Hoque, A. (2007) Alternative volatility models for pricing European currency options. In: 20th Australasian Finance & Banking Conference, 12 - 14 December, Sydney, NSW, Australia.

August 2007
Draft only

Alternative Volatility Models for Pricing European Currency Options

by

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Abstract

This paper focuses on modeling foreign exchange return behavior that would result in more accurate currency options pricing. These alternative approaches namely, implied volatility model (IVM), realized volatility model (RVM) and GARCH (1,1) volatility model (GVM) are used in this study. The results, in general suggest that RVM outperforms both IVM and GVM in pricing currency options. In-sample, there is no significant difference between IVM and GVM, but GVM performs better in pricing options than IVM out-of-sample. An implication of our findings is that the traders can use the RVM for high-frequency intra-day data to exploit significant information for pricing next trading day options more accurately.

Keywords: implied volatility model, realized volatility model, GARCH (1,1) volatility model, in-sample, out-of-sample, European currency options

JEL classification: G12, G13

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* I am grateful to Associate Professor Meher Manzur and Dr Felix Chan for their guidance in preparing this paper. I am also grateful to SIRCA for providing data to support of my research work.

1.0 Introduction

Currency options are traded over-the-counter (OTC) and in organized exchanges. According to Bank for International Settlements (BIS) quarterly review from December 2003 to December 2005, the currency options' annual average growth rates were 12.30% and 34.54% for OTC and organized exchanges, respectively. These growth rates are enormous. Unfortunately, ever since the major contribution by Grabbe (1983) and Garman and Kohlhagan (1983), serious research involving the currency options have been missing in the empirical literature.

The pricing of currency options are closely linked to the expected volatility of the underlying exchange rate over the time until expiration for European options. The volatility is inherently unobservable and its accurate measure is crucial for options pricing techniques. The unobservable volatility can be estimated in several ways. First, this can be done by studying volatility implied by option prices in conjunction with specific option pricing models such as Black-Scholes (B-S). Second, the realized volatility can be used for this purpose. Realized volatility can be defined as the sum of intra-day squared return. A third way to estimate unobserved volatility is by fitting parametric econometric models such as generalized autoregressive conditional heteroscedasticity (GARCH).

In practice, option traders use implied volatility (IV) which is widely believed to be the market's best forecast regarding the future volatility over the remaining life of the option. A number of studies have focused on the predictive power of IV. Earlier research by Latane and Rendleman (1976), Schmalensee and Trippi (1978), Chiras and Manaster (1978), Beckers (1981) indicated that IV was a better predictor of actual volatility than volatility based on historical data. Lamourex and Lastrapes (1993) conducted a joint test of the Hull-White (1987) option pricing model and market efficiency, and they find that although IV helps predict volatility, available information in historical data can be used to improve the market's forecasts as measured by IV. Day and Lewis (1992) show that IV in the equity market contains incremental information relative to the conditional volatility from GARCH models. Similar results are also reported in Fleming et al. (1995), Christensen and Prabhala (1998), Fleming (1998), Bates (2000), and Kazantzis and Tessaromatis (2001). Chang and Tabak (2007) presented evidence that IV in option prices contain information that is not present in past returns for the Brazilian exchange rate against U.S. dollar. In contrast, Canina and Figlewski (1993) find that IV has little predictive power for future volatility. Jorion (1995), however, reports that IV outperforms statistical time-series models in terms of information content and predictive power, but IV appears to be too variable relative to future volatility.

Another strand of research has focused on examining the dynamics of IV. Using S&P 100 index option, Harvey and Whaley (1992) report that IV changes can be predicted ahead of time. This study also indicates that IV tends to fall on Fridays and rise on Mondays. Using CBOE Market Volatility Index (VIX), an average of S&P 100 option IV, Fleming et al. (1995), however, rejects inter-week seasonality. Furthermore, this study indicates that VIX is inversely related to the contemporaneous S&P 100 index return, and that both daily and weekly VIX changes are more sensitive to the negative shock than the positive shock in the market. Simon (1997) also reports similar IV asymmetries for treasury bonds and futures options. Ederington and Lee (1996), however show that the IV in the treasury bonds and Eurodollar options on futures markets tend to decline on the days with scheduled announcements as the uncertainty regarding the impact of the announcement on security prices is resolved. Most of the above studies use daily prices favor the conclusion that option prices provide more accurate forecasts than historical information. Furthermore, those studies using low-frequency data often find that contains more relevant information content for future volatilities.

The recent research has emphasized that the additional historical information in high-frequency intraday data can be used to produce volatility forecasts of higher accuracy. The sum of intraday squared returns is defined as realized volatility (RV). Andersen and Bollerslev (1998) find that the RV provides a more accurate estimate of the latent process that defines volatility than is given by daily squared returns. Andersen, Bollerslev, Diebold and Labys (henceforth ABDL) (2001) derived the theoretical and empirical properties of RV for foreign exchange. Blair et al. (2001) results for equity volatility confirm the conclusion of Andersen and Bollerslev (1998). Further similar empirical evidence is provided in Andersen, Bollerslev, Diebold and Ebens (henceforth ABDE) (2001) for US equities. Brandorff -Nielsen and Shephard (2002) also studied the statistical properties of RV in the context of stochastic volatility model. Their findings can be used in conjunction with a model for the dynamics of volatility to produce a more accurate estimate of actual volatility.

As the most popular extension to Engles (1982) ARCH model, the GARCH model of Bollerslev (1986) has been the most successful model for financial market volatility. In the GARCH (1,1) model, the variance of returns is driven by a combination of the latest squared innovation and the previous conditional variance. Duan (1995) was first to propose an option-pricing model based on the assumption that the exchange rate follows a GARCH process. Ritchken and Trevor (1999) and Heston and Nandi (2000) show the empirical successes of GARCH model for pricing options. Gwilym (2001) finds that the GARCH (1,1) model fits stock return data particularly well. Since the foreign currency return is an analogous to stock return, GARCH (1,1) can be appropriate model to capture the volatility of underlying exchange rate return.

Ederington and Guan (2006) hold that IV measure suffers from an obvious chicken and egg problem: calculation of IV requires the option price, and to calculate the appropriate option price requires a volatility estimate. In addition, Pong et al. (2004) show that IV may be a biased representation of market expectations when option prices do not represent equilibrium market price. Kazantzis and Tessaromatis (2001) also find similar empirical evidence. Further Gospodinov et al. (2006) suggest that an unbiased IV can be extracted from near-the-money options.

This paper focuses on exploring the alternative volatility models, namely, implied volatility model (IVM), realized volatility model (RVM) and GARCH (1,1)-based volatility model (GVM) to find which model can best describe the foreign exchange return behavior that leads to more accurate point for pricing currency options. There are several attractive features of this paper. First, as indicated earlier, in comparison to the volume of work on options on stock, stock index, and bonds, options on currencies have so far received much less attention in empirical research. Growth and popularity of foreign currency option has recently been exploding and in that perspective, the current study on pricing of European options on major currencies, including Euro, is expected to help fill the void. Second, this study pays particular attention to the process of highly persistent nature of the underlying exchange rate volatility that can be used as an input for B-S model, rather than proposing an alternative to B-S model for pricing options. Third, this paper innovates on interpolating unbiased IV from the nearest two at-the-money (ATM) options series: one above and one below the underlying exchange rate. Fourth, the IVM has often been found better than historical price model and GVM for pricing options in the literature. If RVM performs better in pricing options than that of IVM and GVM, this will be a novel approach to identify the underlying exchange rate volatility process for pricing currency options accurately.

