




“Dynamic conditional correlation and probability distribution among Tokyo, London and New York yen/dollar FX markets”

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ARTICLE INFO	Liang-Pei Chu		
	Hai-Chin Yu, Ingyu Chiou, James Jordan-Wagner, Der-Tzon Hsieh and Liang-Pei Chu (2012). Dynamic conditional correlation and probability distribution among Tokyo, London and New York yen/dollar FX markets. <i>Banks and Bank Systems</i> , 7(3)		
	Friday, 19 October 2012		
	"Banks and Bank Systems"		
	LLC “Consulting Publishing Company “Business Perspectives”		

		
NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
0	0	0

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Dynamic conditional correlation and probability distribution among Tokyo, London and New York yen/dollar FX markets

Abstract

This work investigates how volatility co-movements interact with each other in yen/dollar currency markets across Tokyo, London and New York. Using yen/dollar spot rate intraday returns from 1994 to 2003, we found that volatility co-movement exists between the Tokyo, London and New York markets. After estimating the dynamic conditional correlation (DCC) between each pair in the three markets and their DCC probability distributions, some conclusions are drawn. First, the results of the DCC probability distribution between Tokyo and London show that high volatility is associated with a high DCC value because of London's dominance over Tokyo in the currency markets. Second, evidence from the DCC probability distribution between London and New York shows an almost overlapping distribution, implying that London and New York are almost equal, and neither dominates. Third, of the three markets, New York influences Tokyo, but Tokyo does not influence New York. Furthermore, the shapes of the distributions show that the distribution of high DCC is wider than that of low DCC, meaning that risk increases with the dynamic correlation. The implications of these DCC probability distributions could help investors replace global portfolios and manage the latent risk across the Tokyo, London and New York currency markets.

Keywords: co-movement, spillover, dynamic conditional correlation, multivariate GARCH, probability distribution, currency markets.

JEL Classification: F30, G01, G12, G14, G15.

Introduction

The widely expanded and complex volatility in financial asset prices increases the importance of modeling real volatility and correlation. Although some of the literature assumes volatility and correlation to be constant in past years, it is widely recognized that they indeed vary over time. This recognition has spurred a vibrant body of work regarding the dynamic properties of market volatility and realized distribution. A good estimate helps facilitate portfolio optimization, risk management and hedging activities. To date, very little is known about volatility dynamics between currency markets and trading markets over different continents and time zones.

The main purpose of this study is to understand the volatility co-movement of yen/dollar currency markets across Tokyo, London and New York. Through estimating the dynamic conditional correlation (DCC) between each pair, we can analyze the transmission of information across the three largest foreign exchange (hereafter, FX) markets and help investors make better portfolio hedging and risk management decisions across continents. To answer whether the yen/dollar spot markets across different time zones show different characteristics, we explore the following questions: How do volatility co-movements interact with each other in yen/dollar currency markets across Tokyo, London and New York? Do time-varying correlations of the yen/dollar spot rates show different distributions for each pair in the three markets? What are the differences between

the low- and high-volatility DCC between each pair in the three markets?

To answer these questions, we employ the DCC model suggested by Engle (2002) to analyze the DCC of each pair in the three markets, then we estimate the distributions of each DCC and compare the differences in distributions between low and high volatility to more accurately characterize how a shock to one market influences the risk in another.

Among the three largest currency markets, Tokyo is nine hours ahead of London, London is five hours ahead of New York, and there is a two-and-a-half-hour time lag between the closing of the Tokyo market and the opening in London. In contrast, there is a three-hour overlap before the closing in London and the opening in New York. Table 1 shows the opening and closing times for the New York, London and Tokyo markets. Tokyo opens at 00:00 a.m. Greenwich Mean Time (GMT) and closes at 6:30 a.m. GMT. London opens at 9:00 a.m. GMT and closes at 5:00 p.m. GMT. New York opens at 2:00 p.m. GMT and closes at 9:00 p.m. GMT. The order of closing for the three markets is Tokyo, London and New York. This order indicates whether a shock is a spillover or a co-movement. As seen in Table 1 (in Appendix), the New York and London markets overlap, while the New York and Tokyo markets are asynchronous.

Becker et al. (1990) finds evidence of a high correlation between the returns on US stocks of the previous trading day and Japanese equity stocks of the next day. This high correlation between the opening and closing returns in two countries violates the hypothesis of the efficient market. Lin, Engle and Ito (1994) also investigate the manner in which the

returns and volatilities of stock indices are correlated with each other between Tokyo and New York by utilizing intraday data. Their results show no significant lagged spillover in returns or volatilities. Longin and Solnik (1995) find that such correlations increase over time. Ng (2000) examines the size effect and the impact of volatility spillover from Japan and the US to six Pacific Basin equity markets. By employing four different correlation specifications, Ng constructs a volatility spillover model that distinguishes between a local idiosyncratic shock, a regional shock from Japan and a global shock from the US. Ng's evidence shows that a significant spillover exists from Japan and the US to the six Pacific Basin economies. Longin and Solnik (2001) find a contrasting result, showing that high volatility does not lead to an increase in conditional correlations. They demonstrate that correlations are generated mainly by market trends, and it is only in bear markets that conditional correlations strongly increase; conditional correlations do not increase in bull markets.

Research involving multivariate GARCH models typically employs a constant covariance specification. Numerous studies have shown that correlations between markets are time-varying. King and Wadhwani (1990) find that international correlations tend to increase during periods of market crises. In Andersen et al. (2001), their estimates, termed realized volatilities and correlations, are not only model-free but also largely free of measurement error under general conditions. They also find a simple normality-inducing volatility transformation, high contemporaneous correlation across volatilities, high correlation between correlation and volatilities, and dynamic volatilities and correlations. Kasch-Haroutounian (2005) indicates that correlations in developed markets are significantly affected by high volatility, while high volatility does not seem to have a direct impact on the correlations of the transition blue chip indices with the rest of the markets.

The remainder of this paper is organized as follows. Section 1 briefly discusses the data. In section 2, we estimate the probability distributions of the intraday returns of the yen/dollar spot rates and the probability distributions of intraday returns' volatility. In section 3, the panel probability distributions from Mondays to Fridays for the Tokyo, London and New York markets are reported and discussed. We summarize and conclude in the final section.

1. Data description

We obtained daily opening and closing prices of the yen/dollar daily spot rates in the Tokyo, London and New York currency markets from a Wall Street firm over the period from October 1994 to December 2003 (110 months). The yen/dollar exchange rate is

expressed in European terms (yen/\$), i.e., the foreign currency price of one US dollar. Because holidays in Japan, the UK, and the US differ, we aligned the data set by first matching the opening and closing prices of the spot contracts by date and then deleted the dates on which at least one market did not trade.

To examine the return behavior of the yen/dollar exchange rate, we calculated the intraday returns $((Closing_t - Opening_t) / Opening_t)$ for each day. One advantage of using intraday returns is that they significantly reduce the disturbances from potential overnight noise and price transmission momentum from other markets caused by the use of the close-to-close daily return $((Closing_t - Closing_{t-1}) / Closing_{t-1})$.

