Intraday volatility forecasting from implied volatility

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Abstract

Purpose – The purpose of this paper is to examine whether the superiority of the implied volatility from a stochastic volatility model over the implied volatility from the Black and Scholes model on the forecasting performance of future realized volatility still holds when intraday data are analyzed.

Design/methodology/approach – Two implied volatilities and a realized volatility on KOSPI200 index options are estimated every hour. The grander causality tests between an implied volatility and a realized volatility is carried out for checking the forecasting performance. A dummy variable is added to the grander causality test to examine the change of the forecasting performance when a specific environment is chosen. A trading simulation is conducted to check the economic value of the forecasting performance.

Findings – Contrary to the previous studies, the implied volatility from a stochastic volatility model is not superior to that from the Black and Scholes model for the intraday volatility forecasting even if both implied volatilities are informative on one hour ahead future volatility. The forecasting performances of both implied volatilities are improved under high volatile market or low return market.

Practical implications – The trading strategy using the forecasting power of an implied volatility earns positively, in particular, more positively under high volatile market or low return market. However, it looks risky to follow the trading strategy because the performance is too volatile. Between two implied volatilities, it is hardly to say that one implied volatility beats another in terms of the economic value.

Originality/value – This is the first study which shows the forecasting performances of implied volatilities on the intraday future volatility.

Keywords Stocks, Financial forecasting, Financial risk, Economic fluctuations

Paper type Research paper

1. Introduction

Although intraday volatility forecasting has barely been studied, the issue is of interest not only practitioners, but also to academics, as option markets grow. So far, research on volatility forecasting has focused on the performance of a month-ahead future (realized) volatility, which is estimated by daily closing data. According to previous studies, the Black and Scholes (1973) (henceforth BS) approach to implied volatility from option prices is considered the best estimate of future volatility. Latane and Rendleman (1976), an early study on volatility forecasting, showed the positive correlation between implied volatility and ex-post realized volatility, when the cross-section data on the stock option is analyzed. Day and Lewis (1992), Lamoureux and Lastrapes (1993), Jorion (1995), and Fleming (1998) conducted time series analysis and showed that BS implied volatility is efficient, but biased as an estimator of future realized volatility.

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Some later studies question whether BS implied volatility is really the best estimate of future volatility and have attempted to find a better estimator. Guo (1996), Poteshman (2000) and Byun *et al.* (2009) use Heston's (1993) model, which is one of stochastic volatility (henceforth SV) models, to derive the implied volatility from option prices. For the following reason, they commonly believe that the bias from the BS implied volatility can be reduced, if the implied volatility from the SV model is introduced. Owing to the "volatility smile" phenomenon, the BS model is considered not to explain the option market correctly. Bakshi *et al.* (1997, 2000) show that the SV most effectively reduces the problems associated with the BS model. Thus, they introduce the SV model and compare the forecasting performance of Heston's (1993) implied volatility with that of BS implied volatility on future volatility. As they anticipated, the forecasting performance of Heston's (1993) implied volatility is shown to be superior to that of BS implied volatility, when the performance of month-ahead future-realized volatility is analyzed. In particular, Byun *et al.* (2009) show that Heston's (1993) implied volatility dominates not only BS implied volatility, but also VIX and model-free implied volatility for the forecasting performance of future volatility.

In the empirical analysis on the forecasting performance of future volatility, we fill the following gaps that have not been resolved by previous research. For a start, this is the first study, which shows the forecasting performance of implied volatilities with respect to intraday future volatility. Because many current researchers, such as Benavides (2004), Blair *et al.* (2001), Ederington and Guan (2002), Glot (2003), and Neely (2002), show that implied volatility is superior to historical volatility for the forecasting performance of future volatility, this study focuses on the forecasting performance of implied volatility. In particular, this study determines whether the performance of Heston's (1993) implied volatility is still superior to that of BS implied volatility when an hour-ahead future realized volatility is analyzed. In addition, the paper considers whether a trading strategy, which takes advantage of the forecasting power of an implied volatility on a future realized volatility can be effective in making money. Secondly, this study analyses the forecasting performance of future volatility on the KOSPI200 index option market. Most stock option markets are inadequate for analyzing intraday volatility forecasting, because of insufficient trade volume. The KOSPI200 index option market, which is the largest stock index option market in the world in terms of trading volume, seems the ideal candidate for this analysis. According to Table I, no market can beat the KOSPI200 index option market in terms of the number of contracts. Finally, this study analyzes whether the forecasting performance may change when a specific market environment is selected. As Kim *et al.* (2009), Fuertes *et al.* (2008) show, a market condition has an influence on the forecasting performance of an option. In this study, four specific market environments are considered: a highly volatile market, a low-volatility market, a high-return market, and a low-return market. If the forecasting performance is improved within a certain market environment, it is also considered whether the profit from the trading strategy is increased within this environment.

The main finding of this study is that the implied volatility from the SV model does not yield any improvement over BS implied volatility for intraday volatility forecasting, even if both implied volatilities are proven to be informative for an hour-ahead future realized volatility. This result runs contrary to those from previous studies, which demonstrate the superiority of Heston's (1993) implied volatility. This

Rank	Contract	2001	2002	2003	2004	2005	2006	2007
1	KOSPI 200 Options, Korea Exchange	823	1,890	2,838	2,522	2,535	2,414	2,642
2	Eurodollar Futures, CME	184	202	209	298	410	502	621
3	E-mini S&P500 Futures, CME	39	116	161	167	207	258	415
4	10y T-Note Futures, CME	58	96	147	196	215	256	349
5	Euro-Bund Futures, Eurex	178	191	244	240	299	320	338
6	DJ Euro Stoxx 50 Futures, Eurex	38	86	116	122	140	214	327
7	Eurodollar Options on Futures, CME	88	106	101	131	188	269	313
8	DJ Euro Stoxx 50 Options, Eurex	19	40	62	71	91	150	251
9	1d Inter-Bank Deposit Futures, BM&F	46	49	58	100	121	161	221
10	3m Euribor Futures, Liffe	91	106	138	158	167	202	221

Notes: This table shows the ten most active derivative contracts, measured in millions of contracts from 2001 to 2007; the rank is based on the trading volume for 2007
Source: Futures Industry Association (www.futuresindustry.org)

Table I. The world's top 10 derivative contracts

study also shows that the forecasting performances are improved under high volatile market and low return market. This result is consistent with the fact that the trading performance by utilizing the forecasting power of an implied volatility is more effective for making a profit under the same market environment.