The paper is organized as follows. The next section gives the research methodology and the data used in this study. The empirical results are discussed in sections 3. The last section concludes the paper.

2.0 Methodology and Data

For methodology, the first step involves selecting a pricing model for pricing currency options. Under the assumption that the underlying asset return follows the geometric Brownian motion with constant volatility, Black and Scholes (1973) first derived a closed form solution for pricing European options. As widely known, B-S model is mainly used for pricing options on stocks. This model also spawns the field of financial engineering, which is dedicated to designing and implementing such derivatives pricing models. B-S model assumes that no dividends are paid on the stock during the life of the option. This model is extended by Merton (1973) for continuous dividends. Since the interest gained on holding a foreign security is equivalent to a continuously paid dividend on a stock share, the Merton version of the B-S can be applied to foreign security. To value currency option, stock prices are substituted for exchange rates. Unless otherwise stated, B-S model is chosen in this paper for pricing European currency options. We describe the details of the B-S model for pricing currency option as follows:

S_t exchange rate at time *t*;

T expiration time of the option;

C_t price of call option in domestic currency at time *t*;

P_t price of put option in domestic currency at time *t*;

X_t option exercise price in domestic currency at time *t*;

R_t^d rate of return on risk-free domestic asset at time *t*;

R_t^f rate of return on risk-free foreign asset at time *t*;

N cumulative normal distribution function;

σ_t volatility of underlying exchange rate at time *t*.

The price of European call and put option on currency is stated as equations (1) and (2), respectively,

$$C_t = S_t e^{-R_t^f T} N(d_1) - X_t e^{-R_t^d T} N(d_2), \tag{1}$$

$$P_t = X_t e^{-R_t^d T} N(-d_2) - S_t e^{-R_t^f T} N(-d_1), \tag{2}$$

where, $d_1 = \dfrac{\ln(S_t/X_t) + \left(R_t^d - R_t^f + \sigma_t^2/2\right)T}{\sigma_t\sqrt{T}}$, and

$$d_2 = \frac{\ln(S_t/X_t) + \left(R_t^d - R_t^f - \sigma_t^2/2\right)T}{\sigma_t\sqrt{T}} = d_1 - \sigma_t\sqrt{T}.$$

For notation convenience, let's define

$\xi_t = S_t e^{-R_t^f}$, $\eta_t = X_t e^{-R_t^d}$,

and equations (1) and (2) can be rewritten as equations (3) and (4), respectively,

$$C_t = \xi_t N\left(d_1(\sigma_t)\right) - \eta_t N\left(d_2(\sigma_t)\right), \tag{3}$$

$$P_t = \eta_t N\left(-d_2(\sigma_t)\right) - \xi_t N\left(-d_1(\sigma_t)\right). \tag{4}$$

In equations (3) and (4), volatility of underlying exchange rate (σ_t) is not directly observable from market. Our objective is to exploit implied volatility model (IVM), realized volatility model (RVM) and GARCH (1,1) volatility model (GVM) to estimate σ_t of trading day t for pricing options in next trading day $(t+1)$.

2.1 Implied Volatility Model (IVM)

In this section we discuss about the construction of implied volatility (IV). The IV of an option contract is the volatility implied by the options market price based on B-S model. In other words, it is the solution for σ_t given C_t, P_t, ξ_t, η_t in equations (3) and (4). It provides market information about the expected exchange rate volatility for the period until the expiry date of the option. Pong et al. (2004) show that IV may be a biased representation of market expectations when option market prices do not represent equilibrium market prices. Kazantzis and Tessaromatis

(2001) also find similar empirical evidence. Further, Gospodinov et al. (2006) suggest that an unbiased IV can be extracted from near at-the-money (ATM) options. In this study, we, therefore, obtain the IV of underlying exchange rate from Datastream which is interpolated from the nearest two ATM options series: one above and one below the underlying exchange rate.

For a call option, if the nearest two ATM strike prices $X_{c,t}^{a}$ *and* $X_{c,t}^{b}$ are above and below of the underlying exchange rate S_t, respectively, the IV per annum is estimated by equation (5),

$$\hat{\sigma}_{c,t}^{IV} = \sqrt{\ln\left(\frac{S_t}{X_{c,t}^{b}}\right)} x\, W + \sqrt{\ln\left(\frac{X_{c,t}^{a}}{S_t}\right)} x\left(1-W\right), \tag{5}$$

where, W is weighted as 0.9. Similarly, for a put option, if the nearest two ATM strike prices $X_{p,t}^{a}$ *and* $X_{p,t}^{b}$ are above and below of the underlying exchange rate S_t, respectively, the IV per annum is estimated by equation (6),

$$\hat{\sigma}_{p,t}^{IV} = \sqrt{\ln\left(\frac{S_t}{X_{p,t}^{b}}\right)} x\, W + \sqrt{\ln\left(\frac{X_{p,t}^{a}}{S_t}\right)} x\left(1-W\right), \tag{6}$$

where, W is weighted as 0.9. As Whaley (1986), among others, shows that the IV of call option price is lower, on average, than IV of put option price. For consistency, we take the average of IV estimated by equations (5) and (6) as stated by equation (7),

$$\hat{\sigma}_{t}^{IV} = \frac{\hat{\sigma}_{c,t}^{IV} + \hat{\sigma}_{p,t}^{IV}}{2} \tag{7}$$

2.2 Realized Volatility Model (RVM)

In this section, the notion of realized volatility (RV) is introduced, which is an unbiased measure for the unobserved market volatility and has wide application for volatility modeling. In many studies, the absolute daily returns and squared daily returns have been chosen as indicators of daily volatility. However, Andersen and Bollerslev (1998) find that both measures are noisy estimators for daily volatility. They show that the sum of intraday squared returns is a closer proxy for daily volatility than either absolute or squared daily returns, providing that sampling is sufficiently frequent. Further, given the Brownian motion, asset return might have quadratic variation (see Baxter and Rennie, 1996). The quadratic variation process, therefore, measures the realized sample-path variation of the squared return process. The theory of quadratic variation suggests that RV is an unbiased and highly efficient estimator of asset return volatility, as discussed in ABDL(2001) and Brandorff-Nielsen and Shephard (2002). By making use of the theory of quadratic variation and arbitrage-free processes, ABDL (2001, 2003) provide theoretical justification for the construction of RV from high frequency intra-day returns.

