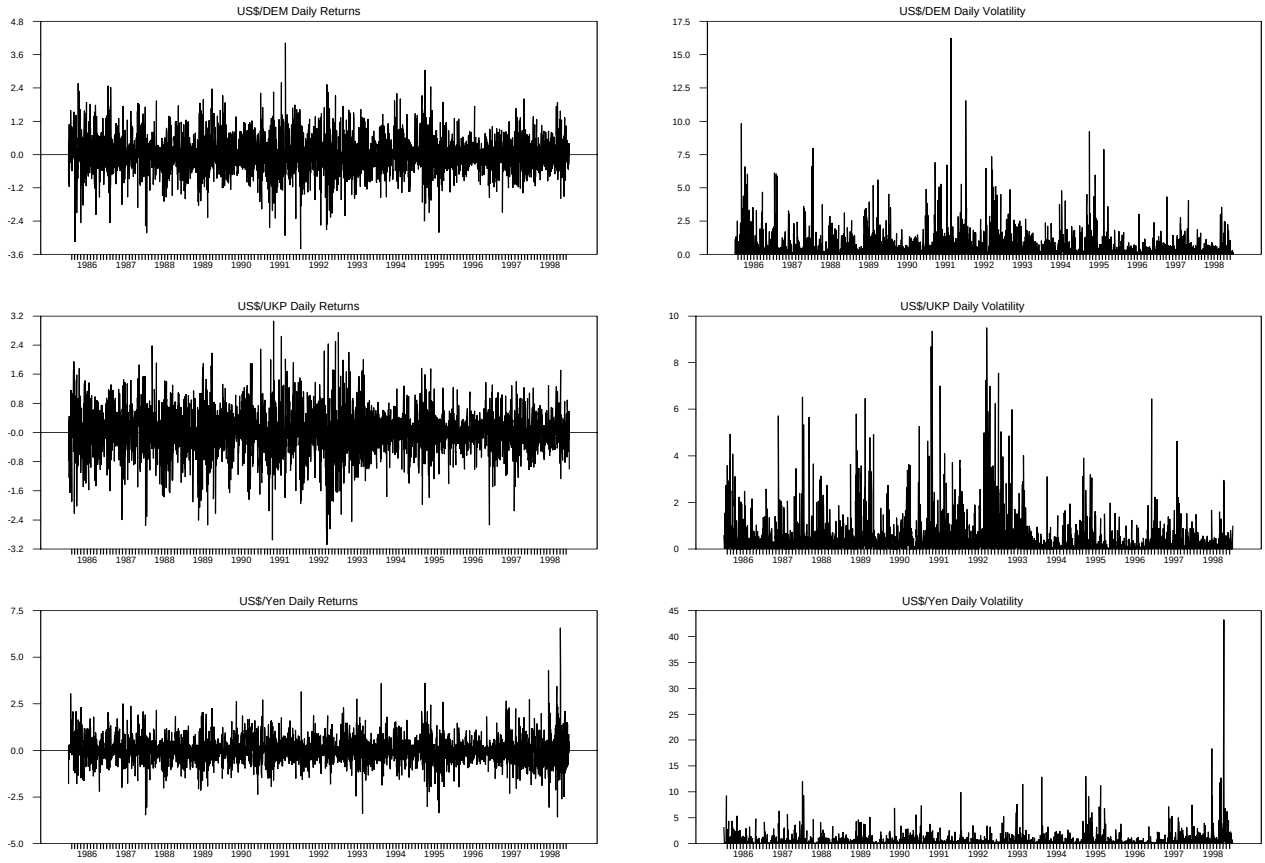


Figure 2: Daily deviations from 90-day Covered Interest Rate Parity Conditions 2-Jan-1986 to 30-Dec-1998