The remainder of this study is organized as follows. Section 2 demonstrates the models used in this study. The process of deriving the 1993 Heston model is presented, followed by the method of estimating realized volatility. In addition, the economic analysis models used in this study are introduced. Section 3 describes the KOSPI200 option market as well as the data used in this study. Section 4 presents the empirical results. First, the volatility estimation results and descriptive statistics of the estimated volatilities are presented. In addition, in-sample pricing errors and out-of-sample pricing errors are considered. Next, the lead-lag relationships between an implied volatility and a realized volatility are shown. Additionally, the lead-lag relationships in both high and low volatility markets, and high-return and low-return markets are shown and the difference in each market environment is described. Finally, the trading strategy of utilizing the forecasting power of implied volatilities with respect to future realized volatility and its simulation result are shown. Section 5 concludes.

2. Models

2.1 Stochastic volatility model

There are two types of SV models, continuous-time SV models and discrete-time SV models. Hull and White (1987), Johnson and Shanno (1987), Scott (1987), Wiggins (1987), Melino and Turnbull (1990), Stein and Stein (1991), and Heston (1993) assume a continuous-time process, and thus belong to the continuous-time SV model. On the other hand, Duan (1995) and Heston and Nandi (2000) use the discrete-time SV model. This present study uses Heston's (1993) model as an SV model, because Bakshi *et al.* (1997, 2000) and Kim and Kim (2005) have demonstrated the superiority of Heston's model, not only in terms of providing the closed-form solution, but also in terms of considering the correlation between the volatility and return of the underlying asset[1]. The stochastic process of stock price and volatility which is assumed in Heston's (1993) model is as below.

$$dS = \mu S dt + \sqrt{\nu_t} S dW_S \tag{1}$$

$$d\nu_t = \kappa(\theta - \nu_t)dt + \sigma\sqrt{\nu_t}dW_\nu \tag{2}$$

where, S is a stock value, μ is the return on the stock, W is a Wiener process, $W_S$and $W_\nu$have a correlation of ρ, ν_t is an instantaneous variance at time t, κ is the speed parameter reverting to the long-term average, θ, and σ is the volatility of volatility.

Using the Fourier transform, under the assumption of the stochastic process described above, the option pricing model follows below:

$$C = SP_1 - Ke^{-r\tau}P_2 \tag{3}$$

$$P_j = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty \text{Re}\left[\frac{e^{-i\phi \ln[K]} f_j(x, v, \tau, \phi)}{i\phi}\right] d\phi \, (j = 1, 2) \tag{4}$$

where, C is a call option, K is the strike price of the call option, r is risk-free interest rate, τ is time to maturity, Re[·] is the real number part of a complex number, i is the imaginary number, $\sqrt{-1}$, $f_j(x, \nu, \tau, \phi) = \exp\left(A(\tau, \phi) + B(\tau, \phi)\nu + i\phi x\right)$, x = ln(S), and A(·) and B(·) are functions of θ, κ, ρ, and σ.

Because the structural parameters are not observable, they have to be estimated. Following Bakshi *et al.* (1997, 2000) and Bates (1991, 2000), we estimate the parameters every hour, by minimizing the sum of squared percentage errors of the difference between the model price and the actual price. Compared to the estimation method using historical data, this one, which uses option prices, can take advantage of forward-looking information contained in option prices. For Heston's (1993) model, the parameters are estimated by minimizing the sum of squared percentage errors of the difference between the model price and the actual price in the following equation:

$$\min_{\sigma,\theta,\kappa,\rho,\nu_t} \sum_{i=1}^{N} \left[\frac{O_i^*(t, \tau, K) - O_i(t, \tau, K)}{O_i(t, \tau, K)}\right]^2 (t = 1, \cdots, T) \tag{5}$$

$O_i^*(t, \tau, K)$ is the model price of option i at time t, and $O_i(t, \tau, K)$ is the market price of option i, at time t. N is the number of options at time t, and T is the number of days in the sample.

2.2 Realized volatility

Because this study has to estimate one-hour realized volatility, high-frequency data is inevitably needed. The shortest available interval in the KOSPI200 index is a minute, so that minute-by-minute data is used for estimating the realized volatility. In addition, the use of the highest frequency data is supported by studies from Andersen *et al.* (2003) and Pong *et al.* (2003). According to these studies, the realized volatility estimated by higher frequency data is better than lower frequency data because it contains more data. Andersen *et al.* (2001) and Andersen *et al.* (2002) also mention that the measurement error from volatility estimates is decreased by this method, as the sampling frequency of the underlying is higher. Based on both the practical and theoretical reasons given above, the realized volatility is estimated as:

$$Vol = \sqrt{\frac{1}{\Delta}\frac{1}{L-1}\sum_{i=1}^{L-1}\left[\ln\left(S_{i+1}/S_i\right)\right]^2} \tag{6}$$

where, Δ is the time interval between i and i + 1 measured in years, L is the number of stock price data, S_i is the stock price at time i.

2.3 Econometric analysis models

To show the lead-lag relationship between an implied volatility and a realized volatility, a Granger causality test is carried out. The bivariate regression model is as below.

$$v_{i,t} = \alpha_0 + \sum_{n=1}^{6}\alpha_n v_{i,t-n} + \sum_{n=1}^{6}\beta_n v_{j,t-n} + \varepsilon_t\, i,j = (1,2),(1,3),(2,1),(3,1) \tag{7}$$

where, $v_{1,t}$, $v_{2,t}$, and $v_{3,t}$ are realized volatility, BS implied volatility, and Heston's (1993) implied volatility, respectively, corresponding to time t.

The Granger causality test reports the *F*-statistics for the joint hypothesis, $\beta_1 = \cdots = \beta_6 = 0$. The null hypothesis is that one volatility (v_j) does not lead the other (v_i).

A dummy variable is added to the Granger causality test to check the lead-lag relationship between an implied volatility and a realized volatility when a specific environment is chosen. The bivariate regression model with a dummy variable is as follows:

$$\begin{aligned} v_{i,t} &= \alpha_0 + \sum_{n=1}^{6}\alpha_n v_{i,t-n} + \sum_{n=1}^{6}\beta_n v_{j,t-n} + \sum_{n=1}^{6} D\gamma_n v_{j,t-n} + \varepsilon_t\, i, \\ j &= (1,2),(1,3),(2,1),(3,1) \end{aligned} \tag{8}$$

where, $v_{1,t}$, $v_{2,t}$, and $v_{3,t}$ are realized volatility, BS implied volatility, and Heston's (1993) implied volatility, respectively, corresponding to time t. D is the dummy variable which is set to 1 under the certain condition, and 0 elsewhere.