The RV is constructed by summing the squared intraday returns sampled at a particular frequency. ABDL (2001, 2003) have shown that as sampling becomes more frequent the RV is an increasingly accurate measure of the integrated return volatility. The optimal frequency for constructing RV is unknown. We construct daily RV series using 5 minutes sampling frequency as two sampling frequencies 5 and 30 minutes are the most popular choices in previous studies (see followed by Pong et al., 2004). If S_i is the exchange rate for 5 minutes sampling frequency, underlying exchange rate return in 5 minutes interval is estimated by equation (8),

$$r_i = \ln\left(\frac{S_i}{S_{i-1}}\right). \tag{8}$$

The realized variance of day t is computed by equation (9),

$$v_t = \sum_{i=1}^{n} r_i^2, \tag{9}$$

where n is the total number of interval for option trading period from 7:30 AM to 2:30 PM, Monday to Friday. Since RV is the standard deviation of the realized variance, equation (10) estimates RV per trading day,

$$\hat{\sigma}_t^{RV} = \sqrt{v_t}. \tag{10}$$

Since intra-day data of trading days are used to provide RV estimate, days when the exchange is closed are ignored and the RV per annum should be calculated as equation (11),

$$\hat{\sigma}_t^{RV} = \sqrt{D v_t}, \tag{11}$$

where, D is 252 trading days per year consistent with the normal assumption of options market.

2.3 GARCH(1,1) Volatility Model (GVM)

In this section we describe how to capture the unobservable exchange rate volatility into GARCH (1,1) model. Financial return volatility data is influenced by time dependent information flows which result in pronounced temporal volatility clustering. It means that at times volatility values tend to cluster, together with smooth transitions from higher to lower volatility and conversely.

This phenomenon is not uncommon to most time series of financial returns, and is a source of non-trivial problems. For example, classic option and derivative pricing models have an unknown volatility parameter which is assumed to be constant over time, and which needs to be estimated from past returns. When volatility changes with time in such contexts, it is not clear how to use past returns to obtain a good estimate of volatility for the current time. There has been considerable research on generalized autoregressive conditional heteroscedastic (GARCH) models for dealing with these problems (see Engle (1982), Bollerslev (1986), Engle and Ng (1993) and Glosten et al. (1993)). As GARCH models are useful and robust when analyzing data that appears to exhibit volatility clustering and excessive kurtosis, we apply the GARCH (1,1) process to estimate volatility of the underlying exchange rate. If S_t is the exchange rate for day t, then regression model with normal-GARCH (1,1) error is

$$\ln S_t = \alpha_0 + \alpha_1 \ln S_{t-1} + \varepsilon_t , \tag{12}$$

$$\varepsilon_t = \kappa_t \sqrt{h_t} , \qquad \kappa_t \sim iid\left(0,1\right),$$

$$h_t = \omega + \beta_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1} . \tag{13}$$

Since h_t is the one-period ahead forecast variance based on the past information in equation (13), it is called conditional variance. The conditional variance equation is a function of three terms:

- A constant term: ω.
- News about volatility from the previous period, measured as the lag of the squared residual from equation (12): ε_{t-1}. (the ARCH term).
- Last period's conditional variance: h_{t-1}. (the GARCH term).

Given this specification, equation (14) estimates GARCH (1,1)-based volatility (GV) per trading day,

$$\hat{\sigma}_t^{GV} = \sqrt{h_t}. \tag{14}$$

As previously, the days when the exchange is closed are ignored and the GV per annum is calculated as

$$\hat{\sigma}_t^{GV} = \sqrt{Dh_t}, \tag{15}$$

where, D is 252 trading days per year consistent with the normal assumption of option market.

2.4 Generating the Price Data

In this section we discuss the computing procedures of implied volatility model price (IVMP), realized volatility model price (RVMP) and GARCH (1,1)-based volatility model price (GVMP) in-sample and out-of-sample. For in-sample procedures, the IV, RV and GV are obtained from equations (7), (11) and (15) respectively, using a total 1022 observations. The estimated IV, RV and GV values are used as inputs for equations (3) and (4) to calculate IVMP, RVMP, and GVMP, respectively, for call and put options as follows:

$$\hat{\Pi}_{c,t+1}^{j} = \xi_{t+1} N\left(d_1\left(\hat{\sigma}_t^i\right)\right) - \eta_{t+1} N\left(d_2\left(\hat{\sigma}_t^i\right)\right), \tag{16}$$

$$\hat{\Pi}_{p,t+1}^{j} = \eta_{t+1} N\left(-d_2\left(\hat{\sigma}_t^i\right)\right) - \xi_{t+1} N\left(-d_1\left(\hat{\sigma}_t^i\right)\right), \tag{17}$$

for $\forall i = IV, RV, GV$ and $\forall j = IVMP, RVMP, GVMP$.

For out-of-sample estimations, the sample is truncated, and two steps are involved to generate volatility model prices based on the alternative volatility models. In step one, the IV, RV and GV are estimated by equations (7), (11) and (15), respectively, for the first two-thirds observations of the sample (i.e. 681 observations). In step two, we follow Pong et al. (2004) for generating future implied volatility (FIV) and future realized volatility (FRV). In this procedure, we use an ARMA (2,1) model

$$v_t^i = \gamma_0 + \phi_1 v_{t-1}^i + \phi_1 v_{t-2}^i + \theta_1 \varepsilon_{t-1} + \varepsilon_t, \tag{18}$$

for $\forall i = IV, RV$, for the remaining one-third of the sample (i.e. 341 observations). Again the values of estimated IV and RV in step one are used in step two.

For future GARCH (1,1)-based volatility (FGV), GRACH (1,1) model is used to generate FGV for the last one-third of the sample (i.e. 341 observations) using GV estimated in step one.

Next, the estimated FIV, FRV, and FGV values are used as input for (3) and (4) to calculate IVMP, RVMP, GVMP, respectively, using the following equations for call and put options, respectively,

$$\hat{\Pi}^{j}_{c,t+1} = \xi_{t+1} N\left(d_1\left(\hat{\sigma}^{i}_{t}\right)\right) - \eta_{t+1} N\left(d_2\left(\hat{\sigma}^{i}_{t}\right)\right), \tag{19}$$

$$\hat{\Pi}^{j}_{p,t+1} = \eta_{t+1} N\left(-d_2\left(\hat{\sigma}^{i}_{t}\right)\right) - \xi_{t+1} N\left(-d_1\left(\hat{\sigma}^{i}_{t}\right)\right), \tag{20}$$

for $\forall i = FIV, FRV, FGV$ and $\forall j = IVMP, RVMP, GVMP$.

2.5 Measuring Price Deviations

In this section we set up the criteria to measure the implied volatility model pricing error (IVMPE), realized volatility model pricing error (RVMPE), and GARCH(1,1)-based volatility model pricing error (GVMPE) for in-sample and out-of-sample. If $\Pi^{ATM}_{i,t+1}$ and $\hat{\Pi}^{j}_{i,t+1}$ represent observed ATM option prices and estimated model-based prices, respectively, we have the following criteria to calculate IVMPE, RVMPE and GVMPE for *n* number of observations in the sample:

(i) The mean squared error (MSE) = $\frac{1}{n}\sum_{t=1}^{n}(\Pi^{ATM}_{i,t+1} - \hat{\Pi}^{j}_{i,t+1})^2$,

(ii) The mean absolute error (MAE) = $\frac{1}{n}\sum_{t=1}^{n}\left|\Pi^{ATM}_{i,t+1} - \hat{\Pi}^{j}_{i,t+1}\right|$,

(iii) The mean absolute percentage error (MAPE) = $\frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{\Pi}^{j}_{i,t+1} - \Pi^{ATM}_{i,t+1}}{\Pi^{ATM}_{i,t+1}}\right|$,

for $\forall i = C, P$ and $\forall j = IVMP, RVMP, GVMP$.

