Intraday analysis on endogenous jumps, US macroeconomic surprises and long memory property in high frequency foreign exchange rates: Cases of the USD-EUR and the JPY-USD exchange rates*

By

Young Wook Han+
Department of Economics
Hallym University

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Abstract

This paper investigates the volatility dynamics of high frequency 30-minute Dollar-Euro and Yen-Dollar exchange rates. Even though the FIGARCH model with normality assumption is found to be a good starting point to study the dynamics of the high frequency returns, it appears to be inappropriate to represent the underlying features of the high frequency returns due to the occurrences of jumps. Hence this paper relies on the FIGARCH model with a mixture distribution that allows for the time-varying jumps which are endogenously determined by the US macroeconomic surprises. This paper generally finds that the macroeconomic surprises induce jumps in the high frequency returns affecting the jump probability asymmetrically depending on the signs and that the jumps increase the long memory persistence of the volatility process.

JEL classifications: C22, F31, G15.

Keywords: High frequency exchange rates, Endogenous jumps, FIGARCH, Long memory property, US macroeconomic surprises, Mixture distribution.

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+ Correspondence: Young Wook Han, Department of Economics, Hallym University, Chuncheon, Gangwon-Do, Korea 200-702. E-mail: ywhan@hallym.ac.kr; Phone: +82-33-248-1820; Fax: +82-33-256-3424.

1. Introduction

There exists a widely spread perception in the empirical literature on foreign exchange rates that the volatility of foreign exchange returns has been changing over time. Given the impacts of the changes in the volatility process on important financial and economic decisions like portfolio management or risk management, it seems to be important to assess the empirical validity of this perception and to investigate the sources and the characteristics of the changing volatility process. So far both of the Autoregressive Conditional Heteroskedasiticity (ARCH) model of Engle (1982) and its extension, the Generalized Autoregressive Conditional Heteroskedasiticity (GARCH) model of Bollerslev (1986) have been most commonly used to analyze the volatility process of foreign exchange returns. See Bollerslev et al. (1992) and Palm (1996) for the excellent surveys of the ARCH and the GARCH applications.

Recently, many empirical studies have found that the volatility process of foreign exchange returns series generally contains a long memory persistence and that the volatility process can be more appropriately characterized by the Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasiticity (FIGARCH) process of Baillie et al. (1996), which is a further extension of the usual GARCH process (see Baillie et al., 2000, 2004; Baillie and Osterberg, 2000; Beine et al., 2002; Beine and Laurent, 2003). In addition, the approximate Quasi-Maximum Likelihood Estimation (QMLE) method has been usually used to estimate the FIGARCH models assuming that the innovations are normally distributed. This normality assumption has been justified by Weiss (1986) and Bollerslev and Wooldrige (1992) which presented that the Gaussian QMLE estimators are consistent if the conditional mean and the conditional variance are correctly specified.

However, the usual normality assumption can be rejected when jumps occur in foreign exchange rates given the specifications of the conditional mean and conditional variance process. These jumps may be caused by the public information (news) about macroeconomic fundamentals or central bank interventions in foreign exchange markets as pointed by Andersen et al. (2003) and Beine and Laurent (2003). In the light of the evidence on the existence of

jumps in the process of foreign exchange rates, this paper models the jumps and looks for an economic explanation for their existence. Since the jumps appear to be quite important in understanding the dynamics of foreign exchange rates, modeling the jumps directly might give interesting additional insight into the mechanism of exchange rate dynamics.

It has been well known in financial economics that information flow is a major determinant of foreign exchange rate movements and the flow can take the form of either public or private information. With respect to the public information, the most common type is the scheduled announcements of macroeconomic indicators. Mostly, this kind of public information is officially forbidden to be announced until the scheduled release time so that there is no prior leakage of the information. Thus, the new public information of macroeconomic indicators reaches all participants in foreign exchange markets at the same time and then the exchange rates will adjust to incorporate the information. Furthermore, as presented by Lyons (2001) and Evans and Lyons (2002) the public information can lead to private information flow and change the order flows of market participants. Hence the issue of how the public information of macroeconomic indicators and foreign exchange rates are incorporated has been important in financial economics even if it has been also one of the least well understood issues.

In order to solve this problem, many empirical studies have examined the process of price discovery in the context of foreign exchange rates. While some papers like Meese and Rogoff (1983), Frankel and Rose (1995) and Evans and Lyon (2002) have suggested that foreign exchange rates and macroeconomic variables are disconnected, other papers have showed that the public information about macroeconomic indicators or central bank interventions are closely linked to foreign exchange rates (see, e.g. Goodhart et al., 1993; Vlaar and Palm, 1997; Alemida et al., 1998; Neely, 1999; Beine and Laurent, 2003; Andersen et al, 2003). Many of the papers have used the public information about the US macroeconomic announcements or US central bank interventions to investigate the impacts of public information on foreign exchange rates. Thus, the jumps in foreign exchange rates can be caused

primarily by the public information about the US macroeconomic indicators since the information results in price changes well above normal and may be better captured by jumps.

The main goal of this paper is to show that the US macroeconomic indicators are closely related to the dynamics of high frequency Dollar-Euro and Yen-Dollar exchange rates. In particular, this paper wants to show that the US macroeconomic surprises (the differences between the surveyed expectations and actual realizations of the US macroeconomic indicators) induce jumps in the high frequency exchange rates and the jumps increase the long memory persistence in the volatility process of the high frequency exchange rates. For the analysis, this paper uses two kinds of new data sets. One is the dataset consisting of four years of real time 30-minute high frequency Dollar-Euro and Yen-Dollar exchange rates, which is provided by Olsen and Associates and the other one is the dataset of the macroeconomic indicators containing the information of surveyed expectations and actual realizations for the US macroeconomic fundamentals provided by the International Money Market Service (MMS). Among many US indicators, this paper selects five major US indicators such as Durable Goods, GDP, PPP, Unemployment and NAPM index. Furthermore, to highlight the effects of the macroeconomic surprises contained in the major macroeconomic indicators, this paper distinguishes positive surprises from negative surprises by computing the difference between the expected surveys and the realizations of the US macroeconomic announcements.

In order to model jumps in the process of the high frequency Dollar-Euro and Yen-Dollar exchange rates, this paper adopts a mixture distribution, the Bernoulli-normal distribution, that allows for the possibility of time-varying jumps endogenously determined by the major US macroeconomic surprises. This paper then extends the basic FIGARCH model of Baillie et al. (1996) by combining the FIGARCH model with the mixture distribution. Thus, this paper finds that the FIGARCH model with the mixture distribution performs quite well and is more appropriate to model the high frequency exchange returns and that the jumps tend to increase the long memory persistence in the volatility process of the high frequency returns series. Interestingly, the US macroeconomic surprises are found to affect the jump probability

asymmetrically depending on the signs: the positive surprises increase the jump probability while the negative surprises decrease the probability. Thus, the US macroeconomic surprises would be given an important role in explaining the jumps in this paper.