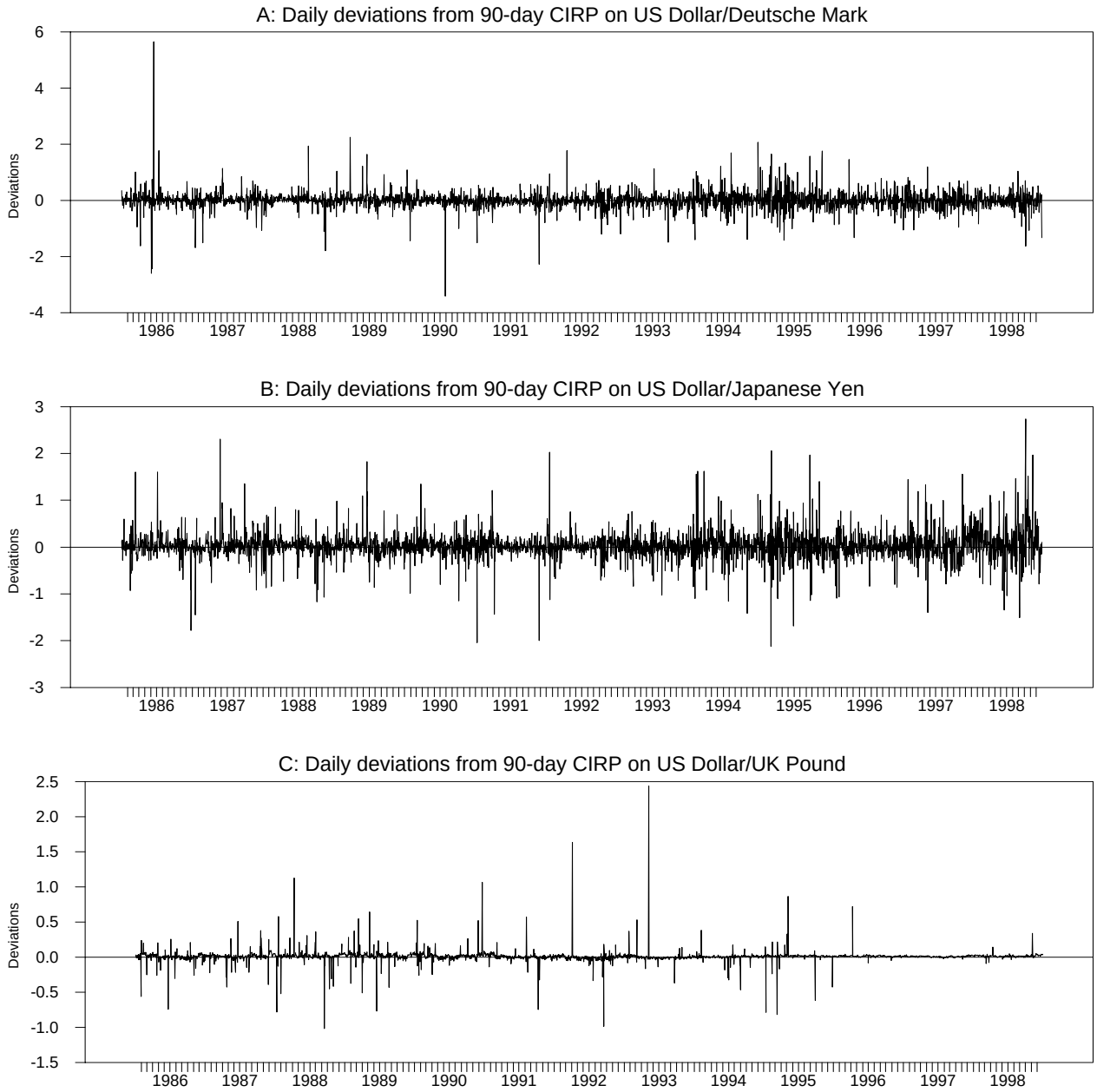


Figure 3: Transaction Bands around 90-day Covered Interest Rate Parity Conditions 2-Jan-1986 to 30-Dec-1998

