THE KOREAN ECONOMIC REVIEW
Volume 17, Number 2, Winter 2001

VOLATILITY FORECASTING MODELS FOR THE WON-DOLLAR EXCHANGE RATE

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This paper attempts to compare the forecasting performance of various volatility models for weekly won-dollar exchange rates in terms of R^2 *and news impact curve with diagnostic tests. We consider both linear GARCH model and nonlinear models such as EGARCH, GJR, GTARCH, and LSTARCH. Empirical results for the* R^2 *comparison suggest that the EGARCH model has an edge in predicting a large value of variances while GTARCH and LSTARCH models outperform alternative models in predicting a small value of variances. According to the news impact curve analysis, all models except the GARCH demonstrate asymmetric movements of exchange rate volatility around the threshold. That is, the conditional volatility increases more in case of a positive exchange rate shock (depreciation) than a negative exchange rate shock (appreciation). Although it is difficult to find definite grounds for choosing between the various models, we conclude from a series of sign bias tests that the EGARCH model is the best in predicting the volatility of weekly exchange rates among alternative models considered.*

JEL Classification: C52, C53, F31
Keywords: Eexchange Rate Volatility, GARCH, News Impact Curve, Asymmetric Response

I. INTRODUCTION

The nonlinear and asymmetric movement of the volatility of returns on financial assets, especially traded in the short term markets is a common feature of any financial market in the world. The asset returns have a tendency to

Received for publication: July 31, 2001. *Revision accepted:* Nov. 1, 2001.

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respond differently with respect to the magnitude and the direction of changes in prices. Many researchers have investigated these asymmetric movements of the volatility of asset price.[1] The results have consistently shown that the volatility is bigger when the price drops than when the price rises.

In particular, the asymmetric volatility of stock returns results from the leverage effect motivated by Black (1976). As value of leveraged firm declines, the equity is more highly leveraged. Then the degree of risk increases with increasing volatility. The association between returns and volatility also stems from volatility feedback effect. Campbell and Hentschel (1992) proposed the alternative mechanism that, as changes in volatility increases, required stock returns increases and thus stock prices drop.

Most researchers have used the GARCH-type models initiated by Bollerslev (1986) to generate volatility forecasts of financial asset prices. Many studies have attempted to capture more precise movement of the volatility by continuously modifying the GARCH specification. It would be simple and relatively less time-consuming for estimation via the GARCH type models but sometimes unrealistic due to the assumption of linearity in explaining volatility movement. Nelson (1991), and Glosten, Jagannathan, and Runkle (1993) develop the EGARCH and the GJR models, respectively, to reflect a nonlinear and asymmetric movement of volatility.

It is, however, noted that the EGARCH and the GJR models assume that the threshold value for the asymmetric movement is zero. Since these models restrict a threshold value for asymmetric movements to zero, any change below or above zero in asset returns is assumed to have differential impacts on the volatility. It would be unrealistic because the volatility tends to respond differently to changes in asset returns above a certain level rather than zero. The main reason would be that investors tend to respond only when the magnitude of changes in asset returns reaches to a certain level. Hence, the threshold value should be generalized to incorporate the value not equal to zero. The generalized threshold ARCH (GTARCH) model might be an appropriate alternative for explaining volatility movements if the non-zero threshold for asymmetric movement exists. Furthermore, to reflect the general pattern of regime shift of volatility, i.e., smooth transition or a discrete and sudden jump into the model, we may rely on the logistic smooth transition ARCH model (LSTARCH) proposed by Anderson, Nam, and Vahid (1999).

Some researchers investigate the volatility models of the exchange rates instead of stock returns. Among them, West and Cho (1995) compare the forecasting performance of various volatility models, using weekly exchange rates for the dollar of five currencies. Brooks and Burke (1998) use appropriately

[1] Among them, using various stock price data, Pagan and Schwert (1990), Engle and Ng (1992), and Koutmos (1998) report that the conditional variance of returns respond asymmetrically to past information.

modified information criteria to select models from the GARCH family. However, most studies with the exception of Koutmos (1993), and Laopodis (1997, 1998) examined the exchange rate volatility ignoring asymmetry.

Since the free-floating system was adopted on December 1997 in Korea, the concern about the volatility of exchange rates in foreign exchange market has increased. Many authors have investigated the trend and the determinants of the exchange rate volatility. Among them, Lee (1999) fails to find significant evidence about the increasing volatility since the late 1997. Chung and Joo (1999) focus on the trading volume as a determinant of the volatility of exchange rates using a GARCH model. Sung and Kim (2000) find the asymmetric effect of news shocks on the volatility of exchange rate using the EGARCH, and GJR models of daily exchange rates.