Figure 1 (see Appendix) shows the time series of the yen/dollar intraday returns for the Tokyo, London and New York markets from October 26, 1994 to December 31, 2003. At first glance, the return behaviors of the three series seem remarkably similar. Additionally, the volatility of returns from mid-1998 to February 1999 is significantly larger than that of previous years. This result was most likely caused by the Asian financial crisis. Overall, although the three currency markets are located in three different continents with differing time zones, there seems to be a high degree of integration between them.

Table 2 presents summary statistics of the intraday returns of the three yen/dollar spot contracts. As we observe, the New York market has the highest average return (0.0088), while the Tokyo market has the lowest (-0.000079). Interestingly, the standard deviations of the intraday returns in the three markets are very close to each other (approximately 0.72). In addition, the return distribution of the Tokyo market is more left-skewed (the largest negative skewness) with a higher peak (the largest kurtosis) than the return distributions of London and New York.

2. Methodology

2.1. Probability distributions of intraday returns.

Let us first introduce the notations. The value of the exchange rate is expressed by $Y(t)$, and the time series of the daily return $R(t)$ of an asset priced at $Y(t)$ is defined as

$$R(t) = \frac{Y_c(t) - Y_o(t)}{Y_o(t)}, \quad (1)$$

where $Y_c(t)$ is the closing price, and $Y_o(t)$ is the opening price. We further define the probability distribution P as a normalized distribution of the daily return $R(t)$ which satisfies

$$\int_{-\infty}^{\infty} P(R) dR = 1. \quad (2)$$

The probability distributions of the intraday returns, $P(R)$, for the London, New York and Tokyo spot rates are shown in Figure 2 (see Appendix). Except for the sharp peaks appearing at $R \approx 0$ in the London and New York markets, the intraday return distributions of the three spot rates are similar. This phenomenon is interesting and worth further investigation.

We next examine the unconditional correlation coefficients for the first moments of the three markets. Panel A of Table 3 (see Appendix) shows that the spot returns of Tokyo are highly correlated with those of London, showing a higher correlation of 0.648 when compared to 0.58 for New York. Martens and Poon (2001) show that using non-synchronous data results in a significant downward bias in correlation compared with the correlations obtained by constructing a sample of all the prices at GMT. Japan and the US have no overlapping opening time across these three markets.

Panel B of Table 3 shows that the unconditional correlation coefficients in London and New York returns series have been lagging. The Tokyo market returns are correlated with the one-day lagged London market returns of 0.3. This is a lower correlation than with the one-day lagged New York market returns of 0.36. Thus, the correlation between New York and Tokyo falls from 0.58 to 0.36. The correlation between London and Tokyo falls from 0.648 to 0.3. The correlations between New York and London remain constant in both cases.

2.2. Time series of volatility. To quantify the volatility, this study adopts the method used by Yu and Huang (2004) and the Boston group (Liu et al., 1999), estimating volatility as the local average of absolute price changes over a time interval T . Generally, T is an adjustable parameter, but this work always takes $T = 5$ days to construct the time series of volatility.

To construct the time series of the volatility of the exchange rate $Z(t)$, first the price change $G(t)$ is defined as the change in the logarithm of the rate

$$G(t) = \ln Z(t + \delta t) - \ln Z(t), \quad (3)$$

where δt denotes the time interval of sampling with $\delta t = 1$ day in the data. Then, volatility $V(t)$ is defined as the average of the absolute value of $G(t)$ over a time window $T = 5 \delta t$, i.e.

$$V(t) = \frac{1}{5} \sum_{n=0}^4 |G(t + n\delta t)|. \quad (4)$$

Figure 3 (in Appendix) shows the calculated time series of volatility for each of the three exchange markets. Interestingly, the data indicate a clustering effect for the periods of high volatility (Gopikrishnan et al., 2000).

2.3. Probability distribution of volatility. To display the distribution of yen/dollar exchange rate return volatility more explicitly, this section constructs the probability distributions of their volatilities across the Tokyo, London and New York markets. To do so, we first use the histogram method to count the value of volatility $N(V_n)$ ranging between $V_n = n(\Delta V)$ and $V_{n+1} = (n+1)(\Delta V)$, $\Delta V = 0.0005$. Here, n is an integer ranging between 0 and ∞ . The probability of the volatility in the interval between V_n and V_{n+1} is then given as

$$P(V_n) \Delta V = \frac{N(V_n)}{\sum_{m=0}^{\infty} N(V_m)} \quad (5)$$

with the normalization

$$\sum_{n=0}^{\infty} P(V_n) \Delta V = 1. \quad (6)$$

Figures 4(a) to 4(c) display the estimated distributions of $P(V_n)$ versus V_n for the three markets, while Figure 4(d) puts the three graphs together to enable a clear comparison.

As observed in Figure 4 (in Appendix), at least two characteristics are worth mentioning. First, each distribution is asymmetric with a peak. Second, each distribution has a longer tail than the Gaussian distribution. As suggested by Yu and Huang (2004), a log-normal function can take both these characteristics into account in calculating the volatility distribution. Following their methodology, we employ the following form of the distribution function:

$$P(V) = \frac{1}{Vw\sqrt{2\pi}} \exp \left[-\frac{1}{2w^2} \left(\ln \frac{V}{V_c} \right)^2 \right]. \quad (7)$$

We estimate V_c and w first, and then calculate the corresponding log-normal parameters μ and σ by calculating

$$\mu = \exp \left[\ln V_c + \frac{w^2}{2} \right] \text{ and}$$

$$\sigma = \sqrt{\exp(2 \ln V_c + w^2) (\exp(w^2) - 1)}.$$

This function contains two adjustable parameters, V_c and w , indicating the peak probability location and distribution width, respectively.

Notably, this distribution function is normalized in the following form:

$$\int_0^{\infty} P(V) dV = 1. \quad (8)$$

The three fitting curves of the log-normal distribution functions are represented by the dotted lines in Figure 4(d).

2.4. Multivariate GARCH using DCCs. It is generally recognized that financial markets are highly integrated in terms of price movement because prices soaring in one market can spill over to another market instantly. To explore the relationship between two markets, we must calculate the correlation coefficient. We specify a multivariate model that is capable of computing the DCC and capturing ongoing market elements and shocks. The DCC model is specified as

$$\rho_{12,t} = \frac{E_{t-1}(r_{1,t}r_{2,t})}{\sqrt{E_{t-1}(r_{1,t}^2)E_{t-1}(r_{2,t}^2)}}, \quad (9)$$

where the conditional correlation $\rho_{12,t}$ is based on information known in the previous period E_{t-1} . To clarify the relationship between the conditional correlations and conditional variances, it is convenient to express the returns as the conditional standard deviation multiplied by the standardized disturbance, as suggested by Engle (2002):

$$h_{i,t} = E_{t-1}(r_{i,t}^2), r_{i,t} = \sqrt{h_{i,t}}\varepsilon_{i,t}, i = 1, 2. \quad (10)$$

