Potential Sources of the Long Memory Property in the Volatility Process of Daily KRW-USD Exchange Rates : Jumps and Structural Breaks*

일별 원-달러 환율의 변동성 과정에서 나타나는 장기기억 특성의 잠재적 원인들: 점프와 구조적 변화

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This paper analyzes the potential sources driving the long memory property in the volatility process of the daily Korean Won (KRW)–US Dollar (USD) exchange rates. Based on the Adaptive FIGARCH model and the jump diffusion model, this paper proposes a new specification of the volatility process, which links the long memory property to jumps and structural breaksall together rather than separately as in previous studies. The model is estimated with the daily data on the KRW–USD exchange rate returns between 1999 and 2007. The empirical results show strong evidence that the Adaptive FIGARCH model combined with the Bernoulli jump process which takes into account the jumps and the structural breaks jointly could explain almost all of the long memory property in the volatility of the KRW–USD exchange returns. The implication is that both the structural breaks and the jumps are the major sources of the long memory property in the volatility.

Key words: adaptive FIGARCH model, Bernoulli jump process, daily KRW–USD foreign exchange rates, FIGARCH model, long memory property, structural breaks
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I. Introduction

Some empirical studies have presented the existence of the long memory property in the volatility process of the Korean exchange rates returns (Lee, 2000 Han, 2003 Jo and Lee, 2004). But, they have not fully explained what drives the long memory property yet. Hence, the main purpose of this paper is to propose a new approach to examine the potential sources of the long memory property in the volatility process of the daily Korean Won per US Dollar exchange rates based on the Adaptive FIGARCH (A-FIGARCH)model of Baillie and Morana (2009) and the Bernoulli jump model of Beine and Laurent (2003). In particular, this paper presents a simple and direct empirical test forthe roles of both the structural breaks and the jumps in driving the long memory property in volatility process of the KRW-USD exchange rate returns. For the empirical test, this paper uses the daily exchange rates of Korean Won (KRW)-US Dollar (USD) for the periods of 1999 through 2007.

For the last two decades, many finance researchers have taken an interest in the financial market volatility which is a key driver in risk managements and asset pricing models. One of the important findings of this literature is that the volatility of financial asset prices changes over time in the manner of a fairly persistent process. This so-called 'long memory property' in volatility is characterized by quite persistent and hyperbolically decaying autocorrelations. There is ample evidence that the long memory property is present regardless of the way the volatility is measured, including the squared returns (Ding et al., 1993; Granger and Ding, 1996), power transformations of absolute returns (Lobato and Savin, 1998), conditional variance (Baillie et al., 1996) and realized volatility (Ebens, 1999; Andersen et al., 2003). Following Ding et al. (1993) which proposed a fractionally integrated volatility model, several long memory volatility models have been developed for financial time series data, and most of them have focused on linear models. Among them are the long memory stochastic volatility (LMSV) models of Breidt et al. (1998) and Harvey (1998), and the long memory autoregressive conditional heteroskedasticity (LM-ARCH) models of Baillieet al. (1996), Bollerslev and Mikkelsen (1996) and Davidson (2004).[1)]

Alongside the research on modeling the long memory volatility process, another line of research concerning the underlying causes or sources for the long memory property has gained popularity in recent years. Many studies in this vein have found that structural breaks (Granger and Hyung, 2004; Starcia and Granger, 2004; Choi and Zivot, 2007) or jumps (Beine and Laurent, 2003 Han, 2007 and 2008) are one of the main sources of the empirically observed long memory.

The structural breaks in financial markets could occur due to country specific crisis, political events and worldwide financial crisis as well as macroeconomic conditions (Aggarwal et al., 1999; David and Veronesi, 2004; Beltratti and Morana, 2006). In particular, Granger and Hyung (2004) and Choi and Zivot (2007) have presented evidence that spurious long memory can be due to the presence of the occasional structural breaks. Starcia and Granger (2004) have also found that a non-stationary model allowing for breaks in the unconditional variance can outperform a long memory model in forecasting. Following the seminar works of Diebold (1988) and Lamoreaux and Lastrapes (1990), which have suggested for the first time that structural breaks in conditional variance process can generate extreme persistence, the subsequent papers by Lobato and Savin (1998), Beine andLaurent (2000), Morana and Beltratti (2004) and Martens et al. (2004) have presented that an appropriate model for the volatility process of financial time series data should

1) See Baillie (1996) for the survey of the long memory process.)

include both long memory property and structural breaks.