In this study we analyzed weekly won-dollar exchange rate volatility using various time series models including GARCH, EGARCH, GJR, TARCH, and LSTARCH. Predictability of alternative models were compared in terms of the R^2 following the approach suggested by Pagan and Schwert (1990). The news impact curve analysis with diagnostic tests proposed by Engle and Ng (1993) was also considered in the model comparisons of capturing the asymmetric effect. Besides comparing the models' forecasting ability, we seek to find a non-linearity and threshold values of residuals for causing the asymmetric volatility responses.

The main empirical findings are that the EGARCH model is the best specification in predicting the volatility of the won-dollar exchange rate among alternative models. We find an asymmetric movement in the volatility such that the Korean won depreciation increases the volatility more than appreciation does. The composition of this paper is as following. Alternative models considered in this study are described in section II. Estimation results on each alternative volatility model are presented in section III. Section IV performs the systematic comparison of volatility models based on R^2 and news impact curve with diagnostic tests. The paper ends with concluding remarks in section V.

Ⅱ. THE MODELS

1. Conditional Mean Equation

The models considered in this paper consist of the conditional mean and the conditional variance equations. The conditional mean equation is assumed to be AR(p) for all models but the conditional variance equation is differentiated among models depending on the assumption of the dynamic process of conditional variance. Consider a simple AR(p) model specification for the exchange rate.

$$\Delta EX_t = C_0 + \sum_{k=1}^{p} C_k \Delta EX_{t-k} + \varepsilon_t \tag{1}$$

where ΔEX_t represents the change in exchange rate at period t and ε_t indicates unpredictable part of changes in exchange rate. C_0 and C_k are coefficients.

2. Conditional Variance Equation

2.1 GARCH Model

For the sake of parsimony of parameters, we restrict the order of the GARCH model to (1,1). The simple GARCH(1,1) specification for the conditional variance equation is as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{2}$$

where $\varepsilon_t = z_t \sqrt{h_t}$ and z_t is independent and identically distributed with zero mean and unit variance. The GARCH model cannot capture asymmetric effects of positive and negative shocks since the conditional variance depends only on the square of the shock.

2.2 EGARCH Model

Unlike linear GARCH models, the EGARCH model suggested by Nelson (1991) does not require imposition of parameter restrictions for the stability of the conditional variance equation. It also does not rule out a negative correlation between current return and future return volatility. The model is as following.

$$\ln h_t = \alpha_0 + \theta z_{t-1} + \gamma(|z_{t-1}| - E(|z_{t-1}|)) + \beta_1 \ln h_{t-1}. \tag{3}$$

The EGARCH model (3) describes the relation between past shocks and the logarithm of the conditional variance. The function, $g(z_t) = \theta z_t + \gamma(|z_t| - E(|z_t|))$ is linear in z_t with slope $(\theta + \gamma)$ when z_t is positive and with slope $(\theta - \gamma)$ when z_t is negative. Thus $g(z_t)$ allows the conditional variance to respond asymmetrically to a rise or fall in exchange rates, respectively.

2.3 Threshold GARCH models

Assuming that there exist two different regimes on the dynamic process of conditional variance, we construct the following nonlinear threshold GARCH specification of the conditional variance equation.

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + (\alpha_2 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}) F(\varepsilon_{t-d}) \tag{4}$$

where $F(\varepsilon_{t-d})$ is a transition function bound between zero and one. ε_{t-d} indicates a transition variable which causes the transition between regimes, and d represents a delay parameter which gives information on the lag of the transition variable. The specification (4) implies a nonlinear GARCH(1,1) model incorporating switching regimes endogeneously controlled by the nature of the transition variable ε_{t-d} into itself. Note that, if $F(\varepsilon_{t-d}) = 0$, then (4) degenerates into the linear GARCH(1,1) model.

Now consider different functional forms of $F(\varepsilon_{t-d})$ in the generalized threshold nonlinear GARCH specification (4). Different functional forms of $F(\varepsilon_{t-d})$ imply different type of transition between regimes such as a transition with discrete jump or with smooth shift.