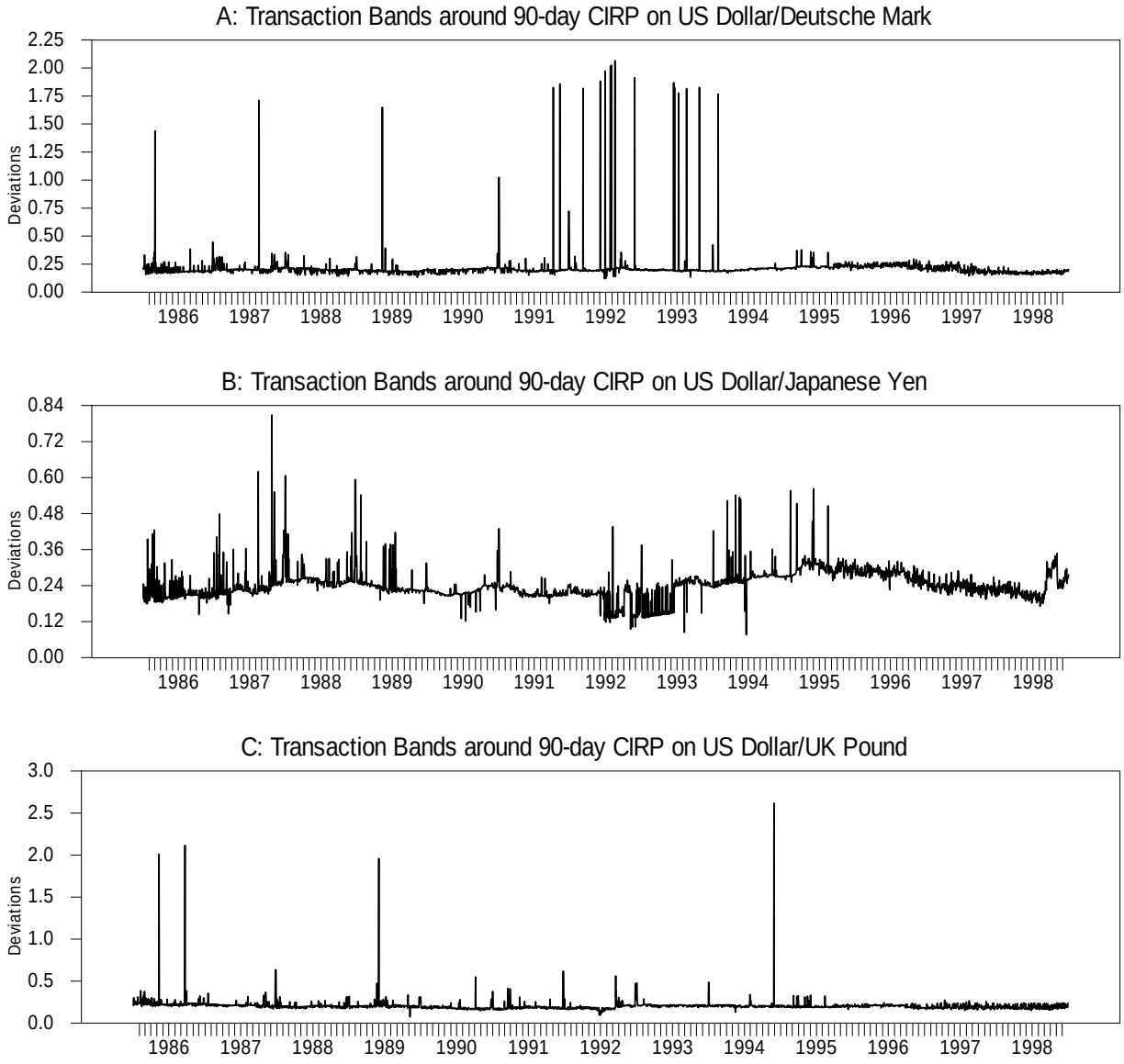


Figure 4: Regime Probabilities of Three Regime Models

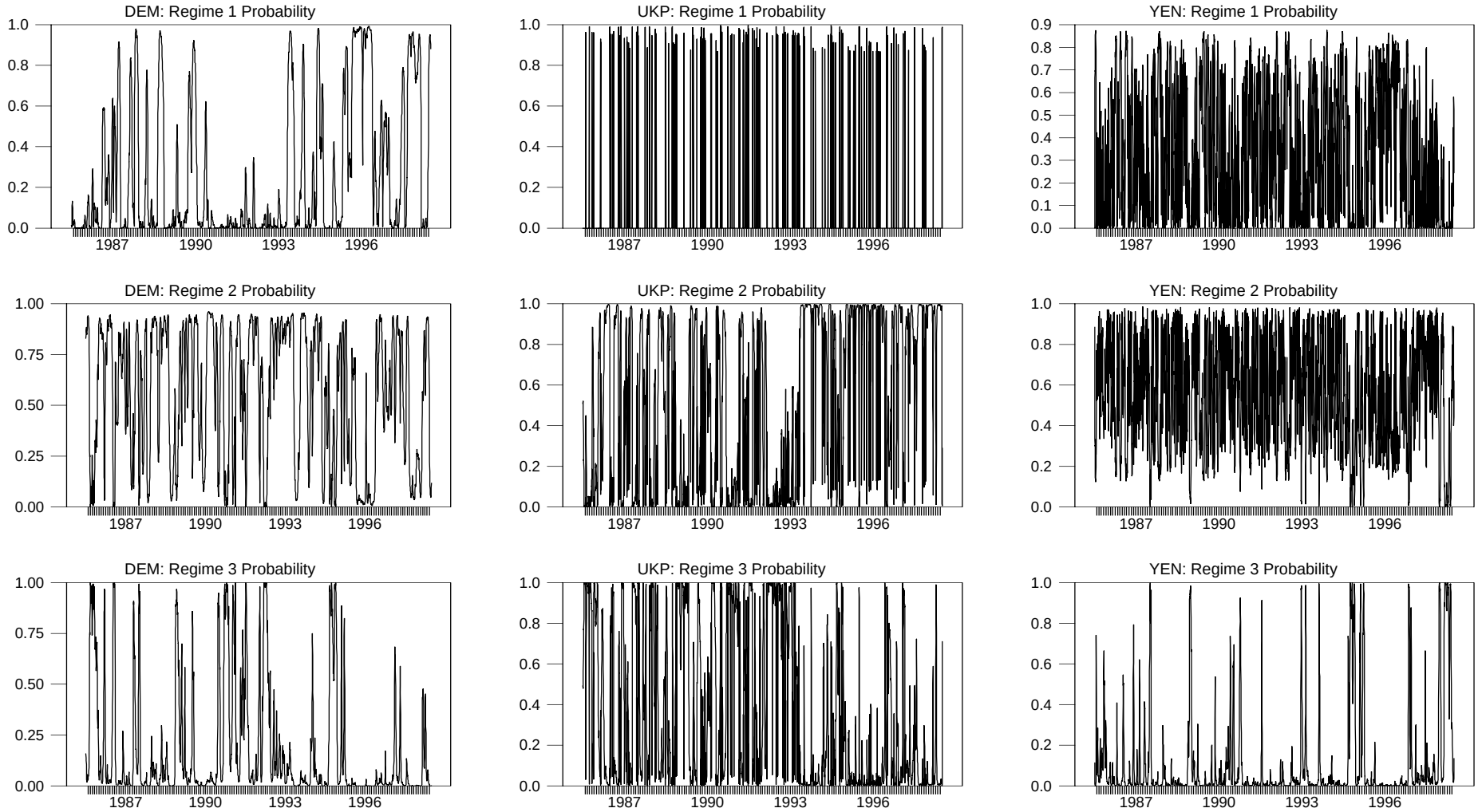


Figure 5: Regime Probabilities of Four Regime Models

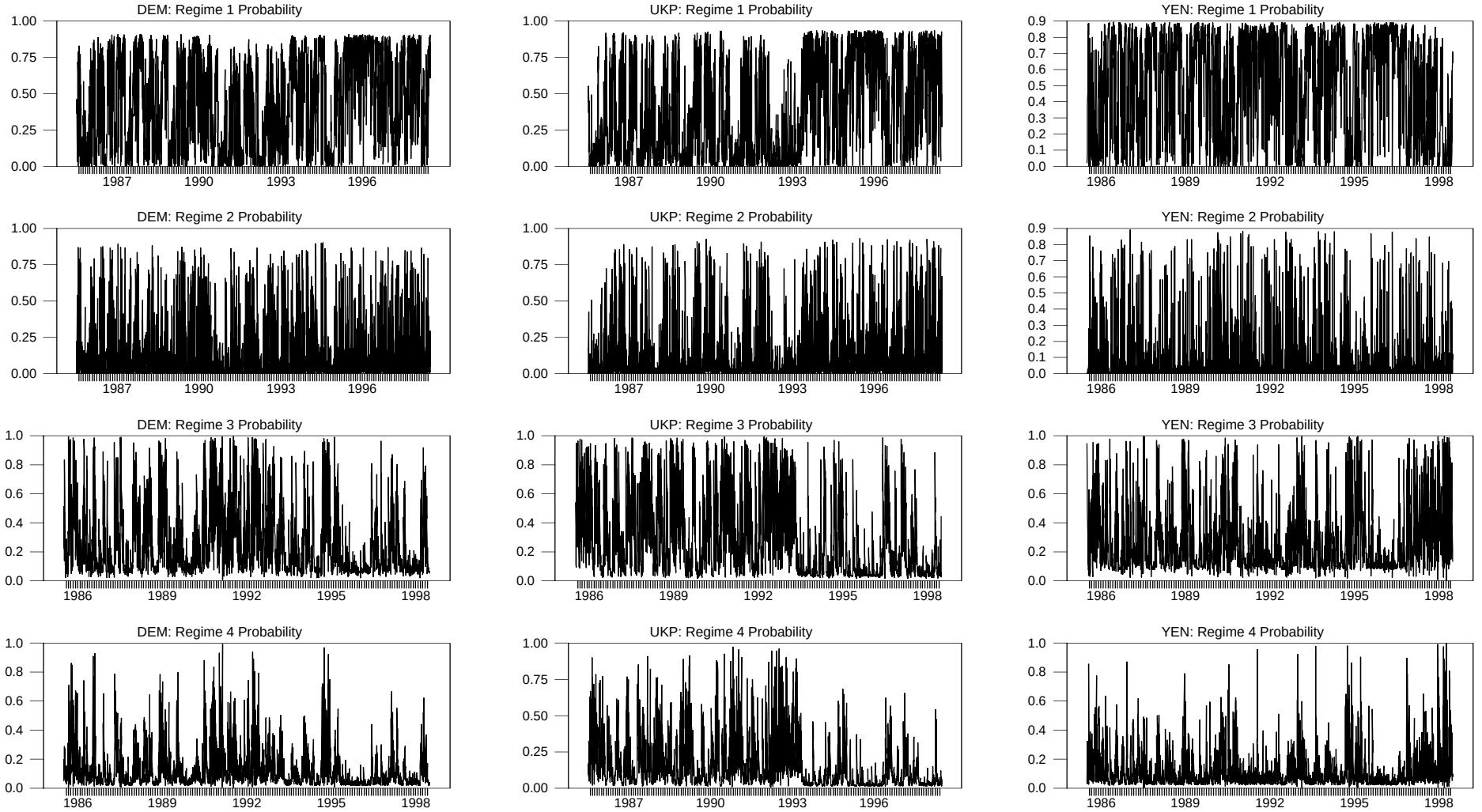


Table 1: Summary statistics of daily FX returns, deviations from 90-day CIP

	DEM	YEN	UKP
	Daily Returns		
Mean	0.0112	0.0163	0.0042
Std. Dev.	0.6750	0.7108	0.6186
Skewness	-0.0010	0.5053	-0.2209