On the other hand, many previous papers have also found out that financial series are characterized by occasional jumps or large shifts (Ghosh, 1997; Goodhart and Giugale, 1993; Goodhart et al., 1993). Even though the jump is closely related to the structural breaks, there are some substantial differencesbetween the two. The jumps in volatility create fat-tailness in the distributions of the volatility measures. Also, the jumps are more drastic but short lived relative to the structural breaks. Andersen et al. (1998) specified and estimated the model of exchange rate dynamics in a novel way by allowing for the possibility of jumps in conditional mean that affectboth conditional mean and conditional variance at the same time. They demonstrated that jumps in exchange rates are linked to public information (macroeconomic fundamentals) and that the volatility estimation can be improved by allowing for jumps. Beine and Laurent (2003) and Han (2007, 2008) have presented that the jumps might lead to outliers in the volatility process of foreign exchange rates, which in turn increase the volatility and generate strong long memory property. And, they have found that the FIGARCH model with the jump process produce a better fit to foreign exchange returns,compared with a competing FIGARCH model without the jump process. Hence, the jumps in the foreign exchange rates are of significant interest since the long memory property in the volatility process of the exchange rate returns cannot be explained fully without any appropriate specification of the jumps.

Given the previous studies summarized above, it seems necessary to link the long memory property in the volatility process with both the jumps and the structural breaks, instead of choosing just one of them as the main source of the long memory, in order to explain the dynamics of the volatility process of the foreign exchange rates more appropriately.

Thus, this paper investigates this possibility by combining the A-FIGARCH model, which accounts for structural breaks, with the Bernoulli jump process.

The estimation results indicate that the augmented A-FIGARCH model outperforms the usual FIGARCH model and the simple A-FIGARCH model. Specially, the long memory property in the volatility process is reduced significantly, once the structural breaks are controlled for. Moreover, the long memory property disappearswhen both the jumps and the structural breaks are allowed at the same time. These findings suggest that the jumps and the structural breaks are the main sources of the observed long memory property in the volatility process.

The rest of this paper is organized as follows. Section IIpresents the basic properties of the daily Korean Won per US Dollar exchange rate returns. The estimation results of the usual FIGARCH model are also presented in this section to show the existence of the long memory property, which could be an intrinsic featurein the volatility process or the result of omitted breaks or jumps. Section III describes the A-FIGARCH model which explains the effects of the structural breaks on the long memory property in the volatility process of the returns, and then reports the estimation results. Section IV presents the final model, and the estimation result of it, obtained by combing the A-FIGARCH model with the Bernoulli jump process in order to account for the long memory property, the jumps, and the structural breaks within a single framework. Then section V concludes briefly.

II. Long memory in volatility: FIGARCH model

This section is concerned with the intriguing features of the daily returns obtained from the KRW-USD spot exchange rates. In particular, it explores the long memory property in the volatility process of the returnswhich has been well documented in Lee (2000), Han (2003) and Jo and Lee (2004). The focus is on the long memory volatility parameters estimated from the FIGARCH model of Baillie et al. (1996). The FIGARCH model is known to provide good descriptions of the daily return volatility, as shown in several previous studies such as Lee (2000), Jo and Lee (2004) and Han (2003).