To understand the DCC-GARCH framework, we start by writing the conditional variance-covariance matrix of

$$H_t \equiv D_t R_t D_t, \quad (11)$$

where $D_t = \text{diag}\{\sqrt{h_{it}}\}$ is a 3×3 diagonal matrix of time-varying standard deviations from univariate GARCH models, and $R_t \equiv \{\rho_{ij}\}_t$ for $i, j = 1, 2, 3$, which is a correlation matrix containing the conditional correlation coefficients. The elements in D_t form the univariate GARCH (p, q) process in the following manner:

$$L = -\frac{1}{2} \sum (n \log(2\pi) + 2 \log|D_t| + \log|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t). \quad (16)$$

The DCC model is designed to allow for a two-stage estimation of the conditional covariance matrix H_t . In the first stage, univariate volatility models are fitted for each of the assets, and estimates of h_{it} are obtained. In the second stage, stock market returns are transformed by their estimated standard deviations, resulting from the first stage, and are used to estimate the parameters of the conditional correlation. The true H matrix is generated using univariate GARCH models for the variances, combined with the correlations produced by the Q. The correlation estimators are given by

$$H_t = \begin{pmatrix} h_{ny,t} & \cdot & \cdot \\ \rho_{ny-ld,t} \sqrt{h_{ny,t}h_{ld,t}} & h_{ny,t} & \cdot \\ \rho_{ny-tk,t} \sqrt{h_{ny,t}h_{tk,t}} & \rho_{ld-tk,t} \sqrt{h_{ld,t}h_{tk,t}} & h_{tk,t} \end{pmatrix}, \quad (17)$$

$$h_{it} = \omega_i + \sum_{p=1}^P \alpha_{ip} \varepsilon_{it-p}^2 + \sum_{q=1}^Q \beta_{iq} h_{it-q}, \forall i = 1, 2, 3. \quad (12)$$

Engle's (2002) DCC (m, n) structure can be written as

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \quad (13)$$

where

$$Q_t = (1 - \sum_{m=1}^M A_m - \sum_{n=1}^N B_n) \bar{Q} + \sum_{m=1}^M a_m (\xi_{t-m} \xi_{t-m}') + \sum_{n=1}^N b_n Q_{t-n}, \quad (14)$$

where $\xi_t = \varepsilon_{it} / \sqrt{h_{it}}$, which is a vector containing standardized errors, $Q_t \equiv \{q_{ij}\}_t$ is the conditional variance-covariance matrix \bar{Q} obtained from the first stage of the estimation, and Q_t^* is a diagonal matrix containing the square root of the diagonal elements of Q_t :

$$Q_t^* = \begin{pmatrix} \sqrt{q_{ny-ny}} & \cdot & \cdot \\ \cdot & \sqrt{q_{ld-ld}} & \cdot \\ \cdot & \cdot & \sqrt{q_{tk-tk}} \end{pmatrix}. \quad (15)$$

What is of interest to us in R_t is

$$\rho_{12,t} = q_{12,t} / \sqrt{q_{11,t}q_{22,t}},$$

which represents the conditional correlation between each pair in the three markets. The DCC-GARCH in equations (10)-(12) is estimated using the maximum likelihood method in which the log-likelihood can be expressed as

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}. \quad (18)$$

2.5. Volatility threshold DCCs. To further check if different sub-periods have various patterns, we utilize the volatility threshold model addressed by Kasch and Caporin (2012)¹ to examine whether increasing volatility (exceeding a specified threshold) is associated with increasing correlation. The volatility threshold DCC model is specified as equation (19). Let V_t be a dummy variables matrix with elements defined as

¹ Kasch and Caporin (2012) extend the multivariate DCC-GARCH of Engle to analyze the relationship between volatilities and correlations. The empirical results indicate that high volatility levels significantly affect correlations in developed markets but not those of the transition blue chip indices with the rest of the markets.

$$v_{ij,t} = \begin{cases} 1 & \text{if } h_{i,t} > fh_i(k) \text{ or } h_{j,t} > fh_j(k) \\ 0 & \text{otherwise} \end{cases}, \quad (19)$$

where $fh_i(k)$ is the k^{th} fractile of the volatility series h_i .

One can now extend the DCC and GDCC (generalized dynamic conditional correlation) models in equation (14) in the following way:

$$Q_t = (1 - \alpha - \beta)\bar{Q} - \gamma\bar{V} + \alpha(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta Q_{t-1} + \gamma V_t, \quad (20)$$

$$Q_t = (\bar{Q} - A\bar{Q}A' - B\bar{Q}B' - \Gamma\bar{V}\Gamma') + A(\varepsilon_{t-1}\varepsilon'_{t-1})A' + BQ_{t-1}B' + \Gamma V_t\Gamma', \quad (21)$$

where $\bar{V} = E[V_t]$, and A , B and Γ are $n \times n$ diagonal matrices.

For the GDCC specification, the dynamics of the individual elements of the covariance matrix Q_t would then be specified as

$$q_{ij,t} = (1 - \alpha_i\alpha_j - \beta_i\beta_j)\bar{q}_{ij} - \gamma_i\gamma_j\bar{v}_{ij} + \alpha_i\alpha_j(\varepsilon_{i,t-1}\varepsilon_{j,t-1}) + \beta_i\beta_jq_{ij,t-1} + \gamma_i\gamma_jv_{ij,t}\sqrt{2}. \quad (22)$$

The sufficient condition for the covariance matrix, Q_t , to be positive is that $(\bar{Q} - A\bar{Q}A' - B\bar{Q}B' - \Gamma\bar{V}\Gamma')$ in

$$v_{ij,t} = \begin{cases} 1 & \text{if } (h_{i,t} > fh_i(k) \text{ and } \varepsilon_{i,t-1} < 0) \text{ or } (h_{j,t} > fh_j(k) \text{ and } \varepsilon_{j,t-1} < 0) \\ 0 & \text{otherwise} \end{cases}. \quad (24)$$

3. Empirical results and analysis

3.1. Univariate volatility model estimates. The alternative GARCH models – EGARCH and GJR – are employed and specified as equations (25) and (26), respectively:

$$\begin{aligned} \text{EGARCH } \ln(h_t) &= \alpha_0 + \alpha_1 \left(\left| \frac{r_{t-1}}{\sqrt{h_{t-1}}} \right| - \sqrt{21\pi} \right) + \\ &+ \alpha_2 \left(\frac{r_{t-1}}{\sqrt{h_{t-1}}} \right) + \beta_1 \ln(h_{t-1}), \end{aligned} \quad (25)$$

$$\text{GJR } h_t = \alpha_0 + \alpha_1 r_{t-1}^2 + \alpha_2 S_{t-1}^- r_{t-1}^2 + \beta_1 h_{t-1}$$

with

$$S_{t-1}^- = \begin{cases} 1 & \text{if } r_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases}. \quad (26)$$