Kurtosis	5.1404	8.0822	5.3694
LB-Linear: $\chi^2(20)$	22.9440	43.6010 ***	44.6530 ***
	{0.2920}	{0.0020}	{0.0010}
LB-Squared: $\chi^2(20)$	341.5700 ***	484.4500 ***	558.3500 ***
	{0.0000}	{0.0000}	{0.0000}
	Daily deviations from 90-day CRIP		
Mean	0.0002	0.0301	0.0104
Std. Dev.	0.3191	0.3056	0.0933
Skewness	1.1472	0.5464	6.2114
Kurtosis	44.2407	14.4815	200.4627
LB-Linear: $\chi^2(20)$	35.4950 **	50.8020 ***	29.1230 *
	{0.0180}	{0.0000}	{0.0850}
LB-Squared: $\chi^2(20)$	134.7600 ***	159.8700 ***	0.5588
	{0.0000}	{0.0000}	{1.0000}
	Transaction Cost Band		
Mean	0.2156	0.2359	0.2120
Std. Dev.	0.0176	0.0026	0.0097
Skewness	10.4859	2.2781	22.0027
Kurtosis	122.4018	19.1865	644.2037
LB-Linear: $\chi^2(20)$	153.5346 ***	17853.16 ***	248.06 ***
	{0.0000}	{0.0000}	{0.0000}
LB-Squared: $\chi^2(20)$	153.1510 ***	8321.4073 ***	1.5675
	{0.0000}	{0.0000}	{1.0000}