〈Figure 1〉 Daily KRW–USD Exchange Rates

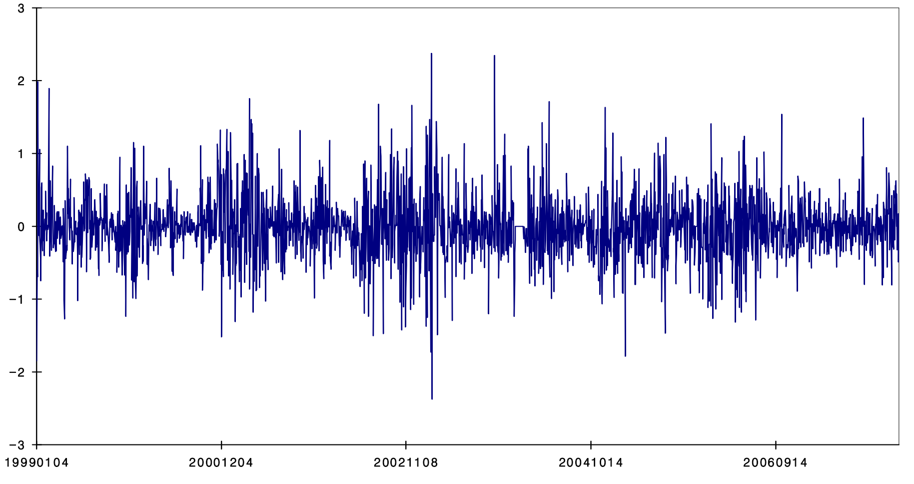
The data sets of the KRW- USD daily spot exchange rates are obtained from the Olsen and Associates for the sample period of January 4, 1999 through December 31, 2007. Each quotation consists of a bid and an ask price and is recorded in time to the nearest second. The spot exchange rate for each daily interval is obtained by the average of the bid rates and the askrates. Excluding the weekendsand the worldwide holidays like Christmas and New Year's Day, the sample has 2335 observations. Figure 1 presents the daily exchange rates of the KRW-USD. The Korean Won have been appreciated against the US Dollar since the late 2004 because of the global weakness of the US Dollar and the strong growth in the exports of Korea. The exchange rate in Figure 1 also appears to have several structural breaks over the period.

The returns of the daily KRW-USD exchange rates are defined in the conventional manner as continuously compounded rates of return and calculated as the first difference of the natural logarithm of prices. The return (y_t) at day t is defined as

$$y_t = 100 \times [\ln(P_t) - \ln(P_{t-1})] \tag{1}$$

where t = 1,..,2335 and P_t is the spot exchange rate at day t.

〈Figure 2〉 Daily KRW-USD Returns



The daily KRW-USD returns which are presented in Figure 2 are oscillating around zero with a strong pattern of volatility clustering and jump. The descriptive statistics for the daily returns are provided in Table 1. The sample mean of the daily return is -0.01 indicating that the

Korean Won is depreciated about 1% against the US Dollar during the sample period. The mean return is statistically insignificant, given the sample deviation of 0.44. However, the returns appear to be not normally distributed since the sample skewness of 0.23 and the sample kurtosis of 5.91 are greater than the levelsof the standard normal distribution and they are statistically significant since the standard errors of the statistics are 0.05 and 0.1 respectively.[2] The Ljung-Box test statistics for serial correlations up to 20 lags, Q(20) and $Q^2(20)$, in the returns and the squared returns of the KRW-USD exchange rates are 23.08 and 445.84 respectively. While the returns do not have the problem of the serial correlations, the squared returns which represent the volatility process contain highly persistent autocorrelations, which is the feature of a long memory process.

〈Table 1〉 Basic descriptions of the daily KRW-USD returns

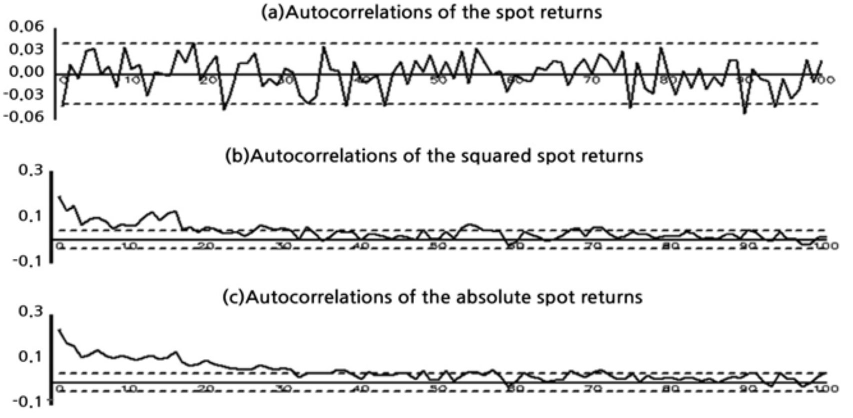
	daily KRW-USD returns
Mean	-0.0102
Standard deviation	0.4369
Skewness	0.2321
Kurtosis	5.9137
Q(20)	23.0812
Q2(20)	445.8425

Note: The Q(20) and $Q^2(20)$ statistics are the Ljung-Box test statistics for 20 degrees of freedom to test for serial correlation in the returns.