The plan for the rest of this paper is as follows: section 2 presents a basic analysis of the high frequency returns series for the Dollar-Euro and the Yen-Dollar exchange rates. For the analysis of the high frequency returns, this paper applies the Flexible Fourier Form (FFF) proposed by Gallant (1981, 1982) to eliminate the intraday periodicity in the high frequency returns and then uses the FIGARCH model of Baillie et al. (1996) to estimate the long memory property in the volatility process of the high frequency filtered returns. Section 3 of the paper describes the US macroeconomic expectations and announcements data and a normal mixture distribution model, the Bernoulli jump process, in order to account for the endogenously determined time-varying jumps in the high frequency returns. Then, the FIGARCH model with the mixture distribution is presented to investigate the effects of the jumps on the high frequency returns. Section 4 provides a conclusion.

2. FIGARCH model with a normal distribution

This section is concerned with the set of 30-minute high frequency US Dollar-Euro and Japanese Yen-US Dollar spot exchange rate data provided by Olsen & Associates of Zurich, in which Reuter FXFX quotes are taken every 30-minutes for the complete calendar years of 1999 through 2002. The sample period is 00:00 GMT, January 4, 1999 through 00:00 GMT, January 1, 2003. Each quotation consists of a bid and an ask price and is recorded in time to the nearest second. Following the procedures of Baillie et al. (2000, 2004), the spot exchange rate for each 30-minute interval is obtained by linearly interpolating the average of the log bid and the log ask at the two closest ticks.

The n-th 30-minute high frequency return for day t is,

$$R_{t,n} = 100*[\ln(S_{t,n}) - \ln(S_{t,n-1})] \qquad (1)$$

where $S_{t,n}$ is the 30-minute spot foreign exchange rate which is the average of the log bid price and the log ask price. It has become fairly standard in this literature to remove atypical data associated with slower trading patterns during weekends (Müller et al., 1990; Bollerslev and Domowitz, 1993). Hence the returns during the weekends from Friday 21:30 GMT through Sunday 20:00 GMT are excluded.

In particular, this definition of the weekend was motivated by the ebb and flow in the daily FX activity patterns documented in Bollerslev and Domowitz (1993). They presented that the weekend data with much lower trading activities are excluded since they cannot provide any economic implications. However, the returns for holidays occurring during the sample are retained in order to preserve the number of returns associated with one week as suggested in the Appendix of Andersen and Bollerslev (1997) and Baillie et al. (2000). The eventual sample used in the subsequent analysis contains 1,042 trading days, each with 48 intervals of 30-minute duration, which realizes a total of 50,016 observations for the high frequency returns.

The 30-minute high frequency returns of the Dollar-Euro and the Yen-Dollar exchange rates are presented in Figure 1 (a) and (b) respectively. They are centered on zero but there exists obvious volatility clustering in the two high frequency return series. The sample means of the 30-minute exchange return are found to be -0.0002 and 0.0001 for the Dollar-Euro and the Yen-Dollar exchange rates which are very close to zero and indistinguishable at the standard significance level given the sample deviations of 0.01 and 0.1. However, both of the returns appear not to be normally distributed since the sample skewness and kurtosis are 0.30 and 17.82 for the Dollar-Euro returns and 0.17 and 16.71 for the Yen-Dollar returns, which are all found to be statistically significant based on the fact that the standard errors of the statistics are 0.011 and 0.022 respectively.[1)] In particular, the estimated kurtosis statistics for the two high frequency returns are found to be relatively large, which implies the rejection of a Gaussian normal distribution assumption. As presented by Andersen et al. (2003), the excess kurtosis may be due to the occurrences of numerous jumps that have taken place in the two high frequency returns.

These jumps could lead to the level and volatility outliers that the normal distribution cannot take into account (Hotta and Tsay, 1998).

Figure 2 (a) and (b) present the first 480 autocorrelation coefficients for the returns, squared returns and absolute returns of the unadjusted (raw) 30-minute Dollar-Euro and Yen-Dollar exchange rates respectively. For the two high frequency returns, there are small, negative but very significant first order autocorrelations. The weak negative correlations may be attributed to a combination of a small time varying risk premium, bid-ask bounce, and/or non-synchronous trading phenomena while higher order autocorrelations are not significant at conventional levels. The autocorrelation functions of the squared and absolute returns of the high frequency returns exhibit a pronounced U-shape pattern, associated with substantial intraday periodicity. The general pattern is consistent with the studies of Wasserfallen (1989), Müller et al. (1990), Baillie and Bollerslev (1991), Dacorogna et al. (1993), Andersen and Bollerslev (1998), Baillie et al. (2000, 2004) and Andersen et al. (2003). The pattern is generally attributed to the opening of the European, Asian and North American markets superimposed on each other as presented by Andersen and Bollerslev (1997).

In order to remove the strong intraday periodicity, this study follows a similar approach used by Andersen and Bollerslev (1997, 1998) and Baillie et al. (2000, 2004), and adopts a two step estimation method. First, the intraday periodicity is removed by applying the FFF approach of Gallant (1981, 1982); see the Appendix of Andersen and Bollerslev (1997) for details. In particular, Baillie et al. (2000) presents that the FFF method appears to be appropriate for representing intraday periodicity without inducing any non-linearity and obvious deficiencies with the model.

The high frequency Dollar-Euro and Yen-Dollar returns are then filtered by the intraday seasonality series estimated from the FFF method, $p_{t,n}$, to generate the filtered returns, which are defined as[2)]

$$y_{t,n} = R_{t,n}/p_{t,n} \qquad (2)$$

A model postulated to describe the filtered returns process is the MA(1)-FIGARCH(1,δ,1) process, which models the short run autocorrelation in the returns, and also generates long memory in the squared and absolute returns,

$$y_{t,n} = \mu + \varepsilon_{t,n} + \theta\varepsilon_{t,n-1} \tag{3}$$

$$\varepsilon_{t,n} = z_{t,n}\,\sigma_{t,n} \tag{4}$$

$$\sigma^2_{t,n} = \omega + \beta\sigma^2_{t,n-1} + [1 - \beta L - (1 - \varphi L)(1 - L)^{\delta}]\varepsilon_{t,n}^{\ 2} \tag{5}$$

where $z_{t,n}$ is an i.i.d.(0,1) process, and the time indexes t = 1,...,1042 days and n = 1,...., 48. When $\delta = 0$, then equation (5) reduces to the standard GARCH (1,1) model; and when $\delta = 1$, then equation (5) becomes the Integrated GARCH, or IGARCH (1,1) model implying the complete persistence of the conditional variance to a shock in squared returns. The attraction of the FIGARCH process is that for $0 < d < 1$, it is sufficiently flexible to allow for intermediate ranges of persistence which represents the slow hyperbolic rates of decay in the autocorrelations of the squared returns. Furthermore, the associated impulse response weights also exhibit quite persistent hyperbolic decay. The FIGARCH process has impulse response weights, $\sigma^2_t = \omega/(1 - \beta) + \lambda(L)\varepsilon^2_t$, where for large lags k, $\lambda_k \approx k^{\delta-1}$, which is essentially the long memory property or 'Hurst effect' of hyperbolic decay. The FIGARCH process is strictly stationary and ergodic for $0 \le \delta \le 1$, and shocks will have no permanent effect.