2.6 Significance Tests of Price Deviations

Next, we examine whether the deviations of estimated prices from the observed prices in section 2.5 (i.e. IVMPE, RVMPE and GVMPE) are statistically different from each other, so that a comparison can be made as to the performance of alternative volatility models for pricing options. Diebold and Mariano (1995) propose a test statistic that explicitly tests the null hypothesis of no difference in the accuracy of two competing forecasts. This statistic can easily be applied to test whether the IVMPE, RVMPE and GVMPE are statistically different from each other.

The original test compares the errors $\left(e_{1,t}, e_{2,t}\right)$, $t=1,........,n,$ produced by two competing forecasts. These forecasts are evaluated using some loss function, $f\left(e\right)$, and the null hypothesis is the equality of the expected forecast performance, $E\left[f\left(e_{1,t}\right)-f\left(e_{2,t}\right)\right]=0.$ For our purpose, the relevant loss function is the MSE, MAE and MAPE computed by each competing volatility model. For n number of observations, the original statistic proposed by Diebold and Mariano (1995) is given by

$$S_1 = \frac{\bar{d}}{\sqrt{\hat{V}\left(\bar{d}\right)}}, \tag{21}$$

where,

$$d_t = f\left(e_{1,t}\right) - f\left(e_{2,t}\right) \quad and \quad t=1,.........,n;$$

$$\bar{d} = \frac{1}{n}\sum_{t=1}^{n} d_t\,; \qquad V\left(\bar{d}\right) = \frac{1}{n}\left[\mathrm{var}(d_t)\right].$$

However, Harvey et al. (1997) showed that the original statistic proposed by Diebold and Mariano (1995) can be over-sized and proposed the following adjusted statistic;

$$S_t^* = \sqrt{\frac{n-1}{n}}\, x\left(S_1\right). \tag{22}$$

We use this adjusted test statistic which follows a t-distribution with $n-1$ degrees of freedom.

2.7 The Data

The data for three major European currency options, namely, British pound, Swiss franc and Euro traded in Philadelphia Stock Exchange from 22 July 2002 to 30 June 2006 are obtained from Datastream. The options are written for maximum 3 months and traded on Mondays through Fridays excluding public holidays from 7:30 AM to 2:30 PM. The data consist of daily ATM options prices, ATM strike prices, closing spot exchange rates, Eurocurrency (i.e. British pound, Swiss franc, Euro) and domestic currency (U.S. dollar) interest rates.

For each sample currency, the daily ATM implied volatility of underlying exchange rate for call and put option are also obtained from Datastream. The GARCH (1,1)-based volatility is generated for daily closing spot exchange rates. In order to construct realized volatility with 5-min frequency Reuter's data, the intra-day exchange rate quotations for the sample currencies against U.S. dollar are extracted from SIRCA database for the sample period. Reuters provides intra-day trade and quote information for over 240 markets around the world with data coverage beginning in January 1996. The Microsoft Structured Query Language (SQL) is used to manipulate the high frequency intra-day exchange rate data as described in Table 1. The total number of quotations for sample period, average number of quotations per day and average number of quotations per 5-min are presented in columns 2, 3 and 4 of Table 1, respectively. In column 3, the average number of quotations per day is computed by the total number of quotations for sample period from column 2 is divided by number of trading days (i.e. 1022). Similarly in column 4, the average number of quotations per 5-min is computed by average number of quotations per day from column 3 is divided by total number of intervals for 5-min frequency per trading day (i.e. 84). Further, 20, 16, 17 corresponds to the average number of quotations per 5-min for British pound, Swiss franc and Euro, respectively, indicate the high volume of quotations due to keep changing the market information.

The total number of 5-min interval quotations for sample period and average number of 5-min interval quotations per day are presented in columns 5 and 6 of Table 1, respectively. In column 6, the average number of 5-min interval quotations per day is computed by the total number of 5-min interval quotations for sample period from column 5 is divided by number of trading days (i.e. 1022). The average number of 5-min interval quotations per day should be 85. For British pound, the average number of 5-min interval quotations per day is 43 and 85 for two sub-sample periods 22/07/2002 – 05/08/2004 and 06/08/2004 – 30/06/2006, respectively. For whole sample, the average number of 5-min interval quotations per day quotation is, therefore, 63 as the average of 43 and 85 of two sub-sample periods. For Swiss franc and Euro, the average number of 5-min interval quotations per day is 84 which are consistent.

Table 1: Intra-day exchange rate data description for realized volatility construction

Exchange rate against U.S. dollar	Sample period: 22/07/2002 - 30/06/2006; Trading hours: 0730 – 1430; Trading days: 1022				
	Total number of quotations for sample	Average number of quotations per day	Average number of quotations per 5-min	Total number of 5-min interval quotations for	Average number of 5-min interval
British pound	1,723,712	1687	20	64,700	64
Swiss franc	1,381,667	1352	16	86,161	84
Euro	1,482,584	1451	17	86,276	84

Average number of quotation per day = Total number of quotations for sample period ÷ number of trading days (i.e.1022);
Average number of quotations per 5-min = Average number of quotation per day ÷ number of 5-min interval per day (i.e.85);
Average number of 5-min interval quotations per day = Total number of 5-min interval quotations for sample period ÷ number of 5-min interval per day (i.e.85).

3.0 Empirical Results

We start with a snapshot of empirical results. Figures 1, 2, and 3 show the time series of implied volatility, GARCH (1,1) volatility and realized volatility for British pound/U.S. dollar, Swiss franc/U.S. dollar and Euro/U.S. dollar exchange rate, respectively. In all Figures, the vertical axis represents volatility in percentage and the horizontal axis represents trading dates. All Figures show the level of implied volatility, GARCH (1,1) volatility and realized volatility in solid line, broken line and non-smoothed solid line, respectively. Consistent with the findings of Jackwerth and Rubinstein (1996) and Doran and Ronn (2005), the sample clearly indicates that implied volatility is higher than realized volatility for all currency exchange rates. GARCH (1,1) volatility is also higher than realized volatility and followed by implied volatility.