The first functonal form is specified as:

$$F(\varepsilon_{t-d}) = \begin{cases} 1, & \text{if } \varepsilon_{t-d} \geq k \\ 0, & \text{if } \varepsilon_{t-d} < k. \end{cases}$$

The indicator function takes one or zero, depending on whether the transition variable, ε_{t-d} is above or below the threshold value, k. Accordingly, the model (4) generates two different dynamic processes of the conditional variance under two different regimes which are called the "upper regime" and the "lower regime". That is, when $F(\varepsilon_{t-d}) = 1$, (4) generates the dynamic processes of the conditional variance under the upper regime. When $F(\varepsilon_{t-d}) = 0$, it generates the dynamic processes of the conditional variance under the lower regime.
Note that, if the value of threshold, k is zero, then the specification is exactly the same as the model proposed by Glosten, Jagannathan, and Runkle (1993). The GJR model allows different reactions of conditional variance to different signs and magnitudes of the shocks by combining the existence of the threshold to the conditional heteroskedasticity. As it can be easily figured out, the specification (4) allows more general specification of the threshold value and the asymmetric coefficients in the conditional variance process.

The second functional form of the indicator function is a logistic function. Unlike the GJR model, it allows the conditional variance to have a smooth and continuous transition between regimes. The indicator function is as the following:

$$F(\varepsilon_{t-d}) = \frac{1}{1 + \exp[-\delta(\varepsilon_{t-d} - k)]}, \quad \delta > 0. \tag{5}$$

The ARCH model with the above conditional variance specification is called by logistic smooth transition ARCH (LSTARCH) model.
The logistic function in the LSTARCH model is a smooth and continuous function of the transition variable, ε_{t-d}. The value of the function lies between

zero and one, depending on the magnitude of $(\varepsilon_{t-d}-k)$ and speed of transition parameter, δ. When the indicator function takes extreme values such as one or zero, equation (4) generates two different dynamics of conditional variance processes. When the power of the exponential part in the logistic function reaches to negative infinity, the value of the indicator function is equal to one. Then equation (4) represents the upper regime. On the other hand, when the power of exponential part in the logistic function reaches to positive infinity, the value of the indicator function is equal to zero. Then (4) represents the lower regime. When ε_{t-d} is equal to k or when δ is equal to zero, the value of the indicator function is 0.5, implying that the current volatility, h_t is on the half way between upper and lower regime.

Also the LSTARCH specification allows for a continuum of shifts between two extreme regimes. Given a positive value of δ, as the magnitude of $(\varepsilon_{t-d}-k)$ becomes positively larger, the value in the exponential part in (5) goes to zero. As a result, the current volatility, h_t approaches to the upper regime. Similarly, as the magnitude of $(\varepsilon_{t-d}-k)$ becomes negatively larger, the value in the exponential part in (5) approaches to infinity. Thereby the current volatility, h_t approaches to the lower regime.

The speed of transition between regimes is dependent on the value of δ. The greater is the value of δ, the faster the transition between regimes occurs. Furthermore, given the magnitude of $(\varepsilon_{t-d}-k)$, when δ reaches to infinity, the LSTARCH model becomes a GTARCH model.

Although asymmetric dynamics of the conditional variance with a regime shift is reflected in both models, the different transition functions capture different aspects of transition. For example, the LSTARCH model allows the transition to occur smoothly and continuously between regimes over time while the GTARCH model allows the transition to occur at the specified threshold value with a discrete and sudden jump.

Ⅲ. ESTIMATION RESULTS

1. Data

We used daily spot exchange rates for the Korean won-US dollar from October 26, 1983 to August 30, 2000. The data set is composed of 880 observations. We constructed the weekly series mainly from the Wednesday data. When Wednesday was a holiday, we used the Tuesday data; when Tuesday was a holiday as well, we used the Thursday data.

To test the existence of a unit root in the series, we applied the augmented Dickey-Fuller test on the logarithm of the series in level and the first difference. The results indicate that the unit root hypothesis for the level cannot be rejected while that for the first difference is rejected.[2] Hence the percentage change rate in exchange rate series were used in the analysis.

[Table 1] Estimation Results for Conditional Mean Equation

$$
\begin{aligned}
\Delta EX_t = \; & \underset{(0.045)}{-0.002}\underset{(0.034)}{-0.073}\Delta EX_{t-1}\underset{(0.034)}{+0.484}\Delta EX_{t-2}\underset{(0.038)}{+0.113}\Delta EX_{t-3}\underset{(0.038)}{-0.015}\Delta EX_{t-4}\underset{(0.038)}{-0.119}\Delta EX_{t-5}\underset{(0.038)}{-0.029}\Delta EX_{t-6} \\
& \underset{(0.038)}{+0.061}\Delta EX_{t-7}\underset{(0.038)}{+0.032}\Delta EX_{t-8}\underset{(0.038)}{-0.149}\Delta EX_{t-9}\underset{(0.038)}{+0.013}\Delta EX_{t-10}\underset{(0.038)}{+0.128}\Delta EX_{t-11}\underset{(0.038)}{-0.083}\Delta EX_{t-12} \\
& \underset{(0.038)}{-0.038}\Delta EX_{t-13}\underset{(0.038)}{-0.094}\Delta EX_{t-14}\underset{(0.038)}{-0.137}\Delta EX_{t-15}\underset{(0.038)}{+0.105}\Delta EX_{t-16}\underset{(0.038)}{+0.141}\Delta EX_{t-17}\underset{(0.038)}{-0.080}\Delta EX_{t-18} \\
& \underset{(0.039)}{-0.058}\Delta EX_{t-19}\underset{(0.038)}{-0.040}\Delta EX_{t-20}\underset{(0.038)}{-0.031}\Delta EX_{t-21}\underset{(0.038)}{+0.168}\Delta EX_{t-22}\underset{(0.035)}{+0.005}\Delta EX_{t-23}\underset{(0.035)}{-0.138}\Delta EX_{t-24} \\
& \underset{(0.206)}{+0.544}DUM
\end{aligned}
$$