The results of the estimation of the univariate volatility models outlined above indicate an asymmetric impact of news on volatility for all series. For each of the series, we select a univariate volatility specification based on the Schwarz Information Criterion. The selected models and corresponding parameter estimates

equation (19) is definitely positive. In case the aim of the empirical analysis is to identify heterogeneity in the response of the markets to the volatility values exceeding some thresholds, it is more suitable to consider a version of the model where the diagonal elements of matrix Γ are allowed to vary. The version of the model in equation (21), which restricts the GARCH dynamics but allows different volatility impacts on the correlations of different asset pairs, could be specified by restricting the diagonal elements of the parameter matrix A and B , for each of the matrices, to be identical. The expression in equation (22) then becomes:

$$\begin{aligned} q_{ij,t} &= (1 - \alpha^2 - \beta^2)\bar{q}_{ij} - \gamma_i\gamma_j\bar{v}_{ij} + \\ &+ \alpha^2(\varepsilon_{i,t-1}\varepsilon_{j,t-1}) + \beta^2q_{ij,t-1} + \gamma_i\gamma_jv_{ij,t}. \end{aligned} \quad (23)$$

In the rest of this paper, we refer to the specification in equation (22) as the Volatility Threshold GDCC (VT-GDCC) and to the specification in equation (23) as the Volatility Threshold DCC (VT-DCC). As emphasized in the introduction to this paper, a range of studies have identified that correlations between assets increase for downside moves, especially for extreme downside moves, rather than for upside moves. To integrate this feature into our specification, we can redefine the dummy variables matrix, V_t , as follows:

are presented in Table 4 (see Appendix). As shown, for the model we select (EGARCH and TGARCH), the asymmetry can be captured by allowing the negative-valued side of the news impact curve to have a steeper slope than the positive-valued side.

Table 5 presents the cross-correlations of the fitted volatility series, and Figure 5 (see Appendix) shows the development of the volatilities over the considered sample period. Obviously, the correlation of volatilities between Tokyo and New York is much lower than the correlation of volatilities between London and New York. From Figure 5, it is clear that the volatilities of the major markets co-move and react to significant international events in a similar manner (Edwards and Susmel, 2001). The reaction of the three markets to the Russian default in August/September 1998 was very strong.

3.2. Conditional correlation estimates. On the basis of the individual standardized residual series obtained as a result of the estimation of the univariate volatility models, the dynamics of the conditional correlation matrix are parameterized as a scalar DCC. The model used in the empirical section was a simple DCC (1, 1)-MVGARCH, where each of the univariate GARCH

models estimated for the conditional variances was selected by finding the minimum of the Akaike information criterion (*AIC*). The models were built in an expanding fashion so that the three countries included the countries in the two-country model plus an additional country. We model the correlation dynamics of the three yen/dollar returns of Tokyo, London and New York to each other. The estimation results are presented in Table 6 for the market analysis.

Tables 7 and 8 summarize the estimated α and β for the three markets. The last row of Table 6 provides the results of the log-likelihood ratio test. The test statistic for the market analysis cannot reject the null hypothesis of the scalar DCC. The plots of the resulting conditional correlation series are presented in Figure 6. The first important feature is that the correlation trends are most likely the same; this is especially observed in the correlations between Tokyo and London/New York. We observe a sharp drop in the correlations between London and New York, which is influenced by the Asian-Russian crisis near 1998. Another common observation is that the correlations for all the developed markets' yen/dollar rates have increased since 1997, notably for the correlation between London and New York.

3.3. Volatility threshold-dynamic conditional correlations (VT-DCCs). Table 9 presents the results of the estimation of the VT-DCC models specified above. The model is estimated at the different predefined volatility threshold levels of 75, 90, 95 and 99 percent fractiles. To further analyze the heterogeneous impacts of volatilities on the correlations of each pair in the three markets, we skip the scalar model of equation (20) by estimating two versions of the model in equation (21), which are specified in equations (22) and (23). Table 9 is based on the specification with the matrix V_t defined as in equation (24). The results in Table 9 deliver strong evidence that the correlations of the developed market indices are significantly influenced by the volatility in one of the markets while exceeding a predefined threshold. In Table 9, the similar estimates for the specifications most likely indicate that the high volatility values are predominantly associated with negative returns.

The results in this section reflect the general picture illustrated in Figure 7 and indicate that transition markets, under *ceteris paribus* conditions, could potentially provide some protection for international investors in turbulent market periods.

3.4. DCC distributions. We also seek to characterize the DCC distributions that have evolved over the past

10 years. The summary statistics in Table 10 show the panel of volatility and DCC; the sample mean suggests that higher volatility accompanies higher DCC. Here, we follow Andersen et al. (2001) to show the DCC-volatility relationship with a flattened response for both low and high volatility values (volatility of London using Panel A and Panel B, and the volatility of New York using Panel C).

To further quantify this volatility effect in correlations, the three panels of Figure 7 show the kernel density estimates of DCC densities to be conditional on the more extreme volatility situation, namely, the volatilities of London and New York are less than their 20th percentile value and greater than their 80th percentile value. We show that the distribution of DCC shifts leftward when the volatility increases. It is obvious that a high DCC value is followed by high volatility, and a low DCC value is followed by low volatility.

For Panel B in Figure 7, there is no significant difference between the distributions of low and high volatility in the DCCs of London and New York. In Panel C, the low volatility distribution of DCC appears to be leptokurtic and skewed to the left; however, the high volatility distribution of DCC is flatter and wider.

Conclusions

Using the DCC model, we estimate the cross-correlation and volatility among the Tokyo, London and New York yen/dollar currency markets from 1994 to 2003. Both time-varying correlations and realized distributions are explored. The results indicate that the distributions of intraday variances are skewed to the right and are leptokurtic.

Further, London yen/dollar returns influence Tokyo, but not vice versa. Hence, the DCC probability distribution of London and Tokyo displays high volatility accompanied with a high DCC value because of London's dominance. In the meantime, New York has a spillover effect on London's variance, and London also has a comovement effect on New York's variance. The results of the DCC probability distributions thus show an overlap without dominance. Last, New York has a spillover effect on Tokyo's variance, while Tokyo does not have any impact on New York's variance. As such, the DCC probability distribution between Tokyo and New York has high volatility with a high DCC value, and the high-DCC distribution is wider than the low-DCC distribution.

In summary, New York seems to dominate London and Tokyo, while London dominates Tokyo. Although Tokyo opens in an earlier time zone, it has never dominated the yen/dollar markets of London or New York.

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Appendix

Table 1. Overlaps in time zones of Tokyo, London and New York FX markets

Countries	GMT Times	Tokyo	London	New York
Tokyo	00:00-06:30	–		
London	09:00-17:00	×	–	
New York	14:00-21:00	×	√	–

Note: √ indicates presence of overlap; × indicates no overlap.

Table 2. Summary statistics of the intraday returns of yen/dollar spot rate among Tokyo, London and New York (1994-2003)

Market	Obs.	Mean	Max.	Min.	Std. dev	Skew.	Kurt.	JB
Tokyo	2395	-0.000079	0.04	-0.08	0.00715	-1.09*	11.23*	13007.29*
London	2395	0.007606	0.03	-0.06	0.00723	-0.55*	4.78*	2389.75*
New York	2395	0.008871	0.04	-0.07	0.00726	-0.66*	6.24*	4040.08*

Note: * Significant from the null at the 1% level. JB is the Jarque-Bera test statistic.