Fig 1: Implied, GARCH(1,1) and Realized Volatility for British pound/US dollar Exchange Rate

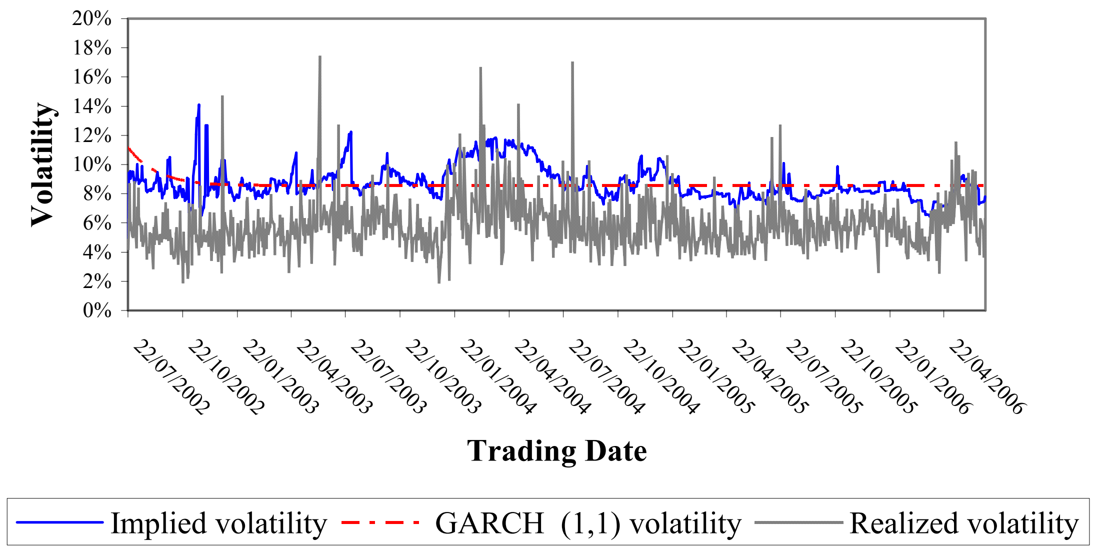
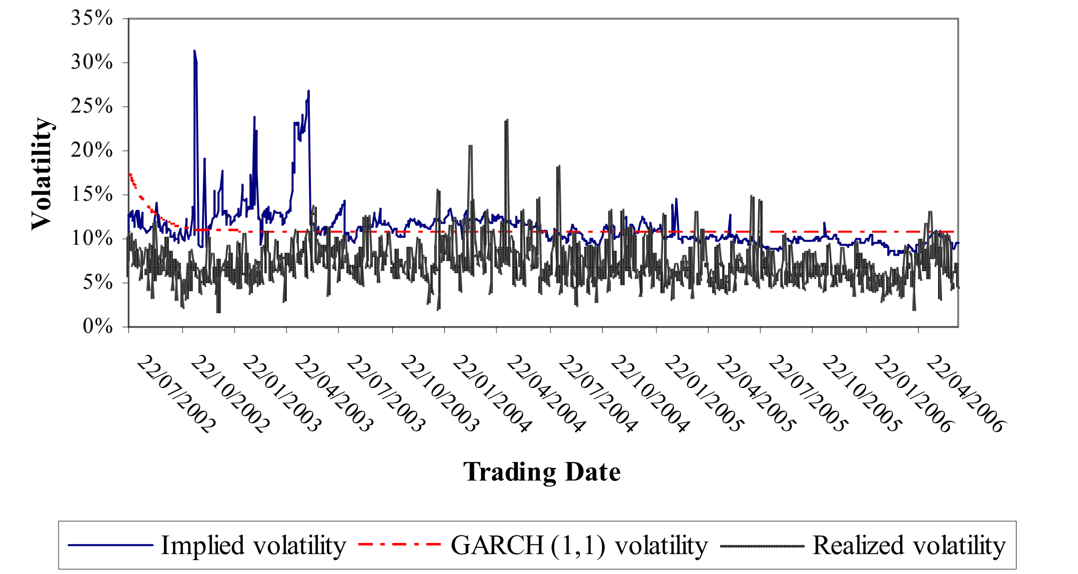
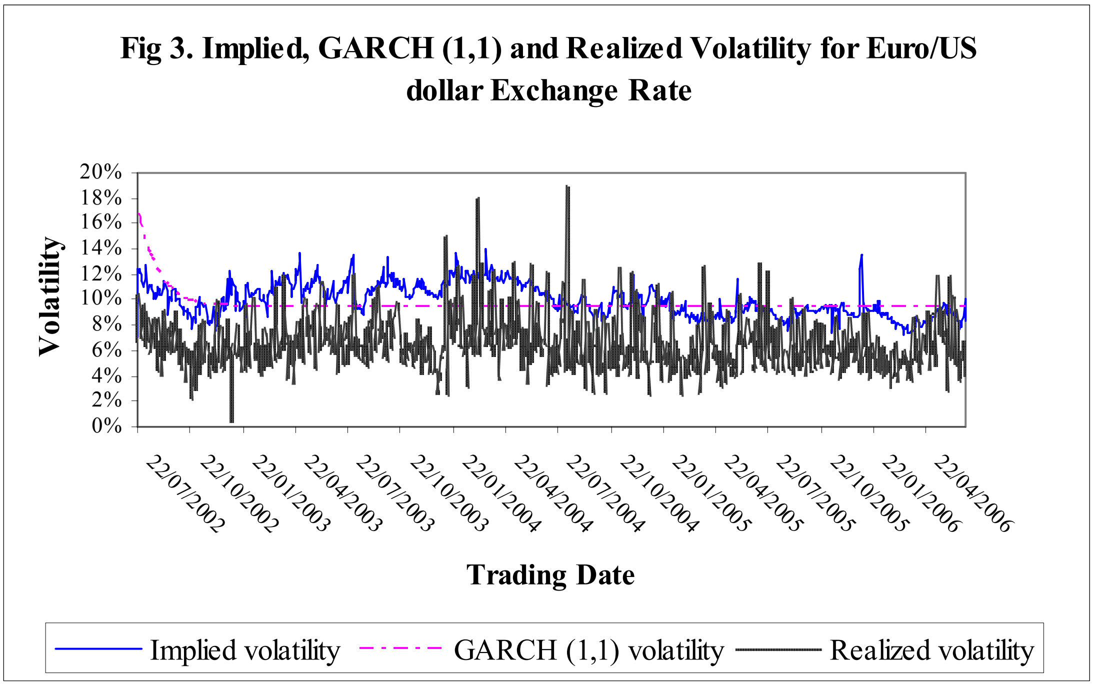


Fig 2: Implied, GARCH (1,1) and Realized Volatility for Swiss franc/US dollar Exchange Rate





3.1 In-sample Results

In this section we compare IVMPE, RVMPE and GVMPE for in-sample to assess the performance of IVM, RVM and GVM, respectively, for pricing next trading day options. The estimation of GARCH (1,1) using equation (12) for 1022 observations of underlying daily closing exchange rate is presented in Table 2. As can be seen the sum of coefficients β_1 and γ_1 of equation (13) is less than 1 indicates the validity of GV based on GARCH (1, 1) estimations for all currency. The estimated GV is used to generate GVMPE which are reported in Tables 4 and 5.

Table 2: In-sample GARCH (1, 1) estimation for GV

Currency	Coefficients		
	ω	β_1	γ_1
British pound	9.47E-07 (1.5259)	0.0294 (2.2005)	0.9381 (31.3732)
Swiss franc	3.39E-06 (1.3091)	0.0084 (1.2478)	0.9216 (16.9635)
Euro	1.72E-06 (1.4995)	0.0165 (1.3969)	0.9354 (24.5264)

GARCH (1,1) estimation by equation (12) for 1022 observations of underlying exchange rate. The coefficients of equation (13) with t-ratios in the parenthesis are presented.