Loglikelihood=-1421.409

Ljung-Box Q(36) on residuals= 45.962
Ljung-Box Q(36) on residuals squared= 104.00

Skewness = 6.937
Kurtosis = 142.573
Jarque-Bera =703312.9

Note: The numbers in the parentheses represent standard errors.

2. Estimation

Prior to the estimation of the conditional volatility, we specified the conditional mean equation as AR(24).[3] A dummy variable was added to the conditional mean equation to reflect the period of the liquidity crisis in Korea from October 30, 1997 to October 29, 1998 since movements of the exchange rate were highly volatile and the speed of depreciation was very fast during the crisis.

Estimation results of the conditional mean equation (1) are contained in Table 1. The dummy variable reflecting the liquidity crisis is statistically significant at the 1 percent level. The estimated coefficient is positive, implying that the conditional mean of the change in exchange rate increased by 0.544 percentage point during that period. The Ljung-Box's Q(36) statistics on residuals is 45.962. This exhibits nonexistence of serial correlation on residuals. However, the Ljung-Box's Q(36) statistics on squared residuals is 104 which rejects signifi-

[2] The augmented Dickey-Fuller statistic for ln EX is -1.721, and that for Δln EX is -10.714 when the lag is restricted to 4. It implies that the exchange rate series should be first-differenced to avoid nonstationarity problem.

[3] The optimal lag length for the conditional mean equation was determined based on Akaike Information Criterion (AIC). Furthermore, we could eliminate serial correlation in residuals by extending AR terms into 24.

cantly the null hypothesis of no autocorrelation. There would be serious ARCH effect on residuals. Hence, the ARCH type specification on the conditional variance equation might be appropriate. The statistic of skewness is positive and the statistic of kurtosis shows that ε_t is leptokurtic. The high Jarque-Berra statistic of residuals from the conditional mean model reveals a non-normality problem.

Like most studies exploring the forecasting ability of alternative models on volatility, we estimated different types of conditional variance using residual series obtained from the estimated conditional mean equation. We assume t-distribution for z_t for defining the log-likelihood function for conditional variance. We also employed the same dummy variable mentioned above for the conditional variance equation to see if the liquidity crisis increased the volatility of exchange rates.

The estimation results in Table 2 suggest that all of estimates of the lagged squared residuals, α_1 and the lagged conditional variance, β_1 are statistically significant at the 1 percent level. Since the sum of estimates of the lagged squared residuals and the lagged conditional variance in each model are less than one, the conditional variance process in each model seems to be stable. The dummy variable reflecting the liquidity crisis turns out to be positive and statistically significant in every model. Thus the liquidity crisis appears to increase not only conditional mean but also the volatility of the exchange rate. Magnitudes of increases in volatility due to the liquidity crisis ranges between 0.242 and 2.601, depending on the specification of the conditional variance equation.

In the EGARCH model, the asymmetric relation between changes in exchange rates and changes in volatility, as represented by θ(=0.099), is positive and slightly above zero and statistically significant at the standard level. Note that the positive value of θ indicates that volatility tends to rise when changes in exchange rate shocks are positive. The degree of cluster of volatility represented by γ is positive and statistically significant, implying that the volatility is clustered.

The estimation results of the GJR model show that the asymmetric relation between changes in exchange rates and changes in volatility, as represented by α_2(=0.052), is positive and slightly above zero, but statistically insignificant at any standard level.[4] Thus the GJR model fails to capture the asymmetry in the effect of news on the volatility in exchange rates.

For the estimation of the LSTARCH model, $\hat{\varepsilon}_{t-1}$ is used as a transition variable.[5] The results show that nonlinear movements of the conditional variance are obvious because estimates of α_2 are statistically significant. The estimated

[4] We assumed $\beta_2=0$ in the estimation of the GJR model as in previous studies.