The Granger causality test with a dummy variable reports the *F*-statistics for the joint hypothesis, $\beta_1 + \gamma_1 = \cdots = \beta_6 + \gamma_6 = 0$. The null hypothesis is that one volatility (v_j) does not lead the other (v_i) when the factor on the degree of volatility is taken into account.

Four dummy variables are introduced; high volatility, low volatility, high return, low return. The dummy variables on high volatility and low volatility are those which are set to 1 for the times associated with the most volatile 10 percent days and for the least volatile 10 percent days, respectively. On the other hand, the dummy variables on high return and low return are those which are set to 1 for the highest 10 percent of days based on a daily return and for times relating to the lowest 10 percent days based on a daily return, respectively.

3. Data

The KOSPI200 option market in Korea is analyzed in order to test the forecasting performance of the implied volatilities on hour-ahead future volatility. Because of the intraday analysis, the trade volume is the most important criterion for selecting the market to be investigated. Table I shows that the KOSPI200 index options market is the largest in the world in terms of the trade volume. Therefore, KOSPI200 index options market is selected for this intraday volatility forecast analysis. The maturity date of KOSPI200 index options is the second Thursday of the option contract month, and option contract months are consecutive periods of three months and one more month from March, June, September, and December. There are at least five exercise prices for each option contract month, which can be increased as option prices move. A KOSPI200 index option contract is fully automated and is a European option which can be exercised only at maturity. In order to obtain a sufficient amount of data to estimate the structural parameters every hour, both the nearest expiration contract and the second nearest expiration contract options are used. The sample period extends from July 1, 2004 through June 29, 2007. The minute-by-minute transaction prices for the KOSPI 200 index options are obtained from the Korea Stock Exchange. Both calls and puts that are near-the-money (henceforth NTM) and out-of-the money (henceforth OTM) are used for calculating both BS implied volatility and Heston's implied volatility. In-the-money (henceforth ITM) options are excluded from the analysis, because their trading volume is very small, so that the reliability of the transacted price is not completely satisfied. Only the last reported transaction price prior to each hour of each option contract is employed in the empirical test. The following rules are applied to filter data needed for the empirical test. Because options with less than six days or more than 60 days to expiration may induce bias, due to low prices and bid-ask spreads, they are excluded from the sample. To mitigate the impact of price discreteness on option valuation, prices lower than 0.02 are not included. Prices not satisfying the arbitrage restriction are excluded as well. After filtering, 50,279 calls and 72,838 puts are used in the empirical test. Because there are 4,473 hours in the sample period, the average number of options used to estimate parameters for each hour is approximately 27. Table II shows the average option price and number of options, based on moneyness and the type of the option (call or put). The three-month CD rates are used as risk-free interest rates[2]. This study estimates an hour-realized volatility through a one-minute frequency of KOSPI200 index data, which is obtained from Korea Stock Exchange.

4. Empirical results

4.1 Volatility estimation results

Table III reports the mean and standard error of the parameter estimates for each model. The implicit parameters are not constrained to be constant over time. While re-estimating the parameters hourly is admittedly potentially inconsistent with the assumption of constant or slow-changing parameters used in deriving the option pricing model, such an estimation is useful for indicating market sentiment. For Heston's (1993) model, the implied correlation coefficient is negative, as we expected. This is consistent with the leverage effect documented by Black (1976) and Christie (1982), whereby lower overall firm values increase the volatility of equity returns, and the volatility feedback effects of Porterba and Summers (1986), whereby higher volatility assessments lead to heavier discounting of future expected dividends and

Moneyness	Price	Number
Call options		
S/K < 0.94	0.3514	18421
0.94 < S/K < 0.96	1.0682	16360
0.96 < S/K < 1.00	2.5478	15498
Total	1.2616	50279
Put options		
1.00 < S/K < 1.03	2.6527	14404
1.03 < S/K < 1.06	1.4604	13706
S/K > 1.06	0.4282	44728
Total	1.0623	72838

Notes: This table reports the average option price and the number of options, based on moneyness and the type of option (call or put). The sample period is from 9:00 1 July 2004 to 15:00 30 June 2007. The minute-by-minute information from the last traded prices prior to every hour of each option contract is used to obtain the summery statistics. S and K denote the spot price and the exercise price of KOSPI200, respectively

Table II.
KOSPI 200 options data

	σ	κ	θ	σ_v	ρ	v_t
BS	0.2020					
	(0.0005)					
SV		15.5809	0.5708	1.1575	−0.5634	0.0478
		(1.7198)	(0.0450)	(0.0127)	(0.0043)	(0.0004)

Notes: The table reports the mean and standard error of the parameters which are estimated hourly for the Black and Scholes (1973) option pricing model (BS) and Heston's (1993) option pricing model (SV). For the BS and SV models, each parameter is estimated by minimizing the sum of squared errors between model and market option prices every hour

Table III.
Parameters

thereby lower equity prices. We evaluate the in-sample performance of each model by comparing market prices with model prices, computed by using the parameter estimates from the current time. Table IV reports the in-sample valuation errors for the BS and Heston's models computed over the complete sample of options, as well as across six moneyness and two option-type categories. First, with respect to all measure, Heston's model shows better performance than the BS model. This is rather an obvious result, when the use of a larger number of parameters in Heston's model is considered. Second, all models show moneyness-based valuation errors. The model exhibits the worst fit for the near-the-money options. The fit, as measured by MAE, steadily improves as we move from near-the-money to out-of-the-money options. Overall, the SV model performs better for in-sample pricing. However, in-sample pricing performance can be biased, due to the potential problem of overfitting to the data. In the out-of-sample pricing, it is possible to determine whether the extra parameters improve the structural fitting, and as a result, cause overfitting. Table V presents the one-hour-ahead out-of-sample pricing results. Both the MAE and MSE results support the notion that Heston's model performs better than the BS model for out-of-sample pricing. This result implies that the presence of more parameters in