The comparison of RVMPE and IVMPE for MSE, MAE and MAPE measures are given in Table 3. For British pound call option, 4.81E-5, 6.07E-5, and -20.76% corresponds to the RVMPE, IVMPE, and difference between RVMPE and IVMPE in per cent, respectively, under MSE measure. Similarly, rest of the Table 3 is populated. The negative differences in column 6 indicate that RVMPE is less than IVMPE under each assessment criteria for all currency options.

Table 3: Comparison of RVMPE and IVMPE for in-sample

Measures	Currency	Options	Model pricing errors		
			RVMPE	IVMPE	$\frac{\text{RVMPE} - \text{IVMPE}}{\text{IVMPE}}\,\%$
MSE	British pound	Call	4.81E-5	6.07E-5	-20.76
		Put	6.90E-5	1.05E-4	-34.29
	Swiss franc	Call	2.31E-5	4.11E-5	-43.80
		Put	1.83E-5	2.48E-5	-26.21
	Euro	Call	3.36E-5	5.19E-5	-35.26
		Put	4.57E-5	6.23E-5	-26.65
MAE	British pound	Call	0.0056	0.0063	-11.11
		Put	0.0065	0.0082	-20.73
	Swiss franc	Call	0.0038	0.0051	-25.49
		Put	0.0033	0.0039	-15.38
	Euro	Call	0.0046	0.0058	-20.69
		Put	0.0049	0.0058	-15.52
MAPE	British pound	Call	0.3650	0.4539	-19.59
		Put	0.3647	0.4871	-25.13
	Swiss franc	Call	0.4039	0.5683	-28.93
		Put	0.4848	0.8212	-40.96
	Euro	Call	0.3609	0.4906	-26.44
		Put	0.3960	0.5085	-22.12

Negative differences indicate that RVPE is less than IVPE by reported percentage.

The Table 4 is constructed as the Table 3 and populated with the data of RVPE and GVPE. As can be seen the negative differences between RVPE and GVPE in the last column under MSE, MAE, and MAPE measures, indicate that the RVPE is lower than GVPE for all currency. In general, the results in Tables 3 and 4 suggest that the RVMP fits in-sample market price better than that of IVMP and GVMP.

Table 4: Comparison of RVMPE and GVMPE for in-sample

Measures	Currency	Options	Model pricing errors		
			RVMPE	GVMPE	$\frac{\text{RVMPE} - \text{GVMPE}}{\text{GVMPE}}$ %
MSE	British pound	Call	4.81E-5	6.46E-05	-25.54
		Put	6.90E-5	1.04E-04	-33.65
	Swiss franc	Call	2.31E-5	3.81E-05	-39.37
		Put	1.83E-5	2.22E-05	-17.57
	Euro	Call	3.36E-5	4.93E-05	-31.85
		Put	4.57E-5	5.62E-05	-18.68
MAE	British pound	Call	0.0056	0.0065	-13.85
		Put	0.0065	0.0083	-21.69
	Swiss franc	Call	0.0038	0.0050	-24.00
		Put	0.0033	0.0039	-15.38
	Euro	Call	0.0046	0.0056	-17.86
		Put	0.0049	0.0056	-12.50
MAPE	British pound	Call	0.3650	0.4743	-23.05
		Put	0.3647	0.5025	-27.42
	Swiss franc	Call	0.4039	0.5615	-28.07
		Put	0.4848	0.6440	-24.72
	Euro	Call	0.3609	0.4824	-25.19
		Put	0.3960	0.5036	-21.37

Negative differences indicate that RVPE is less than GVPE by reported percentage.

Table 5 consists of IVMPE and GVMPE under MSE, MAE and MAPE measures and structured as the Table 3. If more than 10% differences between IVMPE and GVMPE in the last column are notable, the positive differences can only be seen for Swiss franc put for MSE and MAPE criteria and Euro put for MSE criterion. It means the GVMPE is less than IVMPE only for Swiss franc put under MSE and MAPE measures and Euro put under MSE measure. Overall there are no remarkable differences between IVMPE and GVMPE.

Table 5: Comparison of IVMPE and GVMPE for in-sample

Measures	Currency	Options	Model pricing errors		
			IVMPE	GVMPE	$\frac{\text{IVMPE} - \text{GVMPE}}{\text{GVMPE}}$ %
MSE	British pound	Call	6.07E-5	6.46E-05	-6.04
		Put	1.05E-4	1.04E-04	0.96
	Swiss franc	Call	4.11E-5	3.81E-05	7.87
		Put	2.48E-5	2.22E-05	11.71
	Euro	Call	5.19E-5	4.93E-05	5.27
		Put	6.23E-5	5.62E-05	10.85
MAE	British pound	Call	0.0063	0.0065	-3.08
		Put	0.0082	0.0083	-1.20
	Swiss franc	Call	0.0051	0.0050	2.00
		Put	0.0039	0.0039	0.00
	Euro	Call	0.0058	0.0056	3.57
		Put	0.0058	0.0056	3.57
MAPE	British pound	Call	0.4539	0.4743	-4.30
		Put	0.4871	0.5025	-3.06
	Swiss franc	Call	0.5683	0.5615	1.21
		Put	0.8212	0.6440	27.51
	Euro	Call	0.4906	0.4824	1.70
		Put	0.5085	0.5036	0.97

Positive differences indicate that IVPE is greater than GVPE by reported percentage. Negative differences indicate that GVPE is greater than IVPE by reported percentage.

Now we examine whether IVPE, RVPE and GVPE are statistically different from each other under the framework proposed by Diebold and Mariana (1995) and the results are given in Table 6. The IVMPE and RVMPE are statistically different (i.e. $\text{IVMPE}^a \neq \text{RVMPE}^b$) at 1 percent level of significance for all currency options. Further the positive differences in column 3 indicate that RVMPE is less than IVMPE. Similarly, the GVMPE and RVMPE are not statistically equal (i.e. $\text{GVMPE}^a \neq \text{RVMPE}^b$) at 1 percent level of significance and the positive differences in column 4 indicate that RVMPE is less than GVMPE for all currency options. The results shown in columns 3 and 4 of Table 6 are consistent with the results reported in Tables 3 and 4, respectively. In column 5, the results indicate that GVMPE and IVMPE are not statistically different (i.e. $\text{GVMPE}^a = \text{IVMPE}^b$) at 1 percent level of significance for all currency options that supporting the conclusion of Table 5.

Table 6: In-sample model pricing errors equality test

Currency	Options	IVMPE[a] - RVMPE[b]	GVMPE[a] - RVMPE[b]	GVMPE[a] - IVMPE[b]
British pound	Call	4.23*	5.08*	1.86
	Put	7.99*	8.80*	1.08
Swiss franc	Call	10.38*	13.77*	-1.43
	Put	4.80*	5.33*	0.03
Euro	Call	7.22*	11.04*	-2.28
	Put	5.39*	4.74*	-2.54

The test statistic follows a t-distribution with $n-1$ degrees of freedom. * denotes 1% level of significance. The positive values indicate that model pricing error of superscript (a) is greater than the model pricing error of superscript (b). The negative values indicate that model pricing error of superscript (a) is less than the model pricing error of superscript (b).