The above eqs. (3) through (5) are estimated by using non-linear optimization procedures to maximize the Gaussian log likelihood function,

$$\ln(\zeta) = -(T/2)\ln(2\pi) - (1/2)\Sigma_{t=1,..,1042,\ n=1,..48}[\ln(\sigma^2_{t,n} + \varepsilon^2_{t,n}\sigma^{-2}_{t,n})] \tag{6}$$

The inference is usually based on the QMLE of Bollerslev and Wooldridge (1992), which is valid for $z_{t,n}$ being non-Gaussian. On denoting the vector of parameter estimates from a sample of T observations by $\hat{\theta}_T$, the limiting distribution is given by,

$$T^{1/2}(\hat{\theta}_T - \theta_0) \rightarrow N[0, A(\theta_0)^{-1} B(\theta_0) A(\theta_0)^{-1}], \tag{7}$$

where A(.) and B(.) represent the Hessian and outer product gradient respectively; and θ_0 denotes the vector of true parameter values. Equation (7) is used to calculate all the robust standard errors that are reported in the subsequent tables, with the Hessian and outer product gradient matrices being evaluated at the point $\hat{\theta}_T$ for practical implementation.

Table 1 presents the estimation results of applying the above model to the filtered high frequency Dollar-Euro and Yen-Dollar exchange returns. The long memory volatility parameters (δ) are estimated to be 0.19 and 0.27 for the Dollar-Euro and the Yen-Dollar returns, and are found to be statistically significant. Thus, the hypotheses that d = 0 (stationary GARCH) and also d =1 (integrated GARCH) can be comprehensively rejected for the returns using standard significance levels. Table 1 also reports the Robust Wald test statistics denoted by $W_{\delta=0}$ for testing the null hypothesis of GARCH (1,1) versus a FIGARCH (1,d,1) data generating process. Under the null, W will have an asymptotic χ_1^2 distribution and the GARCH (1,1) model is rejected for the high frequency returns at standard significance levels. It presents strong support for the hyperbolic decay and persistence of the FIGARCH model as opposed to the conventional exponential decay associated with the stable GARCH(1,1) model.[3)] Furthermore, a sequence of diagnostic portmanteau tests on the standardized residuals and squared standardized residuals failed to detect any need to further complicate the model.[4)] In general the various diagnostic statistics all indicate that the FIGARCH model is superior to the usual GARCH for modeling the long memory in the conditional variance process of the two high frequency returns series. But, the estimated excess kurtosis are 10.75 and 11.31 for the

high frequency returns of the Dollar-Euro and the Yen-Dollar exchange rates respectively, which are still large implying the rejection of the normal distribution assumption.

3. FIGARCH model with a mixture distribution and a time-varying jump probability associated with US macroeconomic surprises

In the previous section, the basic FIGARCH model with the usual normality assumption seems to represent the dynamics of the high frequency exchange rate returns well and appears to be a good starting point to study the underlying features of the high frequency returns. But, the excess kurtosis statistics estimated from the FIGARCH model for the high frequency returns of the Dollar-Euro and the Yen-Dollar exchange rates reject the usual normal distribution assumption. The use of the normal distribution leads to excess kurtosis.

The excess kurtosis property of the high frequency exchange rate returns may be due to the occurrence of the jumps in the process of the high frequency exchange returns. A potential source of the jumps in the high frequency returns may be important events in foreign exchange markets such as news surprises from macroeconomic fundamentals or central bank interventions (Andersen et al., 2003; Beine and Laurent, 2003). These events concerning expected future flows can result in price changes well above normal and might be better captured by jumps rather than normal innovations. These jumps might lead to the level and volatility outliers which can not be taken into account for by the simple normal distribution as Hotta and Tsay (1998) presented. Thus, the basic FIGARCH models under the assumption of the usual normal distribution seem to be inappropriate to represent the high frequency returns series properly.

This section is concerned with modeling the jumps in the high frequency returns series of the Dollar-Euro and the Yen-Dollar exchange rates. In particular, this paper employs the jump diffusion process proposed by Press (1967) in order to account for the conditional jumps in the 30-minute high frequency returns of the Dollar-Euro and the Yen-Dollar exchange rates. Initially, Press (1967) proposed a jump diffusion model for stock prices under the assumption that the logarithm of the stock price follows a Brownian motion process on which i.i.d. normal distributed

jumps are included. Jorion (1988) used a Press-type model to find some statistical evidence of jumps in the USD-DM exchange rate for the post 1971 free floating period. This jump diffusion model has subsequently been widely employed to model features of the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS) such as the jumps resulting from realignments of the ERM bands and high excess kurtosis. See Vlaar and Palm (1993, 1997), Nieuwland et al. (1994), Neely (1999), Baillie and Han (2001) and others.

This paper relies on a jump diffusion process-FIGARCH model that assumes that the high frequency returns are drawn from a mixture of normal distribution and a diffusion process combined with an additive jump process. In particular, this paper considers this model in the context of a Bernoulli-normal distribution. The Bernoulli distribution models the stochastic jumps in the 30-minute high frequency exchange returns series. The main characteristic of the Bernoulli process is that over a fixed time period, one relevant information arrives in foreign exchange markets and a jump occurs in the high frequency exchange rates with probability (λ) which is drawn from a Bernoulli distribution and is forced in the (0,1) interval. The jump size is given by the random variable $v_{,}$ which is assumed to be NID(ν, δ^2).

Since a constant jump probability model may not provide economic and financial insights as presented by Beine and Laurent (2003), this paper adopts a time-varying jump probability which is endogenously determined. Initially this time-varying jump probability model has been extensively used in the analysis of EMS (European Monetary System) (Nieuwland et al., 1994; Vlarr and Palm, 1997; Neely 1999) and recently Beine and Laurent (2003) have used it in the investigation of central bank interventions. In the previous studies, the jump probabilities seem to be associated with realignments, interest rate differentials or central bank interventions. However, this paper associates the time-varying jump probability with US macroeconomic surprises which are the differences between the expectations data and the realizations data of US macroeconomic indicators based on a voluminous empirical literature which has provided evidence that the jumps in exchange rate series appear to be linked with

macroeconomic fundamentals and the jumps may cause asymmetry and high excess kurtosis in the process (Goodhart et al., 1993; Ghosh, 1997; Almeida et al.,1998; Andersen et al., 2003).