Figure 3 presents the first 100autocorrelation coefficients for the returns, squared returns and absolute returns ofthe daily KRW-USD returns. While

2) 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 $(24/T)^{1/2}$.

〈Figure 3〉 Correlograms of Daily KRW-USD Returns



the autocorrelations in the returns are not significant at conventional levels, the autocorrelations of the squared returns and the absolute returns decay very slowly at a hyperbolic rate. The long memory feature is very significant in the autocorrelations of the squared and absolute returns, and is more apparent in the autocorrelation functions of the absolute returns as noted by Granger and Ding (1996).

A model that is consistent with these stylized facts is the Martingale-FIGARCH(1,d,1) process[3],

$$y_t = \mu + \varepsilon_t \tag{2}$$

$$\varepsilon_t^2 = z_t \sigma_{t,} \tag{3}$$

$$(1-\beta L)\sigma_t^2 = \omega_t + [1-\beta L-(1-\phi L)(1-L)^d]\varepsilon_t^2 \tag{4}$$

As presented by Baillie et al. (1996) and Baillie and Morana (2009), for $0 < d \leq 1$, the unconditional variance of a FIGARCH process is not well defined. However, the process does posses a finite sum of cumulative

3) The exact parametric specification of the model that best represents the degree of autocorrelation in the conditional mean and conditional variance is chosen based on the Box-Pierce portmanteau statistics.

impulse response weights. This makes the FIGARCH model different from other forms of long memory ARCH models proposed by Karanassos et al.(2004). But the FIGARCH model appears to be strictly stationary and ergodic for $0 < d \leq 1$ (Baillie et al., 1996).

Note that the conditional variance of the FIGARCH process is $\sigma^2_t = \omega/(1-\beta) + \gamma(L)\varepsilon^2_t$. For large lag k, the impulse response weight is given as γ_k ck^{d-1} where c is a positive constant. Thus, the conditional variance can be expressed as distributed lags of squared unconditional disturbances with the coefficients decaying at a slow, hyperbolic rate, which is essentially the property of a process with long memory. One of the attractions of the FIGARCH process is that for $0 < d < 1$, it is sufficiently flexible to allow for a wide range of processes with intermediate degrees of persistence.

The above model is estimated by maximizing the Gaussian log likelihood function,

$$\ln(L;\Theta) = -(\frac{T}{2})\ln(2\pi) - (\frac{1}{2})\sum_{t=1}^{T}[\ln(\sigma_t^2) + \varepsilon_t^2\sigma_t^{-2})] \tag{5}$$

where Θ is a vector containing the unknown parameters to be estimated.

The consistency and asymptotic normality of the QMLE for the conditional variance process can be established as in Baillie and Morana (2009). Thus, the inference is usually based on the QMLE of Bollerslev and Wooldridge(1992), which is valid even if z_t is non-Gaussian. Let $\hat{\Theta}_T$ be the vector of parameter estimates obtained by maximizing (5) using a sample of T observations. Then the limiting distribution of $\hat{\Theta}_T$ is

$$T^{1/2}(\hat{\Theta}_T - \Theta_0) \to N[0, A(\Theta_0)^{-1}B(\Theta_0)A(\Theta_0)^{-1}] \tag{6}$$

where A(.) and B(.) represent the Hessian and the outer product of gradient respectively, and Θ_0 denotes the vector of true parameter values.

Equation (6) is used to calculate the robust standard errors that are reported in the subsequent results in this paper, with the Hessian and the outer product of gradient evaluated at the point $\hat{\Theta}_T$ for practical implementation.

〈Table 2〉 Estimated Martingale-FIGARCH (1,d,1) Model for the daily KRW-USD returns

μ	-0.0134**
	(0.0073)
d	0.4652***
	(0.1773)
ω	0.0051**
	(0.0029)
β	0.6705***
	(0.1159)
φ	0.4262***
	(0.1137)
ln(L)	-1193.395
Skewness	0.460
Kurtosis	6.224
Q(20)	16.222
$Q^2(20)$	17.524

Note: 1) QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates.
2) ln(L) is the value of the maximized log likelihood.
3) The sample skewness and kurtosis are for the standardized residuals.
4) The Q(20) and $Q^2(20)$ statistics are the Ljung-Box test statistics for 20 degrees of freedom to test for serial correlation in the standardized residuals and squared standardized residuals.
5) (*,**,***) denote the statistical significance at 10%, 5% and 1% level respectively.