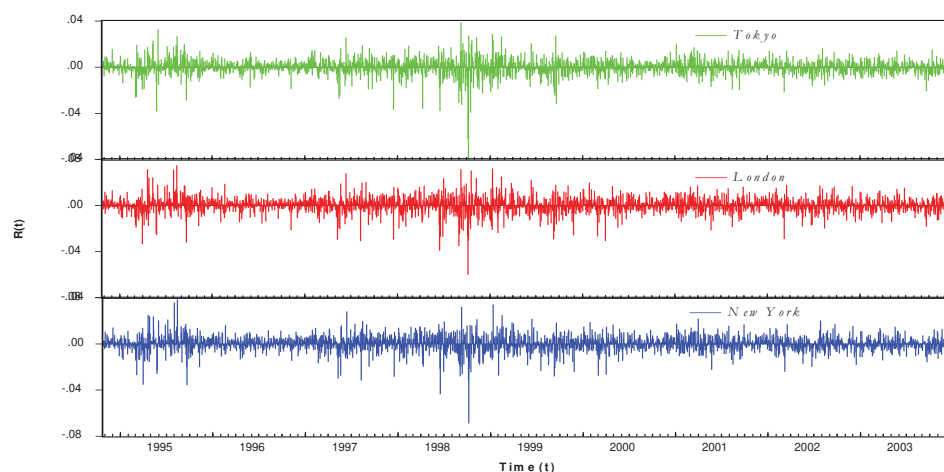


Fig. 1. Time series plots of the intraday returns of the yen/dollar spot rate in Tokyo, London and New York markets

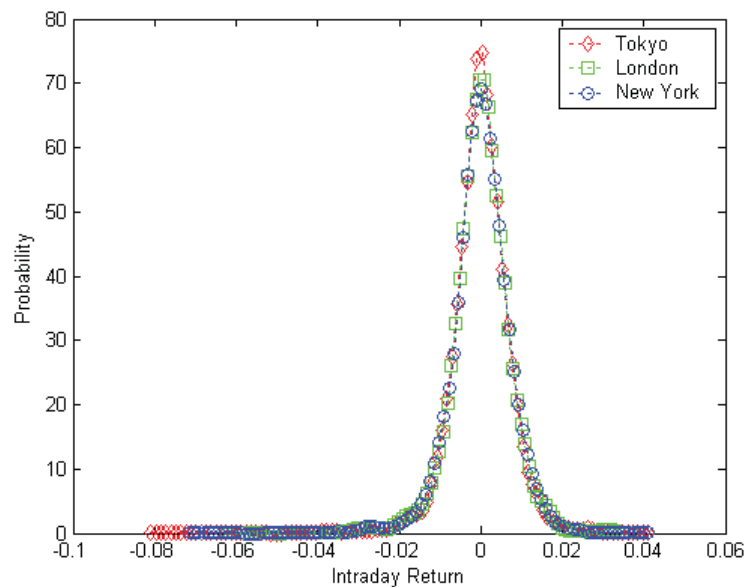


Fig. 2. Probability distribution of intraday returns of the three spot foreign exchange markets: Tokyo, London and New York

Table 3. Unconditional correlation coefficients of daily returns among Tokyo, London and New York (1994-2003)

Panel A. Unconditional correlation coefficients of daily returns in terms of US currency (1994-2003)			
	Tokyo	London	New York
Tokyo	—		
London	0.648	—	
New York	0.580	0.914	—
Panel B. Unconditional correlation coefficients of intraday returns with lags in terms of US currency (1994-2003)			
	Tokyo	London (-1)	New York (-1)
Tokyo	—		
London (-1)	0.300	—	
New York (-1)	0.360	0.914	—

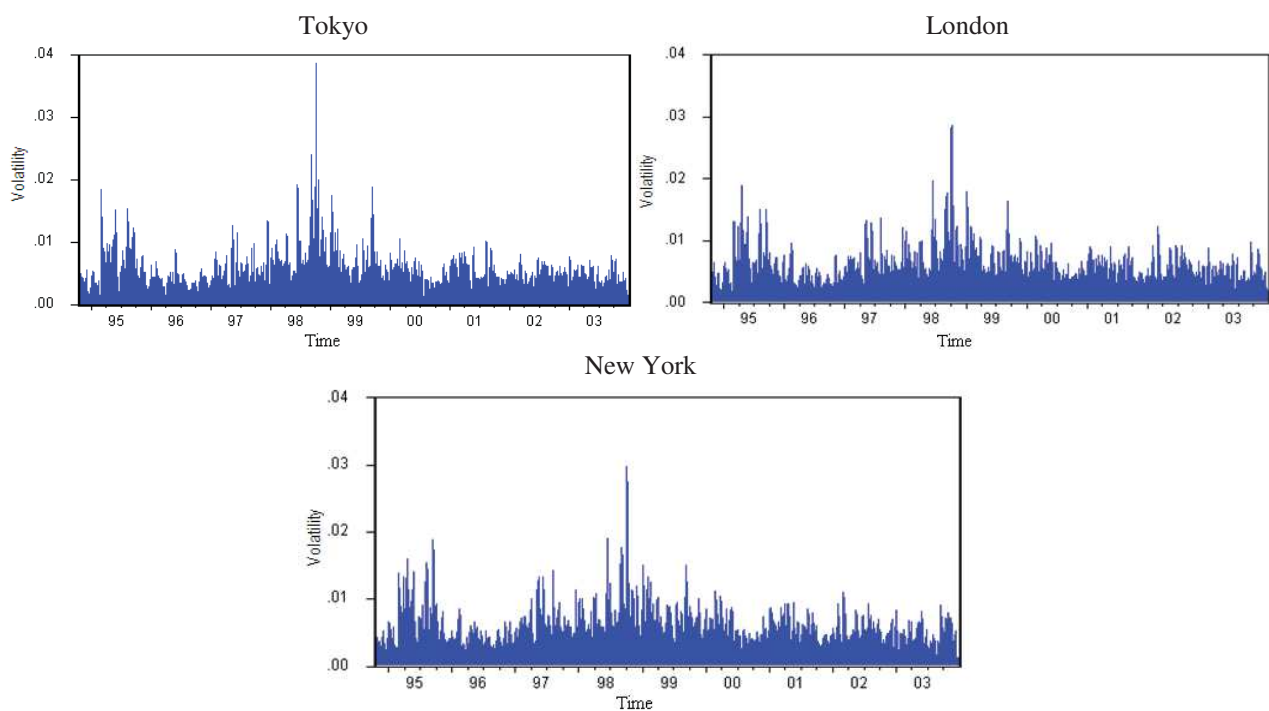


Fig. 3. Time series of volatility of the three yen/dollar currency markets (1994-2003): Tokyo, London and New York