In order to calculate the US macroeconomic surprise, this paper follows the method proposed by Andersen et al. (2003) by using the International Money Market Services (MMS) real time data on expected and realized (announced) US macroeconomic indicators sampled from January 1999 to December 2002. Thus, the US macroeconomic surprise associated with US macroeconomic indicator k is,

$$x^k_{t,n} = (A^k_{t,n} - E^k_{t,n}) / \sigma^k \tag{8}$$

where $A^k_{t,n}$ is the announced (realized) value of a macroeconomic indicator (k) released at time (n) and day(t), $E^k_{t,n}$ is the market expected value of the macroeconomic indicator (k) as distilled in the MMS median forecast, and σ^k is the sample standard deviation of $(A^k_{t,n} - E^k_{t,n})$. In particular, for the MMS expectations data for macroeconomic indicators, MMS has conducted a Friday telephone survey of about forty money managers, collected forecasts of all indicators to be released during the next week and reported the median forecasts from the survey.[5)] For more detailed information about the MMS survey data, see Appendix and the Table 1 in Andersen et al. (2003).

Among many US macroeconomic variables, this paper selects five major variables, Durable goods, PPI, GDP, Unemployment and NAPM index and uses them as the explanatory variables of the jump probability.[6)] Thus, the time-varying jump probability (λ_t) is,

$$\lambda_{t,n} = [1 + \exp(\lambda_0 + \textstyle\sum_{k=1,5} \lambda_k x^k_{t,n})]^{-1} \tag{9}$$

where the $x^k_{t,n}$ are the five US macroeconomic surprises expected to be related to the jump probability. Furthermore, to highlight the effects of the macroeconomic surprises contained in the major macroeconomic indicators, this paper distinguishes positive surprises from negative

surprises and explores the effects of the macroeconomic surprise on the jumps. If the actual realization value is larger than the surveyed forecast value, the surprise is classified as positive since it can contribute to the growth of the economy. But, if the actual value is less than the expected value, it is regarded as negative since it may slow the economy down.

The mixture distribution, the Bernoulli normal distribution, with the time-varying jump probability is combined with the FIGARCH model to analyze the impacts of the jumps on the high frequency returns series. Then the same FIGARCH model as in section 2 is used for the long memory volatility process. Since the statistical and economic motivations for the jumps and the long memory property are quite different, this work chooses the model specification that accounts for the two features in high frequency exchange rates at the same time. Hence, this paper investigates the 30-minute high frequency returns of Dollar-Euro and Yen-Dollar exchange rates by employing the Bernoulli jump diffusion process with the time-varying jump probability associated with the either positive or the negative US macroeconomic surprises to consider the jumps and the FIGARCH model to capture the long memory property. The inclusion of the jump process may reduce the influence of the jumps on the MA(1)-FIGARCH(1,δ,1) specification.

The combined MA(1)-FIGARCH (1,δ,1) model with Bernoulli jump process is,

$$y_{t,n} = \mu + \lambda_{t,n}\nu + \varepsilon_{t,n} + \theta\varepsilon_{t,n-1}, \tag{10}$$

$$\varepsilon_{t,n} = z_{t,n}\,\sigma_{t,n}, \tag{11}$$

$$\sigma^2_{t,n} = \omega + \beta\sigma^2_{t,n-1} + [1 - \beta L - (1 - \varphi L)(1 - L)^{\delta}]\varepsilon_{t,n}^2, \tag{12}$$

The 30-minute high frequency returns are still specified as following a MA(1) process, with the time-varying jump probability of $\lambda_{t,n}$ and the mean jump size of ν. The volatility process is the FIGARCH(1,d,1) model as developed in section 2. The log likelihood function for the combined model has the following form,

$$\ln(\xi) = -(T/2)\ln(2\pi) + \Sigma_{t=1,..262,\ n=1,..,48} \ln\{[(1-\lambda_{t,n})/h_{t,n}]*\exp[-(\varepsilon_{t,n} + \lambda_{t,n}\nu)^2/2h^2_{t,n}] +$$

$$[\lambda_{t,n}/(h^2_{t,n} + \delta^2)^{1/2}]*\exp[-(\varepsilon_{t,n} - (1-\lambda_{t,n})\nu)^2/2(h^2_{t,n} + \delta^2)]\} \qquad (13)$$

The form of the likelihood function for the Bernoulli-normal mixture distribution is basically similar to that proposed by Beine and Laurent (2003) which used central bank interventions as the explanatory variable of the jump probability. Asymptotic standard errors are calculated from the QMLE method of Bollerslev and Wooldridge (1992) as in section 2.

Table 2 represents the maximum likelihood results from the FIGARCH model with the Bernoulli-normal mixture distribution for the high frequency returns series of the Dollar-Euro and the Yen-Dollar exchange rates. Generally, the results are quite similar for the two currencies. LR test is performed to test the null hypothesis of the FIGARCH model with the normal distribution versus the FIGARCH model with the mixture distribution. The large LR test statistics, 3250 and 3370 of the high frequency Dollar-Euro and Yen-Dollar returns, reject the null hypothesis at standard significance levels implying that the FIGARCH model with the mixture distribution outperforms the model with the normal distribution alone. In particular, the main contribution of the FIGARCH model with the mixture distribution lies in the significant decrease in the excess kurtosis and the long memory parameter of the volatility process.[7)] For both the high frequency returns, the kurtosises of the residuals are all significantly decreased to around 1.0 regardless of the fact that the jump probability is associated with the positive or negative surprises.

The long memory parameters (δ) estimated in the FIGARCH model with the mixture distribution are also decreased to around 0.1067 and 0.1063 for the positive and negative surprises in the high frequency Dollar-Euro returns and about 0.1215 and 0.1216 for the two surprises respectively in the high frequency Yen-Dollar returns and they are all very significant. The decrease in the long memory property of the two high exchange returns suggests that the additional volatility caused by the jumps may spuriously induce the higher values of the long

memory persistence. Thus, the long memory persistence of the volatility process in the high frequency exchange rates can decrease when jumps are accounted for appropriately. This is quite consistent with the findings of Diebold and Inoue (1999), Granger and Hyung (1999) and Beine and Laurent (2003) who presented that the long memory property can decrease when structural changes or jumps are properly modeled. It seems to be relevant to introduce the possibility of jumps in the dynamics of the high frequency returns of the Dollar-Euro and the Yen-Dollar exchange rates.