Moneyness	BS	SV
MAE		
S/K < 0.94	0.2060	0.0353
0.94 < S/K < 0.96	0.3081	0.0526
0.96 < S/K < 1.00	0.3144	0.1680
1.00 < S/K < 1.03	0.3462	0.2015
1.03 < S/K < 1.06	0.3735	0.0733
S/K > 1.06	0.2183	0.0554
Total	0.2727	0.0853
MSE		
S/K < 0.94	0.9251	0.1006
0.94 < S/K < 0.96	0.3360	0.0391
0.96 < S/K < 1.00	0.0671	0.0197
1.00 < S/K < 1.03	0.0301	0.0096
1.03 < S/K < 1.06	0.1163	0.0122
S/K > 1.06	0.5551	0.1800
Total	0.4096	0.0906

Notes: This table reports in-sample pricing errors for the KOSPI 200 option with respect to moneyness. S/K is defined as moneyness, where S and K denote the spot price and the strike price, respectively. Each model is estimated every hour during the sample period, and in-sample pricing errors are computed by the difference between the model price, using estimated parameters and the actual prices which are used for estimating the parameters. MAE and MSE denote mean absolute errors and mean squared errors, respectively and they are calculated as shown below:

$$MAE = \sum_{i=1}^{N} |\varepsilon_1|/N$$

$$MSE = \sum_{i=1}^{N} (\varepsilon_i)^2/N$$

where ε_i, is the difference between the model price and the actual price for each sample and N is the number of the sample. BS is the Black-Scholes option pricing model and SV is Heston's (1993) option pricing model

Table IV.
In-sample pricing errors

Heston's model plays a positive role in the structural fitting. One interesting phenomenon observed in Table V is that the fitting error is greatest around near-the-money options when MAE measure is applied, whereas that is the smallest when MSE measure is applied. It can be explained that, as moneyness moves to either in-the-money or out-of-the-money from at-the-money, the distribution of the fitting error looks more fat-tailed.

Table VI shows the descriptive statistics for 4,473 hourly-estimated realized volatilities and two implied volatilities on KOSPI200 option prices from 10:00 July 1 2004, through 15:00 June 30 2007. According to the results in Table VI, the estimated values on realized volatility are, on average, lower than those on implied volatilities. On the other hand, the standard deviation of the estimated realized volatilities is much larger than those of the estimated implied volatilities. The ADF test statistics show that no volatility time series has a unit root.

Moneyness	BS	SV
MAE		
S/K < 0.94	0.2062	0.0431
0.94 < S/K < 0.96	0.3098	0.0755
0.96 < S/K < 1.00	0.3212	0.1910
1.00 < S/K < 1.03	0.3519	0.2217
1.03 < S/K < 1.06	0.3740	0.0970
S/K > 1.06	0.2182	0.0626
Total	0.2745	0.1000
MSE		
S/K < 0.94	0.9546	0.1111
0.94 < S/K < 0.96	0.3469	0.0464
0.96 < S/K < 1.00	0.0691	0.0229
1.00 < S/K < 1.03	0.0311	0.0120
1.03 < S/K < 1.06	0.1171	0.0172
S/K > 1.06	0.5546	0.1921
Total	0.4158	0.0988

Notes: This table reports one hour out-of-sample pricing errors for the KOSPI 200 option with respect to moneyness. S/K is defined as moneyness, where S and K denote the spot price and the strike price, respectively. Each model is estimated every hour during the sample period, and one-hour out-of-sample pricing errors are computed by the difference between the model price, using the parameters estimated by the options which are traded one hour before, and the actual prices. MAE and MSE denote mean absolute errors and mean squared errors, respectively and they are calculated as shown below:

$$MAE = \sum_{i=1}^{N} |\varepsilon_i|/N$$

$$MSE = \sum_{i=1}^{N} (\varepsilon_i)^2/N$$

where ε_i, is the difference between the model price and the actual price for each sample and N is the number of the sample. BS is the Black and Scholes (1973) option pricing model and SV is Heston's (1993) option pricing model

Table V. One hour out-of-sample pricing errors

4.2 Lead-lag relation

Panel A of Table VII contains the Granger causality test results between an implied volatility and a realized volatility for the entire period, from 1 July 2004 to 30 June 2007. An implied volatility is derived from either the BS model or Heston's (1993) model. Though this result indicates that a realized volatility Granger causes any implied volatility, it is found that the implied volatilities Granger cause a stronger realized volatility. This result means that an implied volatility influences a realized volatility more than vise versa. Between the two implied volatilities, BS implied volatility leads a realized volatility more significantly than Heston's implied volatility. This result is the converse of those that appeared in both the in-sample and out-of-sample pricing analyses. This can be inferred from the following rationale. In pricing performance, five parameters in the Heston model function simultaneously. As a result, the pricing performance is attributed, not only from a

Statistics	RV	BS	SV
Observations	4,473	4,473	4,473
Mean	0.148916	0.201962	0.212653
Median	0.121031	0.196401	0.20837
Max.	1.632191	0.331017	0.6949
Min.	0.061580	0.130101	0.000112
Std dev	0.094423	0.035200	0.051026
Skewness	4.205564	0.677648	0.546646
Kurtosis	33.42331	3.230714	5.407161
ADF test statistic	−41.4899	−4.31224	−7.68093

Notes: Descriptive statistics for 4,473 hourly-estimated realized volatilities and two implied volatilities from option prices using BS and Heston (1993) Models on KOSPI200 option for the period from 10:00 July 1 2004 through 15:00 June 30 2007 are presented. Realized volatilities are annualized through multiplying an hour basis volatility by $\sqrt{6 \times 250}$. There are four principals to filter data for empirical analysis. First, the latest transacted option data prior to every hour observed are selected. Second, if there are more than one transaction data for each hour, only one type of data is used. Third, the option whose price is below 0.02 is excluded. Fourth, the option, which does not meet the arbitrage restriction is not included. Realized volatilities are estimated by 60 minute-by-minute data, beginning from every targeted hour. Mean, Media, Max, Min, Standard deviation, Skewness, Kurtosis, and Augmented Dickey-Fuller (ADF) test statistics for 4,473 hourly estimated realized volatility, BS implied volatility (BS), Heston (1993)'s implied volatility (SV) are presented

Table VI.
Descriptive statistics

volatility parameter, but also from four other parameters. On the contrary, the Granger causality result is influenced only by the volatility parameter. This is why the forecasting performance of Heston's implied volatility can be inferior to that of BS implied volatility, even if the pricing performance of the former is superior to that of the latter. This result is also different from those obtained by Poteshman (2000) and Byun *et al.* (2009) which analyze the forecasting performance of both BS implied volatility and Heston's implied volatility on a month-ahead future realized volatility. In their findings, Heston's implied volatility is commonly superior to BS implied volatility for the forecasting performance of future volatility. The results shown in Table VII, on the contrary, indicates that the empirical results, using intraday data, does not support the superiority of Heston's implied volatility for the forecasting performance of future volatility. Panel B of Table VII shows the sub-period results of the Granger causality test. There are six sub-periods, each of which comprises six months. In these results, implied volatilities do not lead a realized volatility, if any specific time period is selected. Thus, it is evident that implied volatilities do not always yield information on an hour-ahead future realized volatility.