[5] The delay parameter, d was set to one.

[Table 2] Estimation Results for Conditional Volatility Models

Coefficients	GARCH	EGARCH	GJR	GTARCH	LSTARCH
α_0	0.006** (0.001)	-0.052** (0.021)	0.006** (0.001)	0.006** (0.002)	0.006** (0.002)
α_1	0.241** (0.0370)		0.194** (0.042)	0.194** (0.037)	0.194** (0.036)
β_1	0.745** (0.027)	0.953** (0.011)	0.752** (0.026)	0.760** (0.028)	0.760** (0.028)
Dummy	2.601** (0.820)	0.242** (0.017)	2.521** (0.781)	2.365** (0.781)	2.366** (0.781)
θ		0.099** (0.018)			
γ		0.296** (0.035)			
α_2			0.052 (0.030)	0.263* (0.123)	0.263* (0.129)
β_2				-0.246 (0.197)	-0.247 (0.203)
δ					8724.765 (150196.7)
k				1.055	1.055** (0.007)
Log-likelihood	-511.388	-596.675	-510.324	-508.098	-508.0978
Skewness	0.215	1.785	0.173	0.217	0.217
Kurtosis	4.670	25.537	4.677	4.602	4.602
Jarque-Bera	106.015	18569.829	104.583	98.299	98.277

Notes: 1) ** and * indicate significance at 5 and 10 percent, respectively.
2) The numbers in the parentheses represent standard errors.

value of δ is 8724.765 but statistically insignificant. This indicates that the transition function takes value close to one. It thus seems that the transition between upper and lower volatility regimes is instantaneous with a sudden jump as in the GTARCH model. The estimated value of threshold, k (=1.055) is positive and statistically significant at the 1 percent level. When ε_{t-1} is equal to 1.055, the value of the transition function is equal to 0.5. It implies that when the previous realized changes in exchange rate deviated from its expectation (zero) by the value of k, the current volatility stays in the middle between two regimes. When the previous error results in a positive (negative) surprise, the current volatility approaches to the upper (lower) volatility regime. It indicates that the LSTARCH, a type of the nonlinear threshold ARCH model, captures the asymmetry well.

In the estimation of GTARCH, the threshold value was taken from results for LSTARCH. Accordingly, the value of k is set to be 1.055. When ε_{t-1} exceeds 1.055, then the transition function, $F(\varepsilon_{t-1})$ is equal to 1. Otherwise, the value of the transition function is zero. It implies that, when the previous error results in a positive surprise greater than 1.055, the current volatility is in upper volatility regime. The estimation results for the GTARCH reported in Table 2 show that the asymmetry in conditional variance process exists because estimates of α_2 is statistically significant.

IV. MODEL COMPARISON

In this section, we compare the predictability of each model. The R^2 comparison method proposed by Pagan and Schwert (1990) is employed for evaluating the ability of each volatility model to capture the nonlinearity and asymmetric effect existent in the exchange rate movement. The news impact curve with diagnostic tests suggested by Engle and Ng (1993) is employed to assess the ability of each volatility model for reflecting the asymmetric effect.

1. The R^2 Comparison

The conditional variance equation implies that, if the squared residual from the conditional mean equation is assumed to be a proxy for the unobservable volatility, then the volatility can be predicted as a conditional variance by given information available for now. The estimated conditional variance, h_t obtained from mapping between the conditional variance and past information is the predictable portion of the unobservable current volatility, ε_t^2.

Based on the expectation behavior described above, Pagan and Schwert (1990) suggest the regression analysis for comparing the predictability of the various volatility models. The model is as following:

$$\hat{\varepsilon}_t^2 = a + b\hat{h}_t + v_t \tag{6}$$

where $\hat{\varepsilon}_t$ is a series of residuals from the conditional mean equation and $\hat{h}_t$ is the estimated conditional variance from various conditional variance equations. Since $E(\varepsilon_t^2/\Omega_{t-1}) = h_t$ such that $\varepsilon_t^2 = h_t + v_t$, the unbiasedness of the conditional variance estimated from each volatility model can be tested by restricting $a = 0$

and $b=1$ of equation (6). Also, R^2 of the regression (6) can be used for comparing the predictive power of the conditional variance estimated from each volatility model.