Now, turn to the values of the jump parameter estimates. For the two high frequency returns, the parameters (σ^2) are all positive and are statistically significant in both cases of which the jumps are associated with either the positive or the negative US macroeconomic surprises. This shows that the additional volatility is associated with the jumps while the parameters (υ) are all negative but are not significant at all in the both cases, which represent that the jumps do not affect the mean process. This implies that the jumps mostly affect the volatility process of the high frequency returns rather than the mean process. Furthermore, the estimated values of the parameters (σ^2) for the positive surprises and the negative surprises are found to be quite similar where the values are 0.0304 and 0.0305 for the Dollar-Euro returns and 0.0373 and 0.0373 for the Yen-Dollar returns respectively. This suggests that the jumps associated with either the positive or the negative macroeconomic surprises almost equally influence the volatility process regardless of the signs of the macroeconomic surprises. Thus, the jumps associated with the US macroeconomic surprises (either positive or negative) increase the volatility of the high frequency returns.

The signs of the estimated parameters (λ_k) for the explanatory variables of the jumps are mostly positive for the positive surprises but they are all negative for the negative surprises. Since the parameters (λ_k) represent the effects of the US macroeconomic surprises on the jump probability, the estimation results show that the jump probability reacts to the US macroeconomic surprise asymmetrically depending on their signs: the positive surprises increase the jump probability but the negative ones decrease the probability. In particular, the

positive surprises of the Durable Goods variable and the negative surprises of the Unemployment variable appear to affect the jump probability most greatly. For the positive surprises, this means that a relatively high positive US macroeconomic surprise increases the probability of a big loss since the mean jump size (υ) is negative (although they are all insignificant). But, the variance of jumps size (σ^2) is very large compared to its mean so that the volatility increases with the positive surprises. Thus, the risk of a big loss may be at least partly compensated by the increase of the expected excess returns due to the rise in the volatility.

Hence, the estimation results seem to be quite understandable given that the jumps associated with US macroeconomic surprises are fully accounted for in the mixture distribution since the jumps may spuriously cause the additional volatility. These results provide evidence that both the positive and the negative US macroeconomic surprises asymmetrically influence the jump probability but the jumps increase the volatility of the high frequency returns equally regardless of the signs of the macroeconomic surprises. Thus, the higher long memory property seems to be related to the volatility adjustments to the jumps which react to the US macroeconomic surprises asymmetrically, and the jumps seem to be the possible driving forces behind the long memory property in the volatility process of the high frequency returns.

4. Conclusions

This paper considers four years of high frequency returns data for the 30-minute Dollar-Euro and Yen- Dollar exchange rates and investigates intrigue features of the high frequency returns. Special attention is devoted to model the jumps and the long memory property appropriately in the MLE estimation procedure.

Employing the mixture distribution model, the Bernoulli-normal distribution model with FIGARCH process and a time-varying jump probability, this paper shows i) that the usual normality assumption appears not to be appropriate for the high frequency exchange returns data mainly due to the occurrences of jumps in the high frequency exchange rate returns, ii) that the major parts of the jumps seem to be closely related to the US macroeconomic surprises in

the foreign exchange markets and iii) that the normal mixture distribution model, the Bernoulli-normal distribution with a time varying jump probability associated with the US macroeconomic surprise is found to be quite successful in representing the jumps and the long memory volatility property of the high frequency returns. Further more, this paper finds that the long memory property in the volatility process of the high frequency returns is decreased when the jumps in the exchange rate process are properly accounted for by the mixture distribution model implying that the additional volatility caused by the jumps may spuriously induce the higher values of the long memory.

This paper also provides evidence that macroeconomic surprises are an important driving force behind the exchange rate dynamics. The jump probability appears to react asymmetrically depending on the signs of the macroeconomic surprises: the positive surprises increase the jump probability while the negative surprises decrease the probability. However, the jumps associated with the macroeconomic surprises (either positive or negative) increases exchange rate volatility, which is in line with the findings in the empirical papers such as Nieuwland et al. (1994), Vlarr and Palm (1997), Neely (1999) and Beine and Laurent (2003). These findings suggest that such a representation model is a possible alternative modeling strategy to a long memory model with a normal distribution or to account for the jumps in the exchange rate dynamics.

Appendix: The International Money Market Services (MMS) Data

1. Examples of MMS median expectations and actual realizations for five major US macroeconomic variables

Macroeconomic variable	Median Expectation[1]	Date of survey	Actual realization	Date of release	Release time (Eastern time)[2]
Durable Goods	-0.5	02-19-99	3.9	02-25-99	08:30am/10:00am[3]
GDP	4.10	06-18-99	4.30	06-25-99	08:30am
PPI	0.10	02-12-99	0.5	02-18-99	08:30am
NAPM	46.5	01-29-99	49.5	02-01-99	10:00am
Unemployment	4.40	01-29-99	4.3	02-05-99	08:30am
Durable Goods	-1.50	03-19-99	-5	03-24-99	08:30am/10:00am
GDP	1.80	09-24-99	1.60	09-30-99	08:30am
PPI	-0.10	03-05-99	-0.4	03-12-99	08:30am
NAPM	50	02-26-99	52.4	03-01-99	10:00am
Unemployment	4.30	02-26-99	4.4	03-05-99	08:30am

Keys) 1. Median expectations data is conducted by telephone survey of about forty money managers, with collected forecasts of all indicators to be released during the next week and reported the median forecasts from the survey.
2. The announcements of US macroeconomic variables are scheduled in advance.
3. Whenever the Durable Goods and GDP variables are released on the same day, the Durable Goods are released at 10:00am.

2. Basic descriptions of US macroeconomic surprises

	Positive	surprises	Negative	surprises
Macroeconomic variable	mean	standard deviation	mean	standard deviation
Durable Goods	64.99	73.66	-73.02	56.33
GDP	87.67	70.65	-81.31	64.48
PPI	112.93	57.83	-77.82	52.35
NAPM	88.62	60.80	-68.57	50.63
Unemployment	96.47	39.11	-110.95	47.45

Endnotes

1. According to Jarque and Bera (1987), the standard errors of the sample skewness and the sample kurtosis in their corresponding normal distributions are $(6/T)^{1/2}$ and $(24/T)^{1/2}$.
2. The autocorrelations of the two high frequency filtered returns presents that the periodicity has been reduced dramatically but the marked persistence exists in the squared and absolute returns. The correlograms of the high frequency filtered returns are not reported in order to preserve space but they can be made available on requests to the author.
3. Beine et al. (2002) and Han (2003) have presented the cumulative impulse functions of FIGARCH models and compared them with those of GARCH and IGARCH models. The FIGARCH model seems to be better represent the hyperbolic decay of the impulse functions than GARCH model.
4. Tests of model diagnostics are performed by the application of the Box-Pierce portmanteau statistic on the standardized residuals. The standard portmanteau test statistic $Q_m = T\Sigma_{j=1,m} r_j^2$, where r_j is the j-th order sample autocorrelation from the residuals is known to have an asymptotic chi squared distribution with m-k degrees of freedom, where k is the number of parameters estimated in the conditional mean. Similar degrees of freedom adjustment are used for the portmanteau test statistic based on the squared standardized residuals when testing for omitted ARCH effects. This adjustment is in the spirit of the suggestions by Diebold (1988). The correlograms of the standardized residuals from the MA (1)-FIGARCH (1,δ,1) model show that the model is quite appropriate to represent the high frequency Dollar-Euro returns, but they are not represented to preserve space. They can be made available on request to the author.
5. Pearce and Roley (1985) and McQueen and Roley (1993) found that the MMS survey data are more accurate than the forecasts from standard autoregressive time series models. Balduzzi et al. (1998) and Andersen et al. (2003) presented that the MMS forecasts data contain valuable information about the forecasted variable and are they are mostly unbiased.