Table 2 presents the estimation results of the above model for the KRW-USD exchange rate returns. The values of Q(20) and $Q^2(20)$ statistics are 16.22 and 17.52, showing that the model specified for the daily Korean returns performsa good job of capturing the autocorrelations in the mean and volatility of the daily return series. In each case there is no evidence of additional autocorrelation in the standardized residuals or squared standardized residuals indicating that the chosen model specification provides an adequate fit. The 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 of the residuals. This statistic 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 for the squared standardized residuals when testing for omitted ARCH effects. The sequence of diagnostic portmanteau tests on the standardized residuals and squared standardized residuals failed to detect any need to further complicate the model. Thus, this basic FIGARCH model appears to be a good representation of the volatility dynamics in the daily returns.

The estimated long memory parameter (d) in the volatility process is 0.46 which is statistically significant at the conventional level. It presents strong support for the existence of the long memory property in the volatility process. However, it should be noted that the basic FIGARCH model does not explain what causes the long memory property in the volatility process. Also, excess kurtosis and skewness remain in the residuals, with the estimated value of 6.22 and 0.46 even after the long memory property is removed effectively by the FIGARCH model.

III. Long memory and structural breaks : Adaptive FIGARCH model

This section considers the structural breaks as a potential source ofthe long memory property in the volatility process of the daily returns by applying the Adaptive FIGARCH or A-FIGARCH model of Baillie and Morana (2009). As presented in the introduction, many previous studies have provided abundantmotivations to allow for the possibility of the structural breaks in the volatility process of financial time series data including foreign exchange rates as the source of the long memory property. One of the quite powerful approaches to account for the structural breaks is to allow the intercept to be time varying as suggested by Baillie and Morana (2009). They have shown that the A-FIGARCH model can derived from the usual FIGARCH model of Baillie et al. (1996),by directly allowing the intercept in the conditional variance equation to be time varying according to the flexible functional formof Gallant (1984).[4)]

The A-FIGARCH model has an advantage of being computationally straightforward and simple adding no additional burden to the estimation of the usual FIGARCH model. The model does not require pre-testing for the numbers of structural break points nor does it require any smooth transition between volatility regimes. Moreover, Baillie and Morana (2009) have found that the A-FIGARCH model shows a superior performance relatively to the basicFIGARCH model in terms of bias and root mean square error (RMSE). Thus, the joint presence of the long memory and the structural break can be assessed by standard hypothesis tests of the fractional differencing parameter and the deterministic trigonometric components.

This paper adopts the A-FIGARCH model in order to show how the structural breaks could affect the long memory property by accounting for

[4)] There are different types of models for time varying unconditional moments such as the flexible coefficient GARCH model of Medeiros and Veiga (2004), the spine GARCH model of Engle and Rangel (2008) and the smooth transition model of Terasvirta and Gonzalez (2006).

jointly the long memory property and the structural breaks in the volatility process of the daily returns. While the mean of the daily returns is still assumed to follow a martingale process as in Section II, the volatility process is represented by the A-FIGARCH (1,d,1,k) model with the trigonometric terms (k) for the Gallant(1984)'s flexible functional form. This is the simplest version and appears to be quite useful in practice as suggested by Baillie and Morana (2009). This model can be written as;

$$y_t = \mu + \varepsilon_t \tag{7}$$

$$\varepsilon_t^2 = z_t \sigma_{t,} \tag{8}$$

$$(1-\beta L)\sigma_t^2 = \omega_t + [1-\beta L - (1-\phi L)(1-L)^d]\varepsilon_t^2 \tag{9}$$

$$\omega_t = \omega_0 + \sum_{j=1}^{k} [\gamma_j \sin(2\pi jt/T) + \delta_j \cos(2\pi jt/T)] \tag{10}$$

The Gaussian loglikelihood function of the model is the same as the martingale-FIGARCH(1,d,1) model in Section II. Also, the estimation and inference for the parameters of the above model can be facilitated by the same method of QMLE as in Section II. The procedure estimates all parameters simultaneously, including those in the flexible function form which specify the time varying intercept in the conditional variance process. For the practical implementation of this approach, one important decision to be made is about the appropriate numberof the trigonometric terms (k) in the Gallant flexible functional form. In this paper, k is selected to be 5 based on the Schwartz Information criterion (SIC).