Concerning the comparison of predictive power of alternative models in terms of R^2, Pagan and Schwert (1990) propose the alternative regression:

$$\ln \hat{\varepsilon}_t^{\,2} = a + b \ln \hat{h}_t + v_t. \tag{7}$$

The above log-linear equation is motivated by the idea of a proportional loss function as a criterion, such that errors in predicting small variance are penalized with more weight in equation (7) than in equation (6). The R^2 from the linear equation (6) thus is more relevant criterion to evaluate predictive power of alternative models for estimating a large value of variances whereas the R^2 from the log-linear equation (7) is a more relevant criterion to evaluate predictive power of alternative models for estimating a small value of variances.

Table 3 contains the estimated value of parameters, standard errors in the parenthesis, R^2 of the regression and the Ljung-Box Q(36) test statistics. Results show that estimated a of all models are statistically insignificant at the 5 percent level, but estimated b of all models are statistically significant at the 1 percent level. The Ljung-Box Q(36) statistics for forecast errors of equation (6) are all insignificant, implying no evidence of serial correlation in forecast errors. According to the rankings by R^2 for predictive power of alternative models from the linear regression, the EGARCH model has a slight edge in predicting ε_t^2 for

[Table 3] Comparison of With-in Predictive Power of the Conditional Variance Models

Model	Linear Regression (6)				Nonlinear regression (7)	
	R^2	a	b	Q(36)	R^2	Q(36)
GARCH	0.070(3)	0.556 (0.645)	0.483** (0.060)	20.802	0.277(4)	37.067
EGARCH	0.080(1)	0.486 (0.641)	0.530** (0.062)	26.933	0.266(5)	37.187
GJR	0.071(2)	0.569 (0.644)	0.485** (0.060)	20.526	0.278(3)	37.297
GTARCH	0.064(4)	0.809 (0.641)	0.337** (0.044)	15.773	0.2782(1)	38.307
LSTARCH	0.064(4)	0.810 (0.641)	0.337** (0.044)	15.759	0.2782(1)	38.304

Note: 1) The numbers in the R^2-column mean the rank among models.
2) The numbers in the parentheses of the R^2-column represent standard errors.

[Table 4] Comparison of Out-of-sample Predictive Power of the Conditional Variance Models.

	Linear			Log-linear		
Model \ Horizon	24	12	1	24	12	1
GARCH	0.962(3)	0.704(3)	0.414(2)	1.811(4)	1.230(1)	1.821(5)
EGARCH	0.926(1)	0.630(1)	0.400(1)	1.838(5)	1.320(5)	1.573(1)
GJR	0.956(2)	0.694(2)	0.428(3)	1.808(3)	1.237(4)	1.807(4)
GTARCH	1.034(4)	0.856(4)	0.649(4)	1.772(1)	1.232(2)	1.769(2)
LSTARCH	1.034(4)	0.857(5)	0.650(5)	1.772(1)	1.232(2)	1.769(2)

Notes: 1) The numbers indicate RMSE(Root Mean Squared Error) for the corresponding model.
2) The numbers in the parentheses imply the rank among the models.

a large value of variances over the models. However, generalized threshold nonlinear models such as the GJR, the GTARCH and the LSTARCH reveal better performance in log-linear regression. It suggests that threshold models have advantage in predicting ε_t^2 for a small value of variances over any other alternative models.