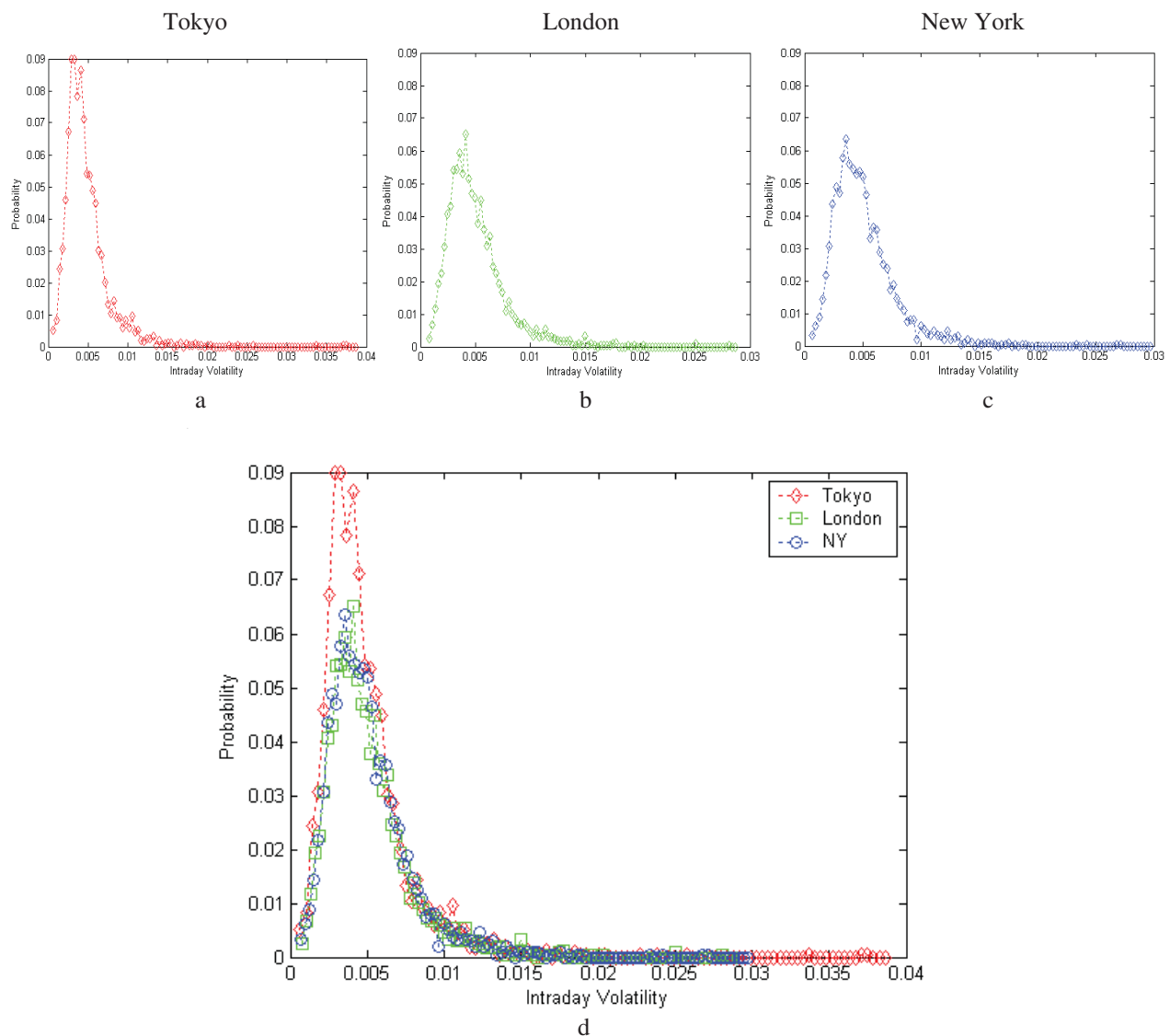


Fig. 4. The probability distribution functions of volatility of the three yen/dollar currency markets: Tokyo, London and New York.

Table 4. Univariate volatility model choice

Markets	Model	Parameter estimates			
		α_0	α_1	β_1	α_2
London	EGARCH	-0.2064 (-6.7518)*	0.0937 (10.2385)*	0.9862 (366.9346)*	-0.0193 (-3.9813)*
New York	GJR	4.62E-07 (4.4221)*	0.0319 (6.2116)*	0.9549 (206.7738)*	0.0094 (1.7926)*
Tokyo	GJR	1.02E-06 (6.4565)*	0.0586 (7.8624)*	0.9130 (113.7442)*	0.0152 (1.7956)*

Note: This table gives the quasi-maximum likelihood estimates of the selected univariate volatility models; t -statistics are given in parentheses. The 10% critical for a two-tailed test with large df (>120) is 1.645. Statistical significance is denoted by *.

Table 5. GARCH volatility correlations

	London	New York
Tokyo	0.8804	0.8219
London	—	0.8965

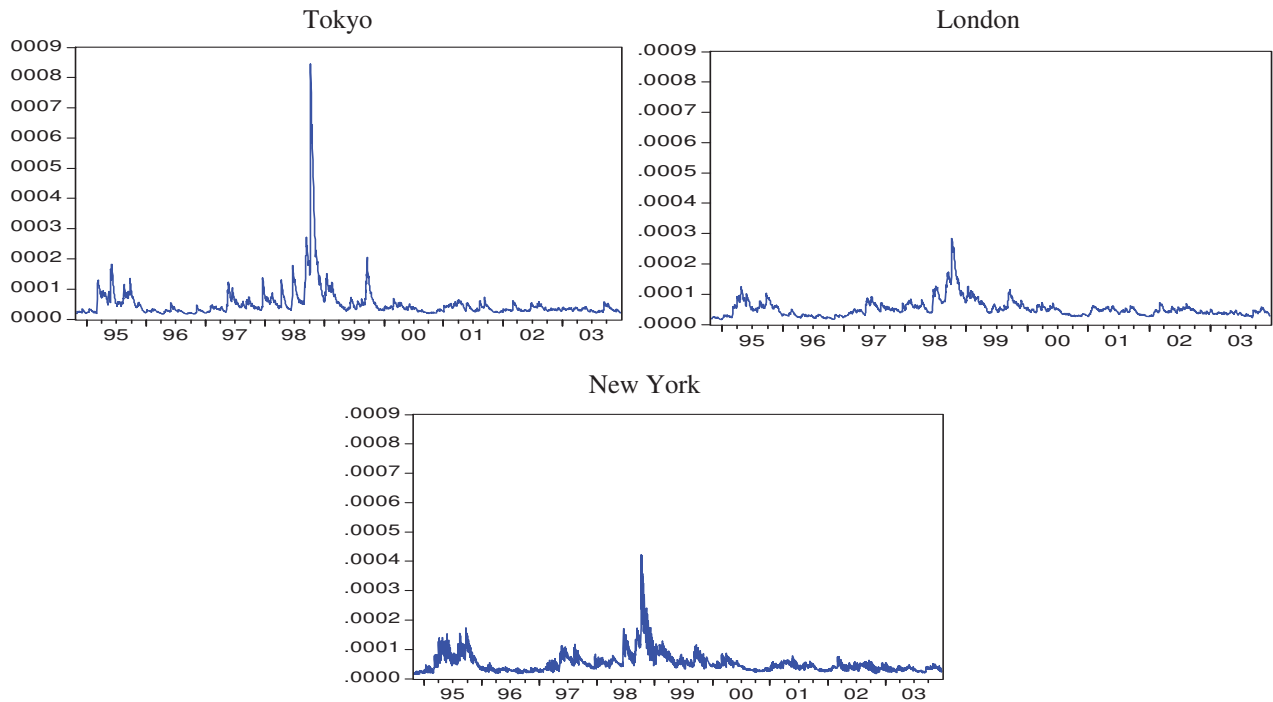


Fig. 5. GARCH volatility of yen/dollar markets: Tokyo, London and New York

Table 6. Time series analysis of DCC conditional correlation coefficients

$X_i = \beta_1 X_i(-1) + \beta_2 X_i(-2), \quad i = 1, 2, 3$			
Index	Tokyo	London	New York
β_1	-0.1987 (-11.93)*	-0.3625 (-27.27)*	-0.3818 (-27.25)*
β_2	-0.0539 (-3.41)*	-0.0978 (-7.62)*	-0.1069 (-8.01)*
LR	-4223.34		

Note: This table gives the log-likelihood estimating DCC model. Std. errors are given in parentheses. The 1% critical for a two-tailed test with large df (>120) is 1.645. Statistical significance is denoted by *.