The estimation results of the above model are reported in Table 3. The Ljung-Box test statistics, Q^2 (20) with the values of 12.57 suggests no evidence of remaining serial correlation or instability. The LR test statistics for the null hypothesis of FIGARCH model against the alternative hypothesis of A-FIGARCH model is 28.84. Under the null, the LR statistics

〈Table 3〉 Estimated Martingale-Adaptive FIGARCH (1,d,1,k) Model for the daily KRW-USD returns

μ	-0.0128**
	(0.0071)
d	*0.3518****
	(0.1463)
β	0.4944**
	(0.2675)
φ	0.3507**
	(0.2019)
ω_0	0.0144**
	(0.0083)
γ_1	-0.0021
	(0.0045)
δ_1	-0.0053**
	(0.0031)
γ_2	0.0061
	(0.0065)
δ_2	0.0001
	(0.0045)
γ_3	0.0060
	(0.0062)
δ_3	-0.0077
	(0.0087)
γ_4	0.0040
	(0.0070)
δ_4	-0.0028
	(0.0060)
γ_5	0.0108**
	(0.0060)
δ_5	0.0001
	(0.0047)
ln(L)	-1178.975
Skewness	0.439
Kurtosis	5.658
Q(20)	17.481
$Q^2(20)$	12.571
LR	28.841

Note: 1) The same as Table 2 except that the number trigonometric terms k is 5, which is selected based on the SIC.
2) LR is the Loglikelihood Ratio test statistics for the null hypothesis of FIGARCH versus A-FIGARCH model.

follows an asymptotic χ^2 distribution. The FIGARCH model is rejected at standard significance levels. These test results indicate that the inclusion of the trigonometric components improves goodness of fit of the model and the A-FIGARCH is superior to the usual FI GARCH as a specification for the volatility of the daily returns, which is consistent with the findings of Baillie and Morana (2009).

The parameter (d) of the long memory is estimated to be 0.35, and is statistically significant. The estimate is much smaller than the level under the basic FIGARCH model without the structural breaks, indicating that the long memory property in the volatility process can be partly explained by the structural breaks. Notably, however, the long memory property still remains statistically significant. Also, excess kurtosis and skewness estimates (0.44 and 5.66) are quite large even after accounting for the underlying structural breaks. This result suggests that the structural breaks may not be enough to explain the long memory property.

IV. Jumps, structural breaks and long memory: Adaptive FIGARCH model with Bernoulli jump process

As presented in introduction, many previous studies have presented that the jumps arequite important in understanding the volatility dynamics of foreign exchange rates. Thus, the jumps could be another possibility to explain the long memory property, which are remained strongly even after the structural breaks are considered. These jumps seem to be responsible for the outliers, and thus might be useful in accounting for the excess kurtosis and skewness, which cannot be taken into account for by the simple normal distribution as Hotta and Tsay (1998) presented. In order to account for the numerous jumps, this paper employs the jump diffusion process proposed by Press (1967) assuming that the returns are drawn from a mixture of normal distributions, i.e. a diffusion process combined with an additive jump process.

The stochastic jumps are assumed to follow the Bernoulli distribution following the suggestions of Beineand Laurent (2003) and Han (2007, 2008). That is, it is assumed that over a fixed time period (*t*), a jump following the arrival of relevant information occurs with probability (λ). While stochastic jumps are generally modelled by a Poisson distribution, the Bernoulli jump process appears to be practically more convenient than the Poisson distribution. Unlike a Poisson process, a Bernoulli process does not require the calculation of infinite sum and the truncation process. In addition to that, Vlaar and Palm (1993) and Baillie and Han (2001) have shown that the results from the Poisson model are generally not much different from those of the Bernoulli distribution model. Thus, this paper chooses the Bernoulli jump process and combines it with the A-FIGARCH model to analyze the impact of both jumps and structural breaks on the long memory property in the volatility process of the daily returns series.