6. For the explanatory variables of the jump probability, a total of ten US macroeconomic variables are used. But, five variables among them are found to be most statistically significant and are presented in this paper. More detailed results can be made available on request to the author.
7. Palm and Vlaar (1997) and Beine and Laurent (2003) presented that the residuals resulted from the mixture distribution are not i.i.d. residuals in a model with time dependent variance. So, in order to solve this problem, they used the normalized residuals instead of standardized residuals.

REFERENCES

Almeida, A., Goodhart, C., Payne, R., 1998. The effects of macroeconomic 'news' on high frequency exchange rate behavior. Journal of Financial and Quantitative Analysis 33, 383-408.

Andersen, T.G., Bollerslev, T., 1997. Intraday periodicity and volatility persistence in financial markets. Journal of Empirical Finance 4, 115-158.

Andersen, T.G., Bollerslev, T., 1998. Deutsche mark-dollar volatility: intraday activity, patterns, macroeconomic announcements and longer run dependence. Journal of Finance 53, 219-265.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Vega, C., 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange. American Economic Reviews 93, 38-62.

Balduzzi, P., Elton, E.J., Green, T.C., 1998. Economic news and the yield curve: Evidence from the U.S. Treasury Market. Salomon Center Working Paper S-98-5. Stern School of Business, New York University.

Baillie, R.T., Bollerslev, T., 1991. Intra-day and inter-market volatility in foreign exchange rates. Review of Economic Studies 58, 565-585.

Baillie, R.T., Bollerslev, T., Mikkelsen, H.-O., 1996. Fractionally integrated generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 74, 3-30.

Baillie, R.T., Cecen, A.A., Erkal, C., Han, Y.W., 2004. Merging the Stochastic with the Nonlinear Deterministic: the Case of High Frequency European Exchange Rates. Journal of International Financial Markets, Institutions & Money 14, 401-418.

Baillie, R.T., Cecen, A.A., Han, Y.W., 2000. High Frequency deutschemark - US dollar returns: FIGARCH representations and non linearities. Multinational Finance Journal 4, 247-267.

Baillie, R.T., Han, Y.W., 2001. Testing Target Zone Models Using Efficient Methods of Moments. Journal of Business and Economic Statistics 19, 273-277.

Baillie, R.T., Osterberg, W.P., 2000. Deviations from daily uncovered interest rate parity and the role of intervention. Journal of International Financial Markets, Institutions and Money Economics 10, 363-379.

Beine, M., Benassy-Quere, A., Lecourt, C., 2002. Central bank intervention and foreign exchange rate: New evidence from FIGARCH estimations. Journal of International Money and Finance 21, 115-144.

Beine, M., Laurent, S., Lecourt, C., 2002. Account for conditional leptokurtosis and closing days effects in FIGARCH models of daily exchange rates. Applied Financial Economics 12, 589-600.

Beine, M., Laurent, S., Lecourt, C., 2003. Central bank interventions and jumps in double long memory models of daily exchange rates. Journal of Empirical Finance 10, 641-660.

Bollerslev, T., Domowitz, I., 1993. Trading patterns and prices in the interbank foreign exchange market. Journal of Finance 48, 1421-1443.

Bollerslev, T., Wooldridge, J.M., 1992. Quasi-maximum likelihood estimation of dynamic models with time varying covariances. Econometric Reviews 11, 143-172.

Bollerlsev, T., Chou, R.Y., Kroner, K.F., 1992, ARCH modeling in Finance: A review of the theory and empirical evidence, Journal of Econometrics 52, 5-59.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307-327.

Dacorogna, M.M., Müller, U.A., Nagler, R.J., Olsen, R.B., Pictet, O.V.,1993. A geographical model for daily and weekly seasonal volatility in the foreign exchange markets. Journal of International Money and Finance 12, 413-438.

Diebold, F. X., 1988. Modeling the persistence of conditional variances: a comment. Econometric Reviews 5, 51-56.

Diebold, F. X., Inoue, A., 1999. Long memory and structural changes. Manuscript, NYU.

Engle, R., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50, 987-1007.

Evans, M.D.D., Lyons, R.K., 2002. Order flow and exchange rate dynamic. Journal of Political Economy 110, 170-180.

Frankel, J.A., Rose, A.K., 1995. A survey of empirical research on nominal exchange rates, in G.Grossman and K. Rogoff (eds.), *Handbook of International Economics*, Amsterdam: North-Holland, 1995.

Gallant, A.R., 1981. On the bias in flexible function forms and an essentially unbiased form: The Fourier flexible form. Journal of Econometrics 15, 211-245.

Gallant, A.R., 1982. Unbiased determination of production technologies. Journal of Econometrics 20, 285-323.

Ghosh, D., 1997. Negative autocorrelation around large jumps in intra-day foreign exchange data. Economic Letters 56, 235-241.

Goodhart, C.A.E., Hall, S.G., Henry, S.G.B., Pesaran, B., 1993. News effects in a high frequency model of the Sterling-Dollar exchange rate. Journal of Applied Econometrics 7, 199-121.

Granger, C.W.J., Hyung, N., 2004. Occasional structural breaks and long memory with an application to the S&P500 absolute stock returns. Journal of Empirical Finance 11, 399-421.

Han, Y.W., 2003. Central bank interventions and long memory property in the daily Korean won-US dollar exchange rates during the Currency Crisis. Journal of the Korean Economy 4, 93-116.

Hotta, L.K, Tsay, R.S., 1998. Outliers in GARCH process, Unpublished manuscript.

Jarque, C. M. and Bera, A.K., 1987. Test for normality of observations and regression residuals. International Statistical Review 55, 163-72.

Jorion, P., 1988. On jump processes in the foreign exchange and stock markets, Review of Financial Studies 1, 427-445.

Lyons, R.K., 2001. The microstructure approach to exchange rates. MIT Press, Cambridge, Massachusetts.

McQueen, G., Roley, V.V., 1993. Stock prices, news and business conditions. Review of Financial Studies 6, 683-707.