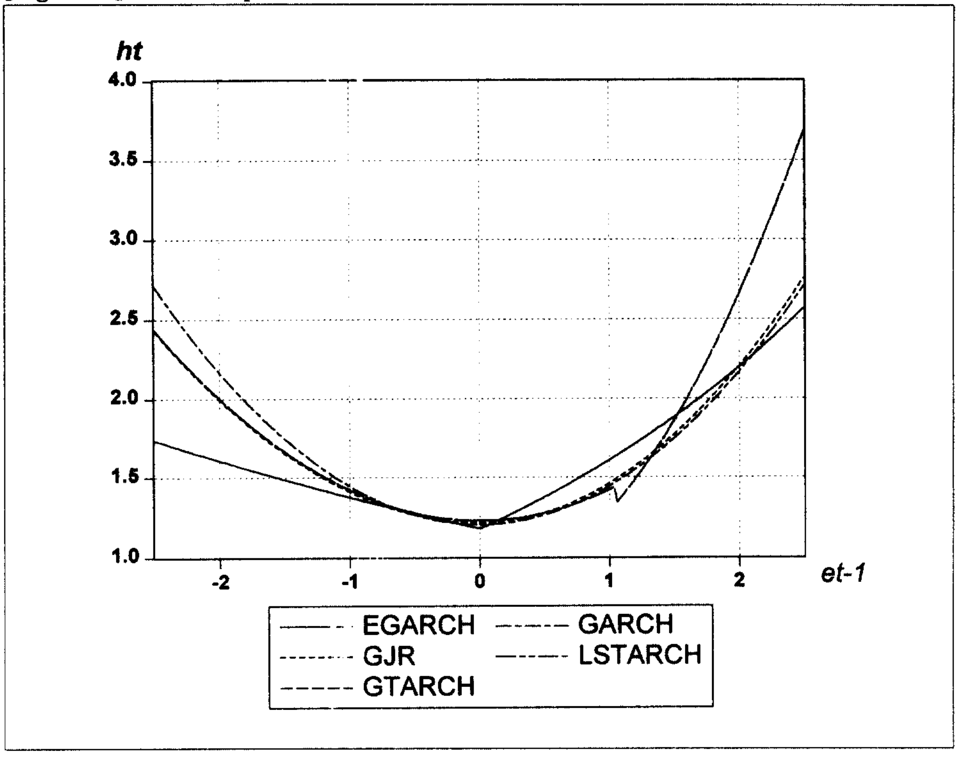
2. The out-of-sample forecast

The performance of the out-of-sample forecast of each model was compared based on root mean squared error(RMSE). Table 4 contains RMSE of equations (6) and (7) for the last 24, 12, and 1 week where the model parameters were estimated using data excluding the last 24, 12, and 1 week. For a linear model (6), the EGARCH model is the best in every forecasting horizon. The GJR model ranks the second in 24 week and 12 week forecasting horizons. For a log linear model (7), the LSTARCH model and the GTARCH model perform the best in 24 week forecasting horizon while the GARCH model does the best in 12 week horizon. Overall, the results of the out-of-sample forecasting comparison are very similar to those by R^2 comparison.

3. News Impact Curve

Engle and Ng (1993) proposed a news impact curve (NIC) analysis as a measure of how new information is incorporated into the volatility estimates. The NIC is the plot of the current conditional volatility (h_t) versus the previous innovation (ε_{t-1}). It is employed as a main tool for comparing the qualitative difference among alternative models in terms of the ability to capture the asymmetric effect on volatility.

[Figure 1] News Impact Curve



For instance, the NIC of the GARCH model is a quadratic function which is symmetric and centered at $\varepsilon_{t-1}=0$. That is, the conditional variances of the GARCH model symmetrically respond to positive and negative exchange rate shocks with the same magnitude. The NIC of the EGARCH model, however, captures the asymmetric impact of positive and negative exchange rate shocks through different exponential functions for $\varepsilon_{t-1}<0$ and $\varepsilon_{t-1}>0$. The NIC of the GTARCH model is discontinuous at threshold (k) with a shift, and is asymmetric with different slopes for its left and right sides of k. The NIC of the LSTARCH model might be continuous or discontinuous at threshold (k) with a shift and is asymmetric with different slopes for its left and right sides of k. If δ is large enough to make the exponential part of the logistic function close to 0, then the NIC of the LSTARCH model might be similar to the NIC of the GTARCH model. Otherwise, it might be continuous and smooth.

The NICs of alternative models are illustrated in Figure 1.[6] According to Figure 1, the NIC of the GARCH is symmetric and centered at $\varepsilon_{t-1}=0$, while the NIC of the GJR and the EGARCH models are asymmetric and show more

[6] In practice, we take h_t at the initial period equal to the unconditional variance, σ^2.

response of volatility when $\varepsilon_{t-1} > 0$. Also the NIC of the GTARCH and the LSTARCH models are asymmetric and discontinuous at estimated k=1.055 with a shift. The slope for the right side of k is steeper than that for the left side. Since estimated δ on the LSTARCH is large enough to make the exponential part of the logistic function close to zero, the NIC of the LSTARCH is almost the same as that of the GTARCH. Overall, all models except the GARCH can capture asymmetric movements of exchange rate volatility when ε_{t-1} exceeds the threshold. This implies that conditional volatility increases more in case of a positive exchange rate shock than a negative exchange rate shock.

4. Sign Bias Tests

We implemented a series of sign bias tests for diagnostics suggested by Engle and Ng (1993) to check whether the model specification is correct. We performed the Sign Bias Test (SBT), the Negative Sign Bias Test (NSBT), the Positive Sign Bias Test (PSBT), and Joint Sign Bias Test (JSBT). These tests examine whether the squared normalized residuals can be predicted by some variables which are not considered in the volatility model.
The regression equations for tests are as following:

$$\hat{z}_t^2 = a + bS_{t-1}^{-} + \lambda' x_t^* + e_t \tag{8}$$
$$\hat{z}_t^2 = a + bS_{t-1}^{-}\hat{\varepsilon}_{t-1} + \lambda' x_t^* + e_t \tag{9}$$
$$\hat{z}_t^2 = a + bS_{t-1}^{+}\hat{\varepsilon}_{t-1} + \lambda' x_t^* + e_t \tag{10}$$
$$\hat{z}_t^2 = a + b_1 S_{t-1} + b_2 S_{t-1}^{-}\hat{\varepsilon}_{t-1} + b_3 S_{t-1}^{+}\hat{\varepsilon}_{t-1} + \lambda' x_t^* + e_t \tag{11}$$