Table 7. DCC conditional correlation estimates: all (three) markets

$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha(\varepsilon_t \varepsilon_t') + \beta Q_{t-1}$			
DCC			
α	0.0030 (2.6183)*	β	0.9966 (679.4743)*
LDCC	-4223.3350		

Note: This table gives the log-likelihood estimating DCC model. Std. errors are given in parentheses. The 1% critical for a two-tailed test with large df (>120) is 1.645. Statistical significance is denoted by *.

Table 8. DCC conditional correlation estimates: each pair in the three markets

$q_{ij,t} = (1 - \alpha_i \alpha_j - \beta_i \beta_j) \bar{q}_{ij} + \alpha_i \alpha_j \varepsilon_{i,t-1} \varepsilon_{j,t-1} + \beta_i \beta_j q_{ij,t-1}$			
GDCC			
$\alpha_{TK} \alpha_{LD}$	0.0167 (3.5956)*	$\beta_{TK} \beta_{LD}$	0.9414 (47.9764)*
$\alpha_{LD} \alpha_{NY}$	0.0037 (4.4689)*	$\beta_{LD} \beta_{NY}$	0.9963 (1198.7665)*
$\alpha_{TK} \alpha_{NY}$	0.0019 (4.3304)*	$\beta_{TK} \beta_{NY}$	0.9976 (1525.7729)*
LGDC	-4144.01		

Note: This table gives the log-likelihood estimating DCC model. Std. errors are given in parentheses. The 1% critical for a two-tailed test with large df (>120) is 1.645. Statistical significance is denoted by *.

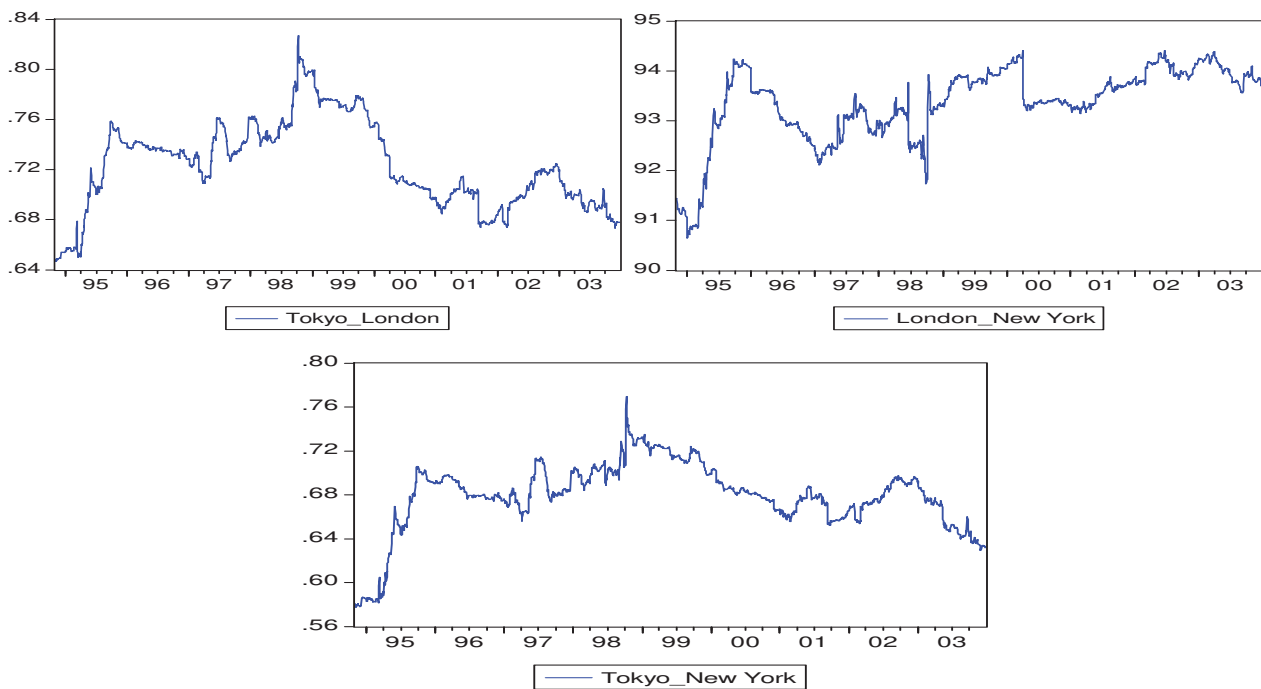


Fig. 6. Conditional correlations between Tokyo and London, London and New York and Tokyo and New York

Table 9. Volatility threshold asymmetric DCC

	Obs.	75%	90%	95%	99%
α^2	2393	0.010 (1.41)	0.019 (2.42)**	0.009 (1.12)	0.025 (2.91)***
β^2	2393	0.898 (15.90)***	0.876 (14.27)***	0.902 (11.31)***	0.825 (7.59)***
$\gamma_{TK}\gamma_{LD}$	2393	0.007 (1.51)	0.015 (1.79)*	0.013 (1.29)	0.037 (1.025)
$\gamma_{LD}\gamma_{NY}$	2393	0.0003 (4.32)***	0.0004 (1.91)*	0.0006 (1.75)*	0.002 (2.79)**
$\gamma_{TK}\gamma_{NY}$	2393	0.007 (1.43)	0.02 (2.24)**	0.02 (1.94)**	-0.631 (-1.66)*
LVT-GDCC		-6167.41	-6166.65	-6167.77	-6168.02

Note: This table gives the quasi-maximum likelihood estimates of the VT-GDCC model with restrictions on the GARCH dynamics of the conditional correlations. *t*-statistics are given in parentheses.