Note:

***, ** and * refer to significance at 1%, 5% and 10% level, respectively.
LB refers to Ljung-Box test of serial correlation. Linear and non-linear. squared) serial correlations of the daily deviations are reported above.
Numbers in curly braces are p-values.

Table 2: Base EGARCH(1,1) estimations of the daily deviations from 90-day CRIP

$$Deviation_t = \alpha_c + \varepsilon_t$$

$$\ln h_t = \beta_c + \beta_{\varepsilon 1}\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_{\varepsilon 2}\left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right) + \beta_h \ln h_{t-1}$$

	DEM		YEN		UKP	
	Deviation	TCband	Deviation	TCband	Deviation	TCband
α_c	-0.0096 **	0.2158 ***	0.0256 ***	0.2313 ***	0.0102 ***	0.1982 ***
	(0.0041)	(0.0036)	(0.0044)	(0.0011)	(0.0017)	(0.0019)
β_c	-0.2566 ***	-2.0204 ***	-0.2270 ***	-0.9880 ***	-0.5818 ***	-1.9098 ***
	(0.0099)	(0.0705)	(0.0121)	(0.2757)	(0.0384)	(0.3552)
$\beta_{\varepsilon 1}$	-0.0234 ***	-0.2692 ***	0.0122 **	0.0515	-0.0034 **	0.4398 ***
	(0.0046)	(0.0092)	(0.0048)	(0.0403)	(0.0017)	(0.1577)
$\beta_{\varepsilon 2}$	0.1812 ***	0.3359 ***	0.1463 ***	0.3962 ***	0.0071 *	0.1465 *
	(0.0076)	(0.0116)	(0.0067)	(0.0747)	(0.0037)	(0.0809)
β_h	0.9388 ***	0.5393 ***	0.9448 ***	0.8890 ***	0.8790 ***	0.6534 ***
	(0.0026)	(0.0167)	(0.0036)	(0.0384)	(0.0083)	(0.0603)
q	3	3	4	5	3	3
LogL	-737.27	4407.70	-597.66	5986.56	3235.25	5114.21
LB-z	16.7910	23.8961	24.6870	26.3534	27.8740 *	19.1577
	{0.6670}	{0.2470}	{0.2140}	{0.1545}	{0.0860}	{0.5116}
LB-z^2	40.7980 ***	9.9225	14.3450	26.5541	0.5657	1.6235
	{0.0040}	{0.9696}	{0.8130}	{0.1483}	{1.0000}	{1.0000}

Notes:

***, ** and * refer to significance at 1%, 5% and 10% level, respectively.

LogL is the estimated log likelihood.
LB-z is the Ljung Box statistic for the test of serial correlation of the standardized residuals, $z_t = \varepsilon_t / \sqrt{h_t}$.

LB-z^2 is the Ljung Box statistic for the test of serial correlation of the squares of standardized residuals.

Asymptotic standard errors in the brackets.
p-values are in curly braces.