where S_{t-1}^{-}=1 if ε_{t-1}<0 and $S_{t-1}^{-}=0$ otherwise, and $S_{t-1}^{+}=1\ S_{t-1}^{-}$. Also, $x_t^* = \tilde{h}(\theta)/h_t^*$ evaluated at the value of maximum likelihood estimates of parameter θ, and h^*_t is the estimated conditional variance.

The SBT examines whether positive or negative return shocks have impacts on the squared residuals using the t statistic on the coefficient b in equation (8). The NSBT and the PSBT check whether the size of the negative and positive shocks have different impact on volatility, respectively. The test statistics for the NSBT and the PSBT are also given by the t statistics on the coefficient b in equation (9) and (10), respectively. The JSBT is Lagrange multiplier (LM) test for adding the three more variables to the conditional variance equation. The test statistic is given by $T \cdot R^2$ in the regression equation (11) where T is the number of observations, and R^2 is the squared multiple correlation. The statistic is asymptotically distributed as x^2 with 3 degrees of freedom under the null hypothesis of b_1=b_2=b_3=0. The failure of the rejection of the null is indicative of misspecification on the conditional variance equation.

All sign bias test results are reported in Table 5. None of the models reject the null in the SBT and the PSBT. It seems that the magnitude of positive shocks is well captured in all models. However, the NSBT results suggest that

[Table 5] Sign Bias Test Results

Model	Sign Bias Test	Negative Sign Bias Test	Positive Sign Bias Test	Joint Sign Bias Test
GARCH	-0.189 (0.130)	0.202* (0.093)	0.090 (0.065)	6.033
EGARCH	-0.322 (0.336)	0.153 (0.241)	0.065 (0.168)	0.874
GJR	-0.164 (0.132)	0.192* (0.095)	0.084 (0.066)	5.168
GTARCH	-0.190 (0.129)	0.198* (0.092)	0.061 (0.064)	5.168
LSTARCH	-0.190 (0.129)	0.198* (0.092)	0.061 (0.064)	5.168

Notes: 1) The numbers in the parentheses represent standard errors.
2) ** and * indicate significance at 5 and 10 percent, respectively.

the coefficients are significant in all models except the EGARCH, indicating that all models except the EGARCH have difficulties in capturing the magnitude of negative shocks. All models pass the JSBT. It is, however, noted that the statistic of the EGARCH is much lower than that of other models. Overall, the EGARCH model dominates the other models in terms of sign bias test results.

V. CONCLUDING REMARKS

In this study, we attempted to evaluate the forecasting ability of five volatility models for the weekly won-dollar exchange rates. Models considered include both symmetric and asymmetric models such as GARCH, EGARCH, GJR, GTARCH and LSTARCH.

Despite non-normality of standardized residuals, estimation results for all models are quite satisfactory. The coefficients are statistically significant and have correct signs. It is also noteworthy that the recent liquidity crisis increased the conditional variance as well as conditional mean of exchange rates.

We compared the predictive ability of alternative models based on various criteria. According to the results of rankings for predictive power in terms of R^2, the EGARCH model has a slight advantage in predicting a large value of variances while the GTARCH and the LSTARCH models seem to forecast well for a small value of variances.

The NIC of all models except the GARCH show the asymmetry of volatility in response to exchange rate shocks. Depreciation positively affects volatility more severely than appreciation. Furthermore, the nonlinearity of volatility suggests that conditional volatility increases more when a large positive exchange rate shock occurs than when a small positive exchange rate shock occurs.

We performed diagnostic checking with various sign bias tests. The NSBT results show that all models except the EGARCH have difficulties in capturing the magnitude of negative exchange rate shocks. Hence, we conclude that the EGARCH model outperforms other alternative models in forecasting the exchange rate volatility.

Asymmetric behavior of exchange rate volatility is of significance to both investors and traders. The policy authorities should also consider seriously the asymmetric movements of volatility when it implements the exchange rate policy. It would be advisable to point out the limitation of the paper. In contrast with a lot of theoretical models for the asymmetry of volatility in the stock market, we did not present good theoretical backgrounds for the asymmetry of exchange rate volatility. The empirical findings in this study, however, could hopefully motivate developing theoretical models that underlie the asymmetric response of volatility to exchange rate shocks.

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