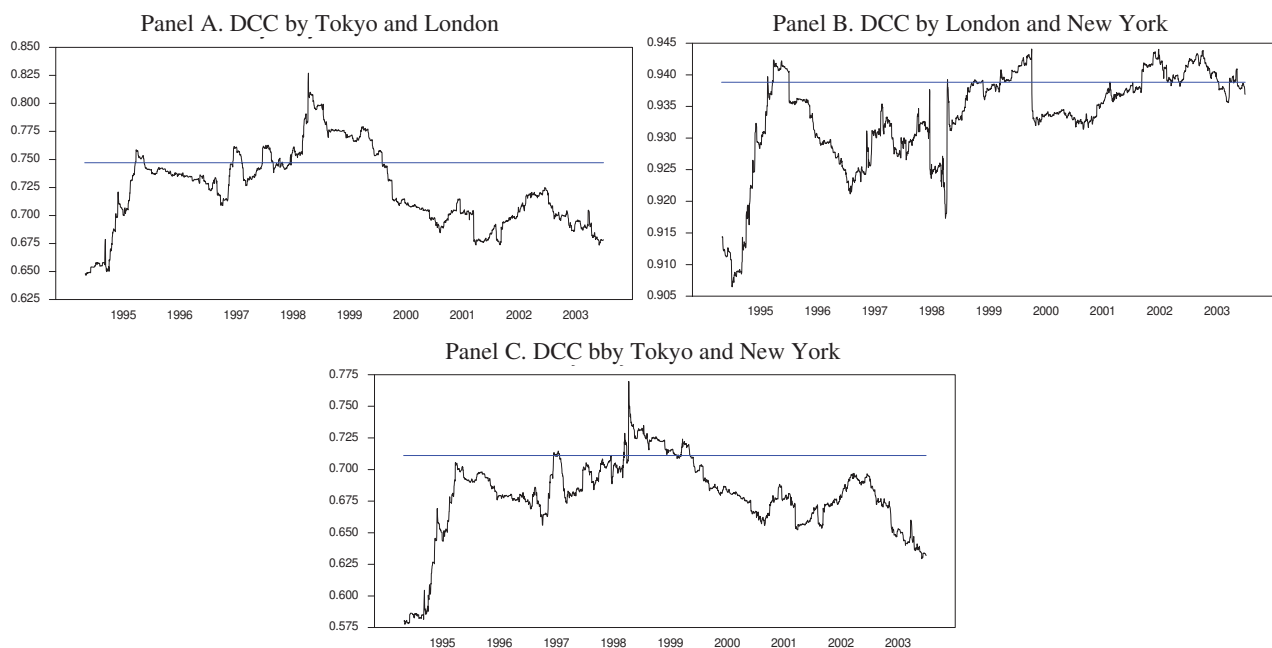


Fig. 7. Volatility threshold asymmetric DCC at the 90 percent fractile

Table 10. DCC distributions between Tokyo and London

Volatility	DCC between Tokyo and London				
	Obs.	Mean	St. dev.	Skew.	Kurt.
0-10%	240	0.706	0.031	-0.514	1.890
10-20%	239	0.702	0.023	-0.120	2.494
20-30%	239	0.705	0.025	0.119	2.755
30-40%	239	0.716	0.029	0.206	2.616
40-50%	239	0.720	0.028	-0.123	2.689
50-60%	239	0.719	0.027	-0.020	2.409
60-70%	239	0.728	0.030	0.036	2.176
70-80%	239	0.737	0.032	-0.325	2.763
80-90%	239	0.741	0.035	-0.740	2.936
90-100%	241	0.759	0.038	-0.835	3.037
Mean	2393	0.723	0.030	-0.232	2.577
Std. dev.	2393	0.018	0.004	0.360	0.348

Note: The table summarizes the DCC for the yen/dollar foreign exchange of Tokyo and London. The sample covers the period from October 26, 1994 through December 31, 2003, for a total of 2393 observations.

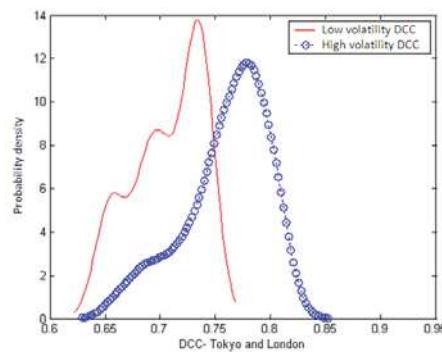


Fig. 8. Conditional distribution of the correlation between Tokyo and London: low volatility versus high volatility

Table 11. DCC distributions between London and New York

Volatility	DCC between London and New York				
	Obs.	Mean	St. dev.	Skew.	Kurt.
0-10%	240	0.928	0.010	-1.091	2.986
10-20%	239	0.934	0.008	-1.776	5.839
20-30%	239	0.935	0.008	-1.646	5.661
30-40%	239	0.935	0.007	-1.572	5.934
40-50%	239	0.935	0.007	-1.346	5.273
50-60%	239	0.935	0.006	-0.936	4.363
60-70%	239	0.936	0.006	-0.897	4.465
70-80%	239	0.935	0.006	-1.086	4.926
80-90%	239	0.933	0.007	-0.886	3.620
90-100%	241	0.931	0.007	-0.373	2.175
Mean	2393	0.934	0.007	-1.161	4.524
Std. dev.	2393	0.002	0.001	0.427	1.268

Note: The table summarizes the DCC for the yen/dollar foreign exchange of London and New York. The sample covers the period from October 26, 1994 through December 31, 2003, for a total of 2393 observations.

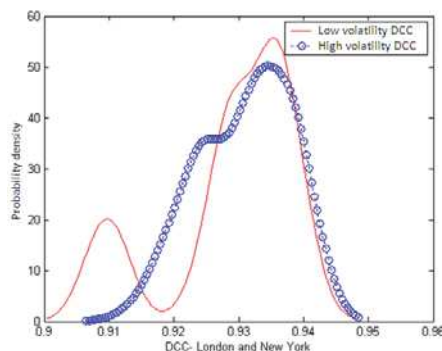


Fig. 9. Conditional distribution of the correlation between London and New York: low volatility versus high volatility

Table 12. DCC distributions between Tokyo and New York

Volatility	DCC between Tokyo and New York				
	Obs.	Mean	St. dev.	Skew.	Kurt.
0-10%	240	0.659	0.034	-1.251	3.475
10-20%	239	0.669	0.026	-2.319	8.275
20-30%	239	0.667	0.027	-1.871	6.507
30-40%	239	0.669	0.030	-1.558	5.717
40-50%	239	0.678	0.025	-1.416	6.804
50-60%	239	0.680	0.024	-1.325	7.104
60-70%	239	0.688	0.021	-0.862	5.328
70-80%	239	0.690	0.027	-1.590	7.062
80-90%	239	0.691	0.033	-1.437	5.093
90-100%	241	0.698	0.038	-1.131	3.614
Mean	2393	0.679	0.029	-1.476	5.898
Std. dev.	2393	0.013	0.005	0.403	1.554

Note: The table summarizes the DCC for the yen/dollar foreign exchange of Tokyo and New York. The sample covers the period from October 26, 1994 through December 31, 2003, for a total of 2393 observations.

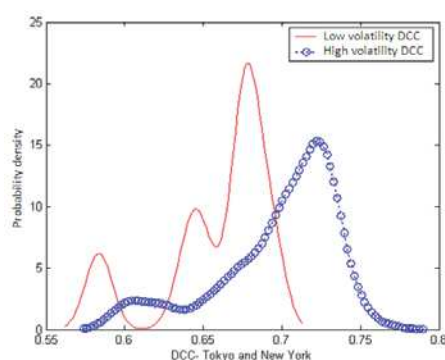


Fig. 10. Conditional distribution of the correlation between Tokyo and New York: low volatility versus high volatility