4.3 Lead-lag relation with a high-volatility market and a low-volatility market

Table VIII shows the results of the Granger causality test when the factor on the degree of the volatility is taken into account. To capture this effect, two dummy variables are introduced. One recognizes a highly volatile market and is set to 1 for the times associated with the most volatile 10 percent days. The other, which recognizes a low-volatility market, is set to 1 for the times associated with the least volatile 10

	BS leads RV	SV leads RV	RV leads BS	RV leads SV
Panel A: total period				
F-stat.	21.9893***	14.8804***	7.8982***	7.2747***
Panel B: sub periods				
2004.7.1 ~ 2004.12.31				
F-stat.	2.6449**	1.4574	1.0481	1.8109*
2005.1.1 ~ 2005.6.30				
F-stat.	1.6386	0.9603	2.3815**	4.3107***
2005.7.1 ~ 2005.12.31				
F-stat.	2.1695**	2.8434***	3.6525***	3.8665***
2006.1.1 ~ 2006.6.30				
F-stat.	5.9440***	6.3337***	0.8640	1.2799
2006.7.1 ~ 2006.12.31				
F-stat.	11.5946***	9.0718***	0.2798	0.4986
2007.1.1 ~ 2007.6.30				
F-stat.	1.1129	0.1481	9.6821***	1.7803

Notes: This table reports the Granger causality test results between an implied volatility and a realized volatility. An implied volatility is derived from option prices, using either the BS or Heston (1993) Model. The bivariate regression model is as shown below:

$$v_{i,t} = \alpha_0 + \sum_{n=1}^{6} \alpha_n v_{i,t-n} + \sum_{n=1}^{6} \beta_n v_{j,t-n} + \varepsilon_t i, j = 1, 2, 3 (i \neq j)$$

$v_{1,t}$, $v_{2,t}$ and $v_{3,t}$ are realized volatility (RV), BS implied volatility (BS), and Heston (1993) implied volatility (SV), respectively, corresponding to time t. The reported F-statistics are the Wald statistics for the joint hypothesis, $\beta_1 = \cdots = \beta_6 = 0$. The null hypothesis is that one volatility (v_j) does not lead the other (v_i). *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent levels

Table VII. Granger causality test results

percent days. Panel A of Table VIII contains the Granger causality test results, when the dummy variable on a highly volatile environment is added to the original Granger causality test presented in Table VII. Compared with the results in Table VII, the values on F-statistics are increased substantially. In particular, it is shown that both BS-implied volatility and Heston's implied volatility lead a realized volatility more strongly. This fact can be understood as follows. The positive relationship between the trade volume and the volatility has been proven empirically in previous studies, such as Hiemstra and Jones (1994), Bessembinder and Segin (1993), and Karpoff (1987). The fact that the high price efficiency can be achieved from the high trade volume is accepted intuitively. Thus, the implied volatilities, which are forward-looking volatilities in a market, can lead a realized volatility better in a highly volatile environment. On the contrary, Panel B of Table VIII presents the Granger causality test results, when the dummy variable on a low-volatility environment is added to the original Granger causality test. As is expected from the results of Panel A, the values on F-statistics are decreased substantially, compared with the results presented in Table VII. Panel B indicates that implied volatilities do not lead a realized volatility statistically in a low- volatility market.

	BS leads RV	SV leads RV	RV leads BS	RV leads SV
Panel A: high volatility				
F-stat	35.1451***	55.8664***	5.8002***	4.4478***
Panel B: low volatility				
F-stat	1.5159	0.0865	0.1820	0.6182

Notes: This table reports the Granger causality test results between an implied volatility and a realized volatility with dummy variables whose values are determined by the degree of the volatility on the KOSPI200 at the date to which they are applied. An implied volatility is derived from option prices, using either BS or Heston (1993) Model. The bivariate regression model with dummy variables is as shown below:

$$v_{i,t} = \alpha_0 + \sum_{n=1}^{6} \alpha_n v_{i,t-n} + \sum_{n=1}^{6} \beta_n v_{j,t-n} + \sum_{n=1}^{6} D_{HV} \gamma_n v_{j,t-n} + \varepsilon_t$$

$$v_{i,t} = \alpha_0 + \sum_{n=1}^{6} \alpha_n v_{i,t-n} + \sum_{n=1}^{6} \beta_n v_{j,t-n} + \sum_{n=1}^{6} D_{LV} \gamma_n v_{j,t-n} + \varepsilon_t i,$$

$$j = (1,2), (1,3), (2,1), (3,1)$$

$v_{1,t}$, $v_{2,t}$, and $v_{3,t}$are realized volatility (RV), BS implied volatility (BS), and Heston's (1993) implied volatility (SV), respectively, corresponding to time t. D_{HV} and D_{LV} are dummy variables which are set to 1 for the times associated with the most volatile 10 percent days and for the times associated with the least volatile 10 percent days, respectively. The reported F-statistics are the Wald statistics for the joint hypothesis, $\beta_1 + \gamma_1 = \cdots = \beta_6 + \gamma_6 = 0$. The null hypothesis is that one volatility (v_j) does not lead the other (v_i) when the factor on the degree of the volatility is taken into account. *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent levels

Table VIII.
Granger causality tests results with dummy variables on volatility

4.4 The lead-lag relation in a high-return market and a low-return market

Table IX shows the results of the Granger causality test when the factor on the degree of the return is taken into account. In order to induce these results, two dummy variables are used as well. One, which recognizes a high-return market, is set to 1 for the times associated with the highest 10 percent days, based on a daily return. The other, which recognizes a low-return market, is set to 1 for the times associated with the lowest 10 percent days, based on a daily return. Panel A of Table IX contains the Granger causality test results, when the dummy variable on the high-return market is added to the original Granger causality test presented in Table VII. Even if the values of the F-statistics are largely statistically significant, they constitute a slight decrease, compared with the results in Table VII. On the contrary, the Granger causality results, which are shown in Panel B, indicate that the values of the F-statistics are increased, when the dummy variable on the low-return market is applied. With respect to the results shown in Table VIII, it is evident that implied volatilities lead a realized volatility more strongly in a period of poor performance. This result is consistent with that presented in Table VIII, in that the negatively skewed feature observed in stock markets implies that a poor-performance period is generally volatile. Although the degree of the lead-lag relationship between an implied volatility and a realized volatility depends on the returns from the stock market, it is less sensitive to returns than to volatility.