Table 3 Markov regime shifting model estimations

Three Regimes			
	DEM	JPY	UKP
P_{11}	0.3715 ***	0.7299 ***	0.1801 ***
	(0.0842)	(0.1665)	(0.0276)
P_{12}	0.5952 ***	0.2610 *	0.3918 ***
	(0.0790)	(0.1549)	(0.0302)
P_{21}	0.4205 ***	0.1773	0.0409 ***
	(0.0806)	(0.1133)	(0.0052)
P_{22}	0.5795 ***	0.8057 ***	0.9394 ***
	(0.0806)	(0.1082)	(0.0098)
P_{31}	0.0442 ***	0.0000	0.0501 ***
	(0.0123)	(0.0001)	(0.0076)
P_{32}	0.0000 ***	0.1172 ***	0.0433 ***
	(0.0000)	(0.0412)	(0.0157)
σ_1	0.0951 ***	0.1047 ***	0.0000 ***
	(0.0146)	(0.0293)	(0.0000)
σ_2	0.4463 ***	0.5147 ***	0.1823 ***
	(0.0440)	(0.0726)	(0.0106)
σ_3	0.93627 ***	1.78492 ***	0.71112 ***
	(0.0851)	(0.2944)	(0.0401)
Log-L	3779.41	3873.58	3231.77
Four Regimes			
	DEM	JPY	UKP
P_μ	0.9533 ***	0.9737 ***	0.9603 ***
	(0.0119)	(0.0091)	(0.0108)
Q_μ	0.0999 **	0.0270	0.1237 **
	(0.0476)	(0.0386)	(0.0608)
P_σ	0.9792 ***	0.9645 ***	0.9764 ***
	(0.0059)	(0.0104)	(0.0061)
Q_σ	0.9449 ***	0.8952 ***	0.9626 ***
	(0.0145)	(0.0308)	(0.0101)
σ_1	0.2195 ***	0.2233 ***	0.1396 ***
	(0.0136)	(0.0149)	(0.0088)
σ_2	0.8253 ***	1.0932 ***	0.6329 ***
	(0.0698)	(0.1227)	(0.0356)
μ_1	-0.0517 ***	-0.0292 **	-0.0196 *
	(0.0129)	(0.0116)	(0.0104)
μ_2	1.1175 ***	1.4545 ***	0.8788 ***
	(0.0966)	(0.2211)	(0.0876)
Log-L	3789.42	3889.21	3286.56

Note:

***, ** and * refer to significance at 1%, 5% and 10% level, respectively.

Asymptotic standard errors are in the brackets.

Three regimes: Regime 1 = low volatility, Regime 2 = medium volatility, and Regime 3 = high volatility.

Four Regimes: Regime 1 = low mean and low volatility, Regime 2 = high mean and low volatility, Regime 3 = low mean and high volatility, and Regime 4 = high mean and high volatility.

Table 4: EGARCH estimations of the influence of regime probability on the conditional mean and variance of the daily CIP deviations

$$Deviation_t = \alpha_c + \delta_i^m \cdot P_{i,t} + \varepsilon_t$$

$$\ln h_t = \beta_c + \delta_i^v \cdot P_{i,t} + \beta_{\varepsilon 1} \cdot \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_{\varepsilon 2} \cdot \left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right) + \beta_h \cdot \ln h_{t-1}$$

Where i = 1,2 and 3 for three regime state probabilities model 1. and i = 1,2,3 and 4 for four regime state probabilities model 2).

	Regime		DEM Mean	DEM Variance	YEN Mean	YEN Variance	UKP Mean	UKP Variance
Three Regimes	one	δ_1	0.0297 *	-0.1359 ***	-0.0469 ***	-0.0225 ***	0.0036	-0.0192 ***
			(0.0179)	(0.0088)	(0.0125)	(0.0070)	(0.0222)	(0.0070)
	two	δ_2	-0.0107	-0.0954 ***	0.0098	-0.0628 ***	0.0018	0.0028
			(0.0183)	(0.0077)	(0.0139)	(0.0071)	(0.0044)	(0.0022)
	three	δ_3	-0.0047	0.0638 ***	0.0083	0.1831 ***	0.0026	0.0623 ***
			(0.0159)	(0.0048)	(0.0167)	(0.0115)	(0.0044)	(0.0038)
Four Regimes	one	δ_1	0.0254 *	-0.0544 ***	-0.0397 ***	-0.0130 **	0.0021	-0.1085 ***
			(0.0134)	(0.0046)	(0.0107)	(0.0062)	(0.0042)	(0.0025)
	two	δ_2	-0.0503 ***	0.0457 ***	0.0229	0.0050	-0.0028	-0.1435 ***
			(0.0195)	(0.0134)	(0.0222)	(0.0209)	(0.0029)	(0.0021)
	three	δ_3	0.0246	0.0441 ***	0.0676 ***	0.0557 ***	0.0256 ***	0.0567 ***
			(0.0195)	(0.0068)	(0.0177)	(0.0094)	(0.0060)	(0.0062)
	four	δ_4	-0.0588 *	0.1598 ***	-0.0077	0.2295 ***	-0.0199 **	0.1471 ***
			(0.0341)	(0.0133)	(0.0266)	(0.0213)	(0.0091)	(0.0066)