For the Bernoulli distribution, the jump intensity (λ) is defined as $\lambda = [1 + \exp(c)]^{-1}$, which lies in the (0,1) interval. Here, c is a constant and consequently the jump probability is constant over time. The size of a jump is assumed to be NID(ν, τ^2) where ν is the mean and τ 2 is the variance. The same A-FIGARCH model as in Section II is used for the structural breaks and the long memory volatility process. Since the statistical and economic motivations for the jumps, the structural breaks and the long memory property are quite different, this paper chooses a model specification that accounts for the three different features at the same time. The daily returns are again specified as following a martingale process with the jump intensity of λ and the jump size of v. The volatility process is the A-FIGARCH (1,d,1,k) model as developed in

Section III. This augmented A-FIGARCH (1,d,1,k) model with the Bernoulli jump can be rewritten as;

$$y_t = \mu + \lambda\nu + \varepsilon_t \tag{11}$$

$$\varepsilon_t \sim (1-\lambda)N(-\lambda\nu, \sigma_t^2) + \lambda N(\nu - \lambda\nu, \sigma_t^2 + \tau^2) \tag{12}$$

$$(1-\beta L)\sigma_t^2 = \omega_t + [1 - \beta L - (1-\phi L)(1-L)^d]\varepsilon_t^2 \tag{13}$$

$$\omega_t = \omega_0 + \sum_{j=1}^{k}[\gamma_j \sin(2\pi jt/T) + \delta_j \cos(2\pi jt/T)] \tag{14}$$

When there is no jump (λ =0), the model is reduced to the simple A-FIGARCH (1,d,1,k) model as in Section III. The log-likelihood function associated with this model takes the following form,

$$\ln(\xi) = -(\frac{T}{2})\ln(2\pi) - \sum_{t=1}^{T}\{[\frac{(1-\lambda)}{\sigma_t}] \times \exp[\frac{-(\varepsilon_t + \lambda\nu)^2}{2\sigma_t^2}] + [\frac{\lambda}{(\sigma_t^2 + \tau^2)^{\frac{1}{2}}}] \times \exp[\frac{-(\varepsilon_t - (1-\lambda)\nu)^2}{2(\sigma_t^2 + \tau^2)}]\} \tag{15}$$

It can be seen that τ^2 is the additional volatility related to jumps and the normal mixture distribution can account for the excess kurtosisand the excess skewness. The form of the likelihood function for the Normal-Bernoulli jump processes is basicall125y the same as that developed by Vlaar and Palm (1993), Baillie and Han (2001) and Beine and Laurent (2003). Asymptotic standard errors are calculated from the QMLE of Bollerslev and Wooldridge (1992) as in Section III. For the estimation of the augmented A-FIGARCH model, the number of trigonometric terms (k) is chosen to be 2 based on the Schwartz Information criterion (SIC), which is lower than the choice for the A-FIGARCH model without the jump process. This may be because some structural breaks are relatively short lived and could be better captured by the jumpsrather than the trigonometric terms.

〈Table 4〉 Estimated Martingale-Adaptive FIGARCH (1,d,1,k) Model with Bernoulli Jump Process for the daily KRW-USD returns

μ	-0.030***
	(0.0073)
c	1.0915**
	(0.2071)
[λ]	[0.251]
υ	0.0702**
	(0.0372)
τ^2	0.3021**
	(0.0441)
d	*0.0201*
	(0.0310)
β	0.7534***
	(0.0455)
φ	0.8739***
	(0.0256)
ω_0	0.0013
	(0.0024)
γ_1	-0.0019**
	(0.0009)
δ_1	-0.0012**
	(0.0007)
γ_2	0.0004
	(0.0006)
δ_2	-0.0026***
	(0.0009)
ln(L)	-1055.878
Skewness	0.145
Kurtosis	3.591
Q(20)	18.475
$Q^2(20)$	14.634
LR	246.134

Note: 1) The same as Table 3 except that the number of trigonometric terms k is 2, which is selected based on the SIC and that a jump intensity λ is included where $0 〈 \lambda 〈 1$, $\lambda = [1 + \exp(c)]^{-1}$andc is the exogenous constant.