3.2 Out-of-sample Results

In-sample test results, in general, indicate that RVM outperforms IVM and GVM in context of pricing options. One may argue that the RVMP fits in-sample better due to its additional explanatory power as a proxy of true exchange rate volatility. It is, therefore, further necessary to compute and compare the IVMPE, RVMPE and GVMPE for out-of-the sample to weigh up the performance of IVM, RVM and GVM, respectively, for pricing options. The estimation of GARCH (1,1) using equation (12) for 681 observations (i.e. two-third of the sample) of underlying daily closing exchange rate is presented in Table 7. As can be seen the sum of coefficients β_1 and γ_1 of equation (13) is less than 1 indicates validity of GV based on GARCH (1, 1) estimations for all currency. The estimated GV is used to generate GVMPE which are reported in Tables 11 and 12.

Table 7: Out-of-sample GARCH (1, 1) estimation for GV

Currency	Coefficients		
	ω	β_1	γ_1
British pound	8.33E-07 (1.5297)	0.0376 (2.3465)	0.9340 (32.5028)
Swiss franc	6.20E-05 (2.8513)	0.0429 (2.6232)	-0.1772 (0.4549)
Euro	1.88E-06 (1.3263)	0.0216 (1.3140)	0.9293 (20.6174)

GARCH (1,1) estimation by equation (12) for first 681 observations of underlying exchange rate (i.e. about two-third of the sample) to generate future GARCH (1,1)-based volatility (FGV) for last 341 observations (i.e. one-third of the sample). The coefficients of equation (13) with t-ratios in the parenthesis are presented.

The estimation of ARMA (2,1) using equation (18) for 681 observations (i.e. two-third of the sample) of RV is presented in Table 8. As can be seen the sum of coefficients φ_1 and φ_2 of equation (18) is less than 1 indicates the validity of RV for out-of-sample based on ARMA (2,1) estimations for all currency. The estimated RV is used to generate RVMPE that are reported in Tables 10 and 11.

Table 8: Out-of-sample ARMA (2, 1) estimation for RV

Currency	Coefficients			
	γ	φ_1	φ_2	θ_1
British pound	0.0016 (1.8037)	1.028 (19.8928)	-0.0548 (1.2267)	-0.8811 (26.3900)
Swiss franc	0.0029 (2.0031)	0.9493 (17.4418)	0.0102 (0.2299)	-0.8620 (22.4425)
Euro	0.0041 (2.1912)	0.9182 (14.6192)	0.0191 (0.4157)	-0.8208 (16.4362)

ARMA (2,1) estimation by equation (18) for first 681 observations of RV (i.e. about two-third of the sample) to generate future realized volatility (FRV) for last 341 observations (i.e. one-third of the sample). Coefficients of equation (18) for RV with t-ratios in the parenthesis are presented.

Similarly, The estimation of ARMA (2,1) using equation (18) for 681 observations (i.e. two-third of the sample) of IV is presented in Table 9. As can be seen the sum of coefficients φ_1 and φ_2 of equation (18) is less than 1 indicates the validity of IV based on ARMA (2,1) estimations for all currency. The estimated IV is used to generate IVMPE that are reported in Tables 10 and 12.

Table 9: Out-of-sample ARMA (2, 1) estimation for IV

Currency	Coefficients			
	γ	φ_1	φ_2	θ_1
British pound	0.0098 (4.0548)	0.8849 (6.3327)	0.0077 (0.0638)	-0.0787 (0.5447)
Swiss franc	0.0028 (1.5079)	1.5428 (13.7267)	-0.5666 (5.7560)	-0.8105 (8.4973)
Euro	0.0047 (3.1708)	1.0253 (12.1898)	-0.0708 (0.9243)	-0.4324 (5.292)

ARMA (2,1) estimation by equation (18) for first 681 observations of IV (i.e. about two-third of the sample) to generate future implied volatility (FIV) for last 341 observations (i.e. one-third of the sample). Coefficients of equation (18) for IV with t-ratios in the parenthesis are presented.

In this section, the construction method of Tables 10, 11 and 12 are same as Table 3 for out-of-sample. The RVMPE and IVMPE and the difference between RVMPE and IVMPE in per cent under MSE, MAE, and MAPE measures are presented in Table 10. As can be seen the negative differences between RVMPE and IVMPE in the last under MSE, MAE, and MAPE measures, indicate that the RVMPE is substantially less than IVMPE for all currency options.

Table 10: Comparison of RVMPE and IVMPE for out-of-sample

Measures	Currency	Options	Model pricing errors		
			RVMPE	IVMPE	$\frac{\text{RVMPE} - \text{IVMPE}}{\text{IVMPE}}$ %
MSE	British pound	Call	3.75E-05	1.21E-04	-69.01
		Put	4.02E-05	1.17E-04	-65.64
	Swiss franc	Call	2.13E-05	6.58E-05	-67.63
		Put	6.99E-06	2.88E-05	-75.73
	Euro	Call	2.92E-05	9.28E-05	-68.53
		Put	1.56E-05	5.41E-05	-71.16
MAE	British pound	Call	0.0050	0.0094	-46.81
		Put	0.0052	0.0091	-42.86
	Swiss franc	Call	0.0038	0.0069	-44.93
		Put	0.0021	0.0047	-55.32
	Euro	Call	0.0045	0.0083	-45.78
		Put	0.0031	0.0064	-51.56
MAPE	British pound	Call	0.3436	0.7016	-51.03
		Put	0.3302	0.6227	-46.97
	Swiss franc	Call	0.4204	0.8069	-47.90
		Put	0.2747	0.6948	-60.46
	Euro	Call	0.3616	0.7090	-48.50
		Put	0.2895	0.6551	-55.81

Negative differences indicate that RVPE is less than IVPE by reported percentage.

The Table 11 includes RVMPE, GVMPE and the difference between RVMPE and GVMPE in per cent under MSE, MAE, and MAPE measures. As can be seen the negative differences between RVMPE and GVMPE in column 6 under MSE, MAE and MAPE comparison criteria, specify that the RVMPE is significantly less than IVMPE for all currency options. The results in Tables 10 and 11 suggest that the RVMP fits out-of-sample market price considerably better than that of IVMP and

GVMP. The out-of-sample results in Tables 10 and 11 are surprisingly similar to the in-sample results reported in Tables 3 and 4, respectively.

Table 11: Comparison of RVMPE and GVMPE for out-of-sample

Measures	Currency	Options	Model pricing errors		
			RVMPE	GVMPE	$\frac{\text{RVMPE} - \text{GVMPE}}{\text{GVMPE}}$ %
MSE	British pound	Call	3.75E-05	9.79E-05	-61.70
		Put	4.02E-05	9.53E-05	-57.82
	Swiss franc	Call	2.13E-05	6.52E-05	-67.33
		Put	6.99E-06	2.83E-05	-75.30
	Euro	Call	2.92E-05	8.10E-05	-63.95
		Put	1.56E-05	4.52E-05	-65.49
MAE	British pound	Call	0.0050	0.0083	-39.76
		Put	0.0052	0.0081	-35.8
	Swiss franc	Call	0.0038	0.0068	-44.12
		Put	0.0021	0.0047	-55.32
	Euro	Call	0.0045	0.0076	-40.79
		Put	0.0031	0.0057	-45.61
MAPE	British pound	Call	0.3436	0.6212	-44.69
		Put	0.3302	0.5505	-40.02
	Swiss franc	Call	0.4204	0.7992	-47.40
		Put	0.2747	0.6839	-59.83
	Euro	Call	0.3616	0.6520	-44.54
		Put	0.2895	0.5855	-50.56

Negative differences indicate that RVPE is less than GVPE by reported percentage.