Notes:

***, ** and * refer to significance at 1%, 5% and 10% level, respectively.

Asymptotic standard errors are in the brackets.

Three regimes: Regime 1 = low volatility, Regime 2 = medium volatility, and Regime 3 = high volatility.

Four Regimes: Regime 1 = low mean and low volatility, Regime 2 = high mean and low volatility, Regime 3 = low mean and high volatility, and Regime 4 = high mean and high volatility.

Table 5: EGARCH estimations of the influence of regime probability on the conditional mean and variance of the transaction cost bands around daily CIP conditions

$$TCBand_t = \alpha_c + \delta_i^m \cdot P_{i,t} + \varepsilon_t$$

$$\ln h_t = \beta_c + \delta_i^v \cdot P_{i,t} + \beta_{\varepsilon 1} \cdot \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_{\varepsilon 2} \cdot \left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right) + \beta_h \cdot \ln h_{t-1}$$

Where *i* = 1,2 and 3 for three regime state probabilities model 1. and i = 1,2,3 and 4 for four regime state probabilities model 2).

	Regime		DEM Mean	DEM Variance	YEN Mean	YEN Variance	UKP Mean	UKP Variance
Three Regimes	one	δ_1	-0.0467 ***	-0.4511 ***	-0.0038 ***	-0.0632 ***	0.0328 ***	-0.0020
			(0.0005)	(0.0276)	(0.0010)	(0.0113)	(0.0031)	(0.0034)
	two	δ_2	-0.0277 ***	0.8364 ***	-0.0069 ***	-0.0274	-0.0025 **	0.6554 ***
			(0.0024)	(0.1568)	(0.0012)	(0.0173)	(0.0013)	(0.0221)
	three	δ_3	0.0027	0.1179	0.0285 ***	0.1091 ***	0.0203 ***	-0.0636 ***
			(0.0190)	(0.4105)	(0.0028)	(0.0162)	(0.0054)	(0.0122)
Four Regimes	one	δ_1	-0.0186 ***	-0.6331 ***	-0.0051 ***	-0.0685 ***	-0.0122 ***	0.1420 ***
			(0.0044)	(0.2405)	(0.0008)	(0.0102)	(0.0036)	(0.0114)
	two	δ_2	0.0152 ***	-0.8738 ***	0.0116 **	0.9913 **	0.0136	-1.7444 **
			(0.0004)	(0.0141)	(0.0057)	(0.4871)	(0.0125)	(0.8266)
	three	δ_3	0.0023	0.9541 ***	-0.0150 *	-0.1343	-0.0214 ***	0.8181 ***
			(0.0071)	(0.2367)	(0.0086)	(0.1251)	(0.0027)	(0.0127)
	four	δ_4	0.0460 ***	0.3109 ***	0.0184 ***	0.1948 ***	0.0440 ***	-0.7088 ***
			(0.0009)	(0.0446)	(0.0030)	(0.0274)	(0.0118)	(0.0681)

Notes:

***, ** and * refer to significance at 1%, 5% and 10% level, respectively.

Asymptotic errors are in the brackets.

Three regimes: Regime 1 = low volatility, Regime 2 = medium volatility, and Regime 3 = high volatility.

Four Regimes: Regime 1 = low mean and low volatility, Regime 2 = high mean and low volatility, Regime 3 = low mean and high volatility, and Regime 4 = high mean and high volatility.