Meese, R., Rogoff, K., 1983. Empirical exchange models of the Seventies: Do they fit out of sample? Journal of International Economics 14, 3-24.

Müller, U.A., Dacorogna, M. M., Olsen, R.B., Pictet, O.V., Schworz, M., Morgenegg, C., 1990. Statistical study of foreign exchange rates, empirical evidence of price change law and intraday Analysis. Journal of Banking and Finance 14, 1189-1208.

Neely, C.J., 1999. Target zones and conditional volatility: the role of realignments. Journal of Empirical Finance. 6, 177-192.

Nieuwland, F., Verschoor, W., Wolff, C.C.P., 1994. Stochastic trends and jumps in EMS exchange rates. Journal of International Money and Finance 13, 699-727.

Palm, F.C., 1996. GARCH models of volatility. In: Maddala, G.S., Rao, C.R. (Eds), Handbook of Statistics, vol. 14. Elsevier, North-Holland, pp209-240. ch.4.

Pearce, D.K., Roley, V.V., 1985. Stock prices and economic news. Journal of Business 58, 49-67.

Press, J., 1967. A compound events model for security prices. Journal of Business. 40, 317-335.

Vlaar, P.J.G., Palm, F., 1993. The message in weekly exchange rates in the European Monetary System: mean reversion, conditional heteroskedasticity and jumps. Journal of Business and Economic Statistics. 11, 351-360.

Vlaar, P.J.G., Palm, F., 1997. Interest rate differentials and excess returns in the European Monetary System. Journal of International Financial Markets, Institutions and Money 7, 1-20.

Wasserfallen, W., 1989. Flexible exchange rates: A closer look. Journal of Monetary Economics 23, 511-521.

Weiss, A.A., 1986. Asymptotic theory for ARCH models: estimation and testing. Econometric Theory 2, 107-131.

Table 1: Estimated MA(1)-FIGARCH (1,δ,1) model for 30-minute high frequency filtered returns

	Dollar-Euro	Yen - Dollar
μ	0.0002	0.0007
	(0.0004)	(0.0004)
θ	-0.0639	-0.0541
	(0.0062)	(0.0060)
δ	0.1949	0.2701
	(0.0132)	(0.0199)
ω	0.0002	0.0005
	(0.0001)	(0.0001)
β	0.9125	0.7336
	(0.0232)	(0.0339)
φ	0.8931	0.6090
	(0.0290)	(0.0408)
ln(L)	49417.502	48054.125
Skewness	-0.116	0.043
Kurtosis	10.746	11.309
Q(50)	88.101	76.119
Q2(50)	58.587	49.852
$W_{\delta=0}$	217.656	184.766

Keys: $S_{t,n}$ is the 30-minute spot exchange rates from 00:30 GMT, January 4, 1999 through 00:00 GMT, January 1, 2003 for a total of 1042 days. $R_{t,n} = 100^* \Delta[\ln(S_{t,n})]$ and $P_{t,n}$ is the estimated intraday periodicity from the Flexible Fourier Form method QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. The quantity ln(L) is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The Q(50) and Q2(50)statistics are the Ljung-Box test statistics for 50 degrees of freedom to test for serial correlation in the raw standardized and squared standardized residuals.

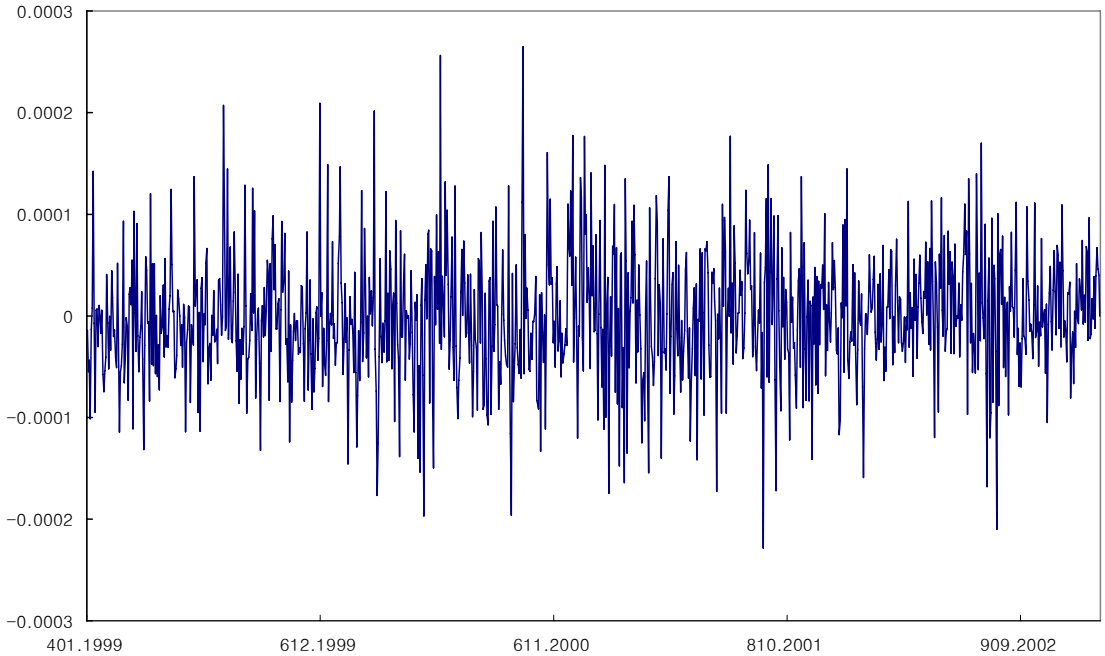
Table 2: Estimated MA(1)-Bernoulli jump process- FIGARCH (1,δ,1) model for the filtered 30-minute high frequency returns

	Dollar-Euro		Yen-Dollar	
	positive surprises	negative surprises	positive surprises	negative surprises
μ	0.0011	0.0011	0.0014	0.0018
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
λ_0	-2.0689	-2.0686	-2.2496	-2.2517
	(0.1225)	(0.1218)	(0.1107)	(0.1092)
λ_D	0.0397	-0.0216	0.0229	-0.0175
	(0.0198)	(0.0052)	(0.0086)	(0.0068)
λ_P	0.0155	-0.0269	-0.0261	-0.0027
	(0.0099)	(0.0102)	(0.0152)	(0.0066)
λ_G	0.0128	-0.0041	0.0064	-0.0199
	(0.0047)	(0.0135)	(0.0053)	(0.0110)
λ_U	0.0276	-0.0326	0.0194	-0.0294
	(0.0112)	(0.0122)	(0.0058)	(0.0072)
λ_N	0.0133	-0.0205	0.0139	-0.0221
	(0.0094)	(0.0106)	(0.0138)	(0.0063)
υ	-0.0041	-0.0038	-0.0051	-0.0069
	(0.0037)	(0.0037)	(0.0043)	(0.0042)
δ^2	0.0304	0.0305	0.0373	0.0373
	(0.0033)	(0.0033)	(0.0039)	(0.0039)
θ	-0.0761	-0.0762	-0.0740	-0.0742
	(0.0048)	(0.0048)	(0.0049)	(0.0049)
δ	0.1067	0.1063	0.1215	0.1216
	(0.0065)	(0.0065)	(0.0059)	(0.0059)
ω	0.0001	0.0001	0.0002	0.0002
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.9047	0.9052	0.6009	0.6037
	(0.0250)	(0.0246)	(0.0440)	(0.0435)
φ	0.8989	0.8995	0.5630	0.5659
	(0.0266)	(0.0261)	(0.0448)	(0.0443)
ln(L)	52674.383	52677.947	51425.793	51433.362
Skewness	1.022	1.022	1.025	1.025
Kurtosis	1.060	1.060	1.067	1.067
Q(50)	91.990	89.353	106.160	105.842
Q2(50)	90.661	88.649	106.041	106.609