Table 12 consists of IVMPE, GVMPE and the difference between IVMPE and GVMPE under MSE, MAE and MAPE measures. In column 6, the positive differences between IVMPE and GVMPE for British pound call and put under all measures, Euro call for MSE criterion and Euro put for all assessment criteria are found as previously the differences more than 10% are notable. In general, the results indicate that the GVMPE is less than IVMPE for out-of-sample.

Table 12: Comparison of IVMPE and GVMPE for out-of-sample

Measures	Currency	Options	Model pricing errors		
			IVMPE	GVMPE	$\frac{\text{IVMPE} - \text{GVMPE}}{\text{GVMPE}}$ %
MSE	British pound	Call	1.21E-04	9.79E-05	23.60
		Put	1.17E-04	9.53E-05	22.77
	Swiss franc	Call	6.58E-05	6.52E-05	0.92
		Put	2.88E-05	2.83E-05	1.77
	Euro	Call	9.28E-05	8.10E-05	14.57
		Put	5.41E-05	4.52E-05	19.69
MAE	British pound	Call	0.0094	0.0083	13.25
		Put	0.0091	0.0081	12.35
	Swiss franc	Call	0.0069	0.0068	1.47
		Put	0.0047	0.0047	0.00
	Euro	Call	0.0083	0.0076	9.21
		Put	0.0064	0.0057	12.28
MAPE	British pound	Call	0.7016	0.6212	12.94
		Put	0.6227	0.5505	13.12
	Swiss franc	Call	0.8069	0.7992	0.96
		Put	0.6948	0.6839	1.59
	Euro	Call	0.7090	0.6520	8.74
		Put	0.6551	0.5855	11.89

Positive differences indicate that IVPE is greater than GVPE by reported percentage. Negative differences indicate that GVPE is greater than IVPE by reported percentage

Now we examine whether IVPE, RVPE and GVPE are statistically different from each other under the framework proposed by Diebold and Mariana (1995) and the results are given in Table 13. The IVMPE and RVMPE are statistically different (i.e. $IVMPE^a \neq RVMPE^b$) at 1 percent level of significance for all currency options. Further the positive differences in column 3 indicate that RVMPE is less than IVMPE. Similarly, the GVMPE and RVMPE are not statistically equal (i.e. $GVMPE^a \neq RVMPE^b$) at 1 percent level of significance and the positive differences in column 4 indicate that RVMPE is less than GVMPE for all currency options. The results in columns 3 and 4 of Table 13 convey the information same as the results stated in Tables 10 and 11, respectively. It can also be seen that the GVMPE and IVMPE are statistically different (i.e. $GVMPE^a \neq IVMPE^b$) at 1 percent level of significance for all currency. As can be seen the negative differences between GVMPE and IVMPE in the last column indicate that GVMPE is less than IVMPE which also supporting the conclusion of Table 12.

Table 13: Equality of pricing error out of the sample test

Currency	Options	IVMPE[a] - RVMPE[b]	GVMPE[a] - RVMPE[b]	GVMPE[a] - IVMPE[b]
British pound	Call	13.31*	11.26*	-22.94*
	Put	11.35*	9.19*	-22.42*
Swiss franc	Call	14.91*	14.60*	-2.63*
	Put	13.66*	13.45*	-2.68*
Euro	Call	14.36*	12.56*	-15.75*
	Put	12.94*	10.94*	-16.26*

The test statistic follows a t-distribution with $n-1$ degrees of freedom. * denotes 1% level of significance. The positive values indicate that model pricing error of superscript (a) is greater than the model pricing error of superscript (b). The negative values indicate that model pricing error of superscript (a) is less than the model pricing error of superscript (b).

Overall, the in-sample and out-of-sample results for RVMPE against IVMPE and GVMPE are remarkably similar. While the IVMPE and GVMPE are consistent for in-sample, there are some notable differences for out-of-sample.

4.0 Conclusion

Due to explosive growth and popularity of foreign currency option, we focus on pricing of European options for European major currencies, including Euro traded in Philadelphia Stock Exchange. Our study pays particular attention to the highly persistent nature of exchange rate volatility process. We explore implied volatility model (IVM), realized volatility model (RVM) and GARCH (1,1) volatility model (GVM) to propose the volatility model that can best describe the foreign exchange return behavior to lead more accurate point for pricing currency options.

The summary of the assessment procedure for IVM, RVM and GVM are as follows. First, we compute the volatility model pricing error as the variation of the volatility model price and ATM options market price under MSE, MAE, and MAPE measures for in-sample and out-of-sample. Secondly, we compare the volatility model pricing errors to assess the capability of different models to capture the underlying foreign exchange return behavior of trading day t for pricing next trading day $(t+1)$ options accurately. Further supporting of the above assessment, we compare the volatility model pricing errors under the framework proposed by Diebold and Mariana (1995) for in-sample and out-of-sample.

We find that the RVMP fits in-sample as well as out-sample market price considerably better than that of IVMP and GVMP. The overall evidence presented in this research work strongly suggests that RVM outperforms IVM and GVM in context of pricing options for both in-sample and out-of-sample. It happens as RVM contains more significant information than the information embedded in IVM and GVM of trading day t for pricing next trading day $(t+1)$ options. Since, the IV is interpolated from ATM option strike prices, the IVM can capture the foreign exchange return behavior only for the specific point of time of the trading day t at which the ATM option strike price is extracted. Similarly, the GVM can describe only for closing time foreign exchange return behavior of the trading day t as the GV is generated for daily closing exchange rate. Further, the RV is constructed from 5-min interval intra-day data. The RVM, therefore, sum up the information of foreign exchange return behavior for the whole trading day t that changes in every 5 minutes interval. In other words, the RVM constructing from high-frequency intraday data that contain adequate information of trading day t which cannot be accommodated by the standard daily level volatility models such as IVM and GVM for pricing next trading day $(t+1)$ options accurately.

Recently, Andersen at el. (in press) suggested modeling and forecasting the realized volatility of exchange rate, stock and bond returns by extracting the component due to jumps. Consistent with the findings of Andersen at el. (in press), jumps appeared in the realized volatility time series in Figures 1, 2, and 3 in section 3. Further Lanne (2007) addresses this issue by decomposing the realized volatility into its continuous sample path and jump components, and modeling and forecasting them separately instead of directly forecasting the realized volatility which improved out-of-sample forecasts. As far as the jump component is concerned, further improvements of RVM might be attainable by the use of model proposed by Lanne (2007) for pricing options more accurately. We left it for the future research.

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