	BS leads RV	SV leads RV	RV leads BS	RV leads SV
Panel A: high return				
F-stat	16.2800***	7.8994***	3.3811***	0.3500
Panel B: low return				
F-stat	23.6066***	16.0076***	31.3276***	10.3163***

Notes: This table reports the Granger causality test results between two volatilities selected from a realized volatility and two implied volatilities from option prices using the BS and Heston (1993) Models with dummy variables whose values are determined by the degree of the return from the KOSPI200 for the date to which they are applied. The bivariate regression model with dummy variables is as shown below:

$$v_{i,t} = \alpha_0 + \sum_{n=1}^{6} \alpha_n v_{i,t-n} + \sum_{n=1}^{6} \beta_n v_{j,t-n} + \sum_{n=1}^{6} D_{HR} \gamma_n v_{j,t-n} + \varepsilon_t$$

$$v_{i,t} = \alpha_0 + \sum_{n=1}^{6} \alpha_n v_{i,t-n} + \sum_{n=1}^{6} \beta_n v_{j,t-n} + \sum_{n=1}^{6} D_{LR} \gamma_n v_{j,t-n} + \varepsilon_t$$

$$i,j = (1,2),(1,3),(2,1),(3,1)$$

$v_{1,t}$, $v_{2,t}$, and $v_{3,t}$ are realized volatility (RV), BS implied volatility (BS), and Heston (1993)'s implied volatility (SV), respectively, corresponding to time t. D_{HR} and D_{LR} are dummy variables which are set to 1 for the times associated with the highest 10 percent days based on a daily return and for the times associated with the lowest 10 percent days based on a daily return, respectively. The reported *F*-statistics are the Wald statistics for the joint hypothesis, $\beta_1 + \gamma_1 = \cdots = \beta_6 + \gamma_6 = 0$. The null hypothesis is that one volatility (v_j) does not lead the other (v_i) when the factor on the degree of the return is taken into account. *, **, and *** are statistically significant at 10 percent, 5 percent and 1 percent levels

Table IX. Granger causality tests results with dummy variables on return

4.5 Trading simulation

The following trading strategy is set to utilize the forecasting power of implied volatilities on one-hour-ahead future volatility. First, an estimated future realized volatility is derived from either lagged BS implied volatilities or lagged Heston's implied volatilities. The coefficients on the lagged variables are calculated by the ordinary least squared (OLS) method. If the estimated future realized volatility is greater (smaller) than the BS implied volatility derived from the option price at an observation hour, the option is considered underpriced (overpriced). A long (short) strategy, which longs (shorts) one unit of call option and shorts (longs) a delta unit of index, and unwinds the positions in an hour, is executed when the option falls within the most underpriced (overpriced) 10 percent hours of the sample selected. Among several options traded in the same hour, NTM option is selected for this trading strategy. The delta, which is needed to make delta-neutral strategies as explained above, is calculated as follows:

$$\Delta_t = \frac{\partial C_t}{\partial S_t} = N(d_1) \tag{9}$$

where:

$$d_1 = \frac{\ln(S_t/K_t) + (r_t + 0.5 \times \sigma_t^2) \times \tau}{\sigma_t \sqrt{\tau}},$$

C_t, S_t, K_t, r_t, and σ_t are the call option price, KOSPI200 index price, NTM strike price, risk free rate, and BS implied volatility, respectively, corresponding to time t and $N(\cdot)$ is the cumulative normal density function. The profit or loss from the trading strategy at time t is obtained as shown below:

$$\pi_t^{Long} = \left[\left(C_{t+1} - C_t\right) + \Delta_t\left(S_t - S_{t+1}\right) \right], \pi_t^{Short} = \left[\left(C_t - C_{t+1}\right) + \Delta_t\left(S_{t+1} - S_t\right) \right] \quad (10)$$

Table X reports the trading simulation results. When a full period is selected, the long strategy earns a positive profit, regardless of the methods of estimating future realized volatility. A short strategy, by contrast, loses money. These results can be inferred for the following reason. A person who has long (short) option and short (long) delta neutral underlying, earns a positive profit when the convexity-oriented gain from the movement of the underlying is greater (smaller) than the decrease in option value from the time-decaying effect. However, in this trading strategy, whose duration is only an hour, time decaying effect is too small to impact on the trading performance. Therefore, the long strategy yields a positive average performance, whereas the short strategy yields a negative average performance. This trading strategy is also applied to four specific market environments; a highly volatile market, a low-volatility market, a high-return market, and a low-return market. A high (low)-volatility market sample covers the hours associated with the most (least) volatile 10 percent days, and a high (low)-return market sample covers the hours associated with the highest (lowest) 10 percent days, based on a daily return. The trading performance from high-volatility market is better than that from a low-volatility market and the trading performance from the low-return market is better than that from the high-return market. This result is consistent with those observed for the lead-lag relationship analysis. It can be inferred that lagged implied volatilities exert a stronger influence on future realized volatility with a high-volatility or a low-return market. As a result, the trading strategy executed in such a market environment performs better. The methods of deriving estimated future realized volatility does not impact significantly on the trading performance. However, because the z statistics results presented in Table X are low, it is risky to follow this trading strategy. Also, these trading simulation results do not consider transaction costs.