Keys: i) The same as Table 1 except that a jump intensity of $\lambda_{t,n}$ where $0<\lambda<1$ and $\lambda_{t,n}= [1 + \exp(\lambda_0+ \sum_{k=1,5} \lambda_i x^k_{t,n})]^{-1}$and is specified by the Bernoulli process. And, the jump size ($v_{t,n}$) is assumed to be NID(ν, δ^2). ii) The parameters, λ_D, λ_P, λ_G, λ_U and λ_N represent the estimated values for Durable Goods, PPI, GDP, Unemployment and NAPM index respectively.

Figure 1: 30 minute Spot Returns [1000*(ln(S_t)- ln(S_t))]

(a) Dollar-Euro



(b) Yen-Dollar

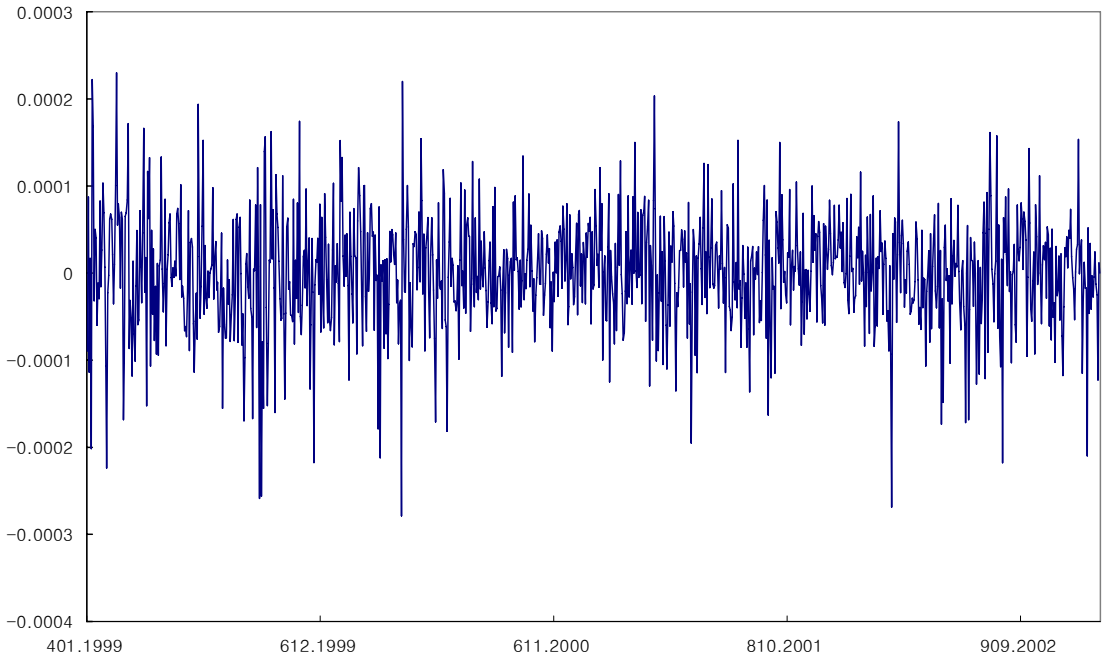
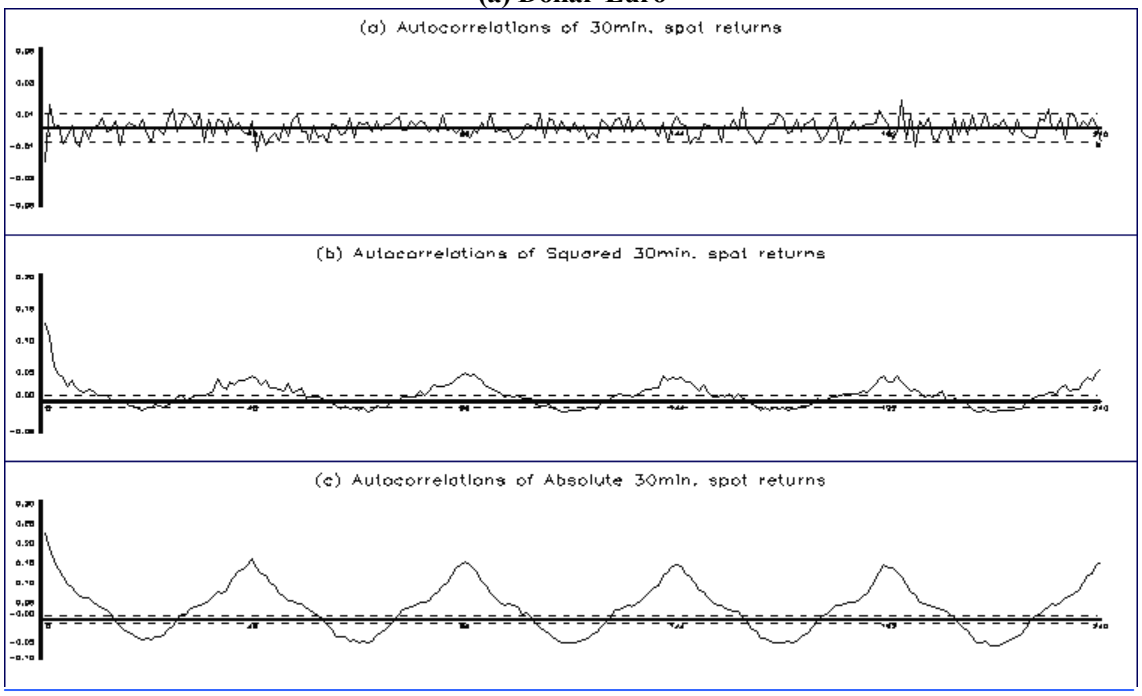


Figure 3: Correlograms of 30-minute Spot Returns

(a) Dollar-Euro



(b) Yen-Dollar