2) The jump size is assumed to be NID(υ ,τ^2)

In Table 4 are the estimation results for the augmented A-FIGARCH model. The LR test statistics for the null hypothesis of the A-FIGARCH without the jump process versus the A-FIGARCH model with the jump process is 246.134. The null model is rejected at standard significance levels, indicating that the A-FIGARCH model with the jump process is more appropriate specification for the daily returns than the model without the jump process. Furthermore, the values of the kurtosis and the skewness are 0.15 and 3.59, which are close to the values of 0 and 3 under the normal distribution, suggesting that the excess kurtosis and the skewness of the daily returns are also taken care of by the augmented A-FGARCH model. These results are in line with the results of Beine and Laurent (2003) and Han (2007, 2008).

The estimate of the jump probability (λ) is 0.25, which is calculated from the estimate of the constant (c): c is estimated to be 1.09, with statistical significance. And, the effects of the jumps on the volatility process are found to be significant since the estimated variance of the jump size (τ^2) is 0.3 and it is statistically significant. Also, the long memory parameter (d) in the volatility process is estimated to be 0.02 which is quite smaller compared to the values of the FIGARCH and the A-FIGARCH model. It is found to be statistically insignificant at the conventional significance level indicating that the long memory property in the volatility disappeared. These results provide statistical evidence that both the structural breaks and the jumps are the major sources of the long memory property.

V. Conclusion

For over two decades, the long memory property in the volatility process of financial time series including foreign exchange rates have been an important issue in the area of finance since volatility is a key driver in risk management and asset pricing process. Many previous studies have tried to figure out the causes and sources of the long memory property in the volatility process. While some papers have claimed that the long memory property is spurious since it is resulted from the structural breaks, other papers have believed that relatively short lived jumps are the main source of the long memory property. However, neither of these two groups provided full explanations for the empirically observed long memory property in the volatility process. Even after accounting for the structural breaks or the jumps, they have found that strong long memory property still remains in the volatility process.

Hence, this paper considers the structural breaks and the jumps jointly as the sources of the long memory property in volatility process of the daily KRW-USD exchange rates over the periods of 1999 through 2007. For this purpose, this paper augments the Adaptive FIGARCH model, which includes the long memory and the structural breaks in its specification but not jumps, with a Bernoulli jump process. This approach is in sharp contrast with previous studies which have considered only one of the two factors either the structural breaks or the jumps, but not both. The main empirical result of this paper is that when both the structural breaks and the jumps are controlled for, the long memory property in the volatility almost disappears. Thus, this paper provides statistical evidence that the structural breaks and the jumps are the main sources of the long memory property.

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요 약

본 논문은 일별 원-달러 환율의 변동성에서 나타나는 장기기억 특성을 유발시키는 잠재적인 근원을 분석하였다. Adaptive FIGARCH 모형과 Jump diffusion모형을 토대로 본 논문은 장기기억 특성을 구조적 변화와 점프현상을 연계시키는 변동성과정의 새로운 단순한 경험적 모형을 제시하였다. Adaptive FIGARCH모형과 Bernoulli 점프과정을 이용한 새로운 모형을 이용하여 원-달러 환율 변화율의 변동성에서 나타나는 장기기억 특성을 추정하여 장기기억 특성이 두 가지 관측 할 수 있는 변수, 구조적 변화와 점프현상과 매우 직접적으로 관련이 있음을 밝혔다. 따라서 구조적 변화와 점프현상은 모두 변동성에서의 장기기억 특성을 설명하는데 중요한 역할을 수행하는 것으로 밝혀졌다. 이러한 경험적 결과는 구조적 변화와 점프현상을 모두 고려한 Adaptive FIGARCH모형과 Bernoulli 점프과정을 이용한 새로운 모형이 원-달러 환율의 변동성에서 나타나는 장기기억 특성을 거의 모두 설명할 수 있음을 나타내어 구조적 변화와 점프현상이 변동성의 장기기억 특성의 주요 근원임을 보여주는 통계적 근거를 제시하였다.

※ **국문 색인어:** 구조적 변화, 일별 원-달러 환율, 장기기억 특성, adaptive FIGARCH model, Bernoulli jump process, FIGARCH model