5. Conclusion

There are no previous studies aimed at determining the best model for the forecasting performance of intraday future volatility. As a volatile market grows, it becomes more and more important to evaluate the forecasting performance of intraday future volatility, not only from an academic prospective, but also in practical terms. Since the KOSPI200 index options market is the most liquid equity option market in the world in terms of trading volume, it is examined with respect to the intraday-volatility forecasting performance. Among various models, the BS and Heston (1993) models are

Table X. Trading simulation results

Sample period	Sample number		Average		Max.		Min.		SD		Z statistics	
Panel A: estimated realized volatility is derived from lagged BS implied volatilities												
Full	447	(447)	0.01	(−0.01)	2.37	(0.55)	−0.37	(−2.64)	0.17	(0.22)	0.06	(−0.04)
High volatile	45	(45)	0.05	(−0.01)	1.27	(0.28)	0.27	(−0.28)	0.24	(0.12)	0.21	(−0.09)
Low volatile	45	(45)	−0.01	(−0.04)	0.20	(0.15)	−0.34	(−1.82)	0.10	(0.29)	−0.10	(−0.13)
High return	45	(45)	0.08	(0.00)	2.37	(0.21)	−0.37	(−0.39)	0.40	(0.11)	0.20	(0.04)
Low return	45	(45)	0.10	(−0.05)	1.72	(0.28)	−0.21	(−2.07)	0.32	(0.34)	0.32	(−0.13)
Panel B: estimated realized volatility is derived by lagged Heston (1993)*'s implied volatilities*												
Full	447	(447)	0.02	(−0.00)	2.46	(0.34)	−0.57	(−2.08)	0.26	(0.14)	0.09	(−0.00)
High volatile	45	(45)	0.05	(−0.00)	0.61	(0.14)	−0.27	(−0.16)	0.17	(0.07)	0.31	(−0.03)
Low volatile	45	(45)	0.04	(−0.04)	2.46	(0.19)	−0.43	(−1.82)	0.39	(0.33)	0.10	(−0.13)
High return	45	(45)	0.05	(−0.00)	2.37	(0.20)	−0.57	(−0.26)	0.41	(0.08)	0.13	(−0.03)
Low return	45	(45)	0.11	(−0.00)	2.64	(0.28)	−0.61	(−0.19)	0.52	(0.08)	0.22	(−0.04)

Notes: This table reports the trading simulation results by utilizing the relative value between an implied volatility and the estimated one-hour-ahead future volatility. A long (short) strategy, which longs (shorts) one unit of call option and shorts (longs) delta unit of index, and unwinds the positions in an hour, is executed when an implied volatility is associated with the most underpriced (overpriced) 10 percent hours in the sample selected. The implied volatility in the strategies is BS implied volatility at the time when a strategy is executed. The estimated future volatility is derived in two ways. One is estimated by lagged BS implied volatilities, and the other by lagged Heston (1993)'s implied volatilities. The coefficients on the lagged variables are calculated by the ordinary least squared (OLS) method. The delta, which is needed to make delta-neutral strategies above, is calculated as below:

$$\Delta_t = \frac{\partial C_t}{\partial S_t} = N(d_1) \text{ where } d_1 \frac{\ln(S_t/K_t) + (r_t + 0.5 \times \sigma_t^2) \times \tau}{\sigma_t \sqrt{\tau}}$$

C_t, S_t, K_t, r_t, and σ_t are call option price, KOSPI200 index price, NTM strike price, risk free rate, and BS implied volatility, respectively, corresponding to time t and N(·) is the cumulative normal density function. Among several option prices corresponding to the strike prices traded, only the NTM option is selected for the trading simulation. A high (low) volatile period sample covers the times associated with the most (least) volatile 10 per cent days, and high (low) return period sample covers the times associated with the highest (lowest) 10 percent days based on a daily return. The profit or loss from the trading strategy at time t is obtained as: $\pi_t^{Long} = \left[(C_{t+1} - C_t) + \Delta_t (S_t - S_{t+1}) \right]$, $\pi_t^{Short} = \left[(C_t - C_{t+1}) + \Delta_t (S_{t+1} - S_t) \right]$. Average, max., min., standard deviation, and z statistics of the trading performance are reported. The performances of the short strategy are in parentheses selected, because these have been previously compared with one another and have proven to be superior to others, in terms of the forecasting performance of future volatility.

The lead-lag relation results show that both BS and Heston implied volatilities lead a realized volatility. Unlike previous studies, such as Poteshman (2000) and Byun *et al.* (2009), which analyzed the forecasting performance of one-month-ahead future realized volatility, Heston's implied volatility is not proven to be superior to BS implied volatility in terms of forecasting performance. In this respect, to make the assumptions flexible in Heston's model, such as the non-zero market price of volatility risk and non-zero correlation between innovations is not worth the effort to improve the empirical deficiency which the BS model has when intraday volatility forecasting is investigated.

The lead-lag relationship between an implied volatility and a realized volatility changes when a specific market environment is selected. In a highly volatile market, the lead-lag relationship is stronger. This result suggests that implied volatilities are more meaningful for the future realized volatility. Conversely, the lead-lag relationship is weaker in a low-volatility market. On the other hand, the return on the KOSPI200 index is another important factor for the strength of the lead-lag relationship. Whereas the lead-lag relationship is weaker in a high-return environment, it is stronger in low-return environment. These results appear to make sense, in that the negatively skewed feature observed in stock markets implies that a low-performance period is generally volatile.

The trading simulation results support the lead-lag relation results between an implied volatility and a realized volatility. When the trading strategy, which utilizes the forecasting power of an implied volatility on an hour-ahead future realized volatility, is applied, positive performance can be achieved. In addition, the trading strategy seems to be more effective when applied in a highly volatile market and a low-return market. However, as the z statistics of the trading performance imply, using the trading strategy seems very risky.

Notes

1. The existing empirical studies showed the negative correlation between the volatility and the return of the underlying asset, risk neutral distribution with negative skewness and the low strike price which has a large volatility, referred to as "volatility sneer". This is consistent with the leverage effect documented by Black (1976) and Christie (1982). The negative correlation phenomenon can be explained by the fact that falling stock prices will bring about a relatively higher debt equity ratio, which, in turn, will have a leverage effect on the enterprise, which makes the volatility of the earnings per share greater. This ultimately has the effect of amplifying the stock price volatility.
2. Korea does not have a liquid Treasury bill market, so the three-month CD rates are used, in spite of the mismatch of maturity of options and interest rates.

References

Andersen, T.G., Bollerslev, T. and Diebold, F.X. (2002), "Parametric and nonparametric volatility measurement", working paper, prepared for *Handbook of Financial Econometrics*.

Andersen, T.G., Bollerslev, T., Diebold, F.X. and Ebens, H. (2001), "The distribution of stock return volatility", *Journal of Financial Econometrics*, Vol. 61 No. 1, pp. 43-76.

Andersen, T.G., Bollerslev, T., Diebold, F.X. and Labys, P. (2003), "Modeling and forecasting realized volatility", working paper, National Bureau of Economic Research.

Bakshi, G., Cao, C. and Chen, Z. (1997), "Empirical performance of alternative option pricing models", *Journal of Finance*, Vol. 52 No. 5, pp. 2003-49.

Bakshi, G., Cao, C. and Chen, Z. (2000), "Pricing and hedging long-term options", *Journal of Econometrics*, Vol. 94 Nos 1-2, pp. 277-318.

Bates, D. (1991), "The crash of '87: was it expected? The evidence from options market", *Journal of Finance*, Vol. 46 No. 3, pp. 1009-44.

Bates, D. (2000), "Post-'87 crash fears in the S&P 500 futures option market", *Journal of Econometrics*, Vol. 94 Nos 1-2, pp. 181-238.

Benavides, G. (2004), "Predictive accuracy of futures option implied volatility: the case of the exchange rate futures Mexican peso – US dollar", working paper.

Bessembinder, H. and Segin, P.J. (1993), "Price volatility, trading volume, and market depth: evidence from the futures markets", *Journal of Financial and Quantitative Analysis*, Vol. 28 No. 1, pp. 21-39.

Black, F. (1976), "Studies of stock price volatility changes", *Proceedings of the 1976 Meeting of the American Statistical Association, Business and Economic Statistic Section*, pp. 177-81.

Black, F. and Scholes, M. (1973), "The pricing of options and corporate liabilities", *Journal of Political Economy*, Vol. 81 No. 3, pp. 637-59.

Blair, B.J., Poon, S. and Taylor, S.J. (2001), "Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns", *Journal of Econometrics*, Vol. 105 No. 1, pp. 5-26.

Byun, S.J., Rhee, D.W. and Kim, S. (2009), "Empirical comparison of alternative implied volatilities on the forecasting performance of future volatility", working paper, KAIST.

Christie, A. (1982), "The stochastic behavior of common for alternative stochastic processes", *Journal of Financial Economics*, Vol. 10 No. 4, pp. 407-32.

Day, T. and Lewis, C. (1992), "The information content of option prices and a test of market efficiency", *Journal of Econometrics*, Vol. 52, pp. 267-87.

Duan, J.C. (1995), "The GARCH option pricing model", *Math Finance*, Vol. 5 No. 1, pp. 13-32.

Ederington, L. and Guan, W. (2002), "Is implied volatility an informationally efficient and effective predictor of future volatility?", *Journal of Risk*, Vol. 4 No. 3, pp. 29-46.

Fleming, J. (1998), "The quality of market volatility forecasts implied by S&P 100 index option prices", *Journal of Empirical Finance*, Vol. 5 No. 4, pp. 317-45.

Fuertes, A.M., Izzeldin, M. and Kalotychou, E. (2008), "On forecasting daily stock volatility: the role of intraday information and market conditions", City University London.

Glot, P. (2003), "Implied volatility indexes and daily value-at-risk models", working paper, University of Namur.

Guo, D. (1996), "The information content of implied stochastic volatility from currency options", *Canadian Journal of Economics*, Vol. 29 Nos 1/2, pp. 559-61.

Heston, S.L. (1993), "A closed-form solutions for options with stochastic volatility with applications to bond and currency options", *Review of Financial Studies*, Vol. 6 No. 2, pp. 327-43.

Heston, S.L. and Nandi, S. (2000), "A closed-form GARCH option valuation model", *Review of Financial Studies*, Vol. 13 No. 3, pp. 585-625.

Hiemstra, C. and Jones, J.D. (1994), "Testing for linear and nonlinear granger causality in the stock price-volume relation", *Journal of Finance*, Vol. 49 No. 5, pp. 1639-64.

Hull, J. and White, A. (1987), "The pricing of options with stochastic volatilities", *Journal of Finance*, Vol. 42 No. 2, pp. 281-300.

Johnson, H. and Shanno, D. (1987), "Option pricing when the variance is changing", *Journal of Financial and Quantitative Analysis*, Vol. 22 No. 2, pp. 143-51.

Jorion, P. (1995), "Predicting volatility in the foreign exchange market", *Journal of Finance*, Vol. 50 No. 2, pp. 507-28.

Karpoff, J.M. (1987), "The relation between price changes and trading volume: a survey", *Journal of Financial and Quantitative Analysis*, Vol. 22 No. 1, pp. 109-26.

Kim, I.J. and Kim, S. (2005), "Empirical comparison of alternative stochastic volatility option pricing models: evidence from Korean KOSPI 200 index options market", *Pacific Basin Finance Journal*, Vol. 12 No. 2, pp. 117-42.

Kim, S., Kim, I.J. and Nam, S.O. (2009), "The lead-lag relationship between stock index options and the stock index market: model, moneyness, and news", *International Journal of Managerial Finance*, Vol. 5 No. 3, pp. 311-32.

Lamoureux, D. and Lastrapes, W. (1993), "Forecasting stock-return variance: toward an understanding of stochastic implied volatilities", *Review of Financial Studies*, Vol. 6 No. 2, pp. 293-326.

Latane, H.A. and Rendleman, R.J. (1976), "Standard deviations of stock price ratios implied in option prices", *Journal of Finance*, Vol. 31 No. 2, pp. 369-81.

Melino, A. and Turnbull, S.M. (1990), "Pricing foreign currency options with stochastic volatility", *Journal of Econometrics*, Vol. 45 Nos 1-2, pp. 239-65.

Neely, C.J. (2002), "Forecasting foreign exchange volatility: is implied volatility the best we can do?", working paper, Federal Reserve Bank of St Louis, St Louis, MO.

Pong, S., Shackleton, M., Taylor, S. and Xu, X. (2003), "Forecasting currency volatility: a comparison of implied volatilities and AR(FI)MA models", working paper.

Poterba, J. and Summers, L. (1986), "The persistence of volatility and stock market fluctuations", *American Economic Review*, Vol. 76 No. 5, pp. 1142-51.

Poteshman, A.M. (2000), "Forecasting future volatility from option prices", working paper, University of Illinois at Urbana-Champaign, Urbana-Champaign, IL.

Scott, L.O. (1987), "Option pricing when the variance changes randomly: theory, estimation, and an application", *Journal of Financial and Quantitative Analysis*, Vol. 22 No. 4, pp. 419-38.

Stein, E.M. and Stein, J.C. (1991), "Stock price distribution with stochastic volatility: an analytic approach", *Review of Financial Studies*, Vol. 4 No. 4, pp. 727-52.

Wiggins, J.B. (1987), "Option values under stochastic volatility: theory and empirical estimates", *Journal of Financial Economics*, Vol. 19 No. 2, pp. 351-77.

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