Roll-Over Parameters and Option Pricing

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Abstract

In this paper, we examine the empirical performance of several options pricing models with respect to the roll-over strategies of parameters. We compare the pricing and hedging performances of several models using the traditional roll-over strategy of the parameters, the nearest-to-next approach with those using the new roll-over strategy, the next-to-next approach. It is found that when we use the nearest-to-next strategy, the SVJ and SV models show better performance than the AHBS-type models for pricing options. Among AHBS-type models, simpler model with less parameter shows better performance than other models. That is, for the AHBS-type models, the presence of more parameters actually cause over-fitting but that does not cause over-fitting problem for the mathematically complicated models. For the hedging performance, the AHBS-type models show better performance than the mathematically complicated models but, the differences among the models are not significant. When we use the next-to-next strategy, the results are changed. The next-to-next strategy decreases the errors of all options pricing models. The pricing errors of the AHBS-type models are decreased largely by the next-to-next strategy. AHBS-type models show better performance than the mathematically complicated models for pricing options. That is, the next-to-next strategy mitigate over-fitting problem of AHBS-type models, but the improvement of the mathematically complicated models including the BS model using the next-to-next strategy is not much.

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I. Introduction

Since Black and Scholes published their seminal article on option pricing in 1973, there have been various theoretical and empirical researches on option pricing. One important direction in which the Black and Scholes (1973) model can be modified is to generalize the geometric Brownian motion, which is used as a process for the dynamics of log stock prices. For example, Merton(1976) and Naik and Lee (1990) propose a jump-diffusion model. Hull and White (1987), Johnson and Shanno (1987), Scott (1987), Wiggins (1987) and Heston (1993) suggest a stochastic volatility model. Naik (1993) considers a regime-switching model. Duan(1995) and Heston and Nandi(2000) develop an option pricing framework based on the GARCH process. Madan, Carr, and Chang (1998) use a three-parameter stochastic process, termed the VG process, as an alternative model for capturing the dynamics of log stock prices.

Bakshi, Cao, and Chen (1997, 2000) and Kim and Kim (2005) have conducted a comprehensive empirical study on the relative merits of competing option pricing models. They have found that taking stochastic volatility into account is of the first order in importance for improving upon the Black and Sholes model. However, in striking empirical findings, Dumas, Fleming and Whaley (1998), Jackwerth and Rubinstein (2001) and Li and Pearson (2007), Kim (2009) and Choi and Ohk (2011) examine the performance of a number of these mathematically sophisticated models and find that they predict option prices less well than a pair of ad hoc approaches sometimes used by option traders. Ad hoc approaches can be an alternative to the complicated models for pricing options and are called as ad hoc Black and Scholes models (henceforth AHBS).

There are two versions of the ad hoc approach. In the “relative smile” approach, the implied volatility skew is treated as a fixed function of moneyness, S/K and the implied volatility for a fixed strike K varies as the stock index S varies. This is also known as the “sticky volatility” method. In the “absolute smile” approach, the implied volatility is treated as a fixed function of the strike price K and the implied volatility for a fixed strike does not vary with S. This is also known as the "sticky delta" method. Dumas, Fleming and Whaley (1998), Jackwerth and Rubinstein (2001) and Li and Pearson (2007), who report the AHBS model outperforms other models, adopt the "absolute smile" approach. On the other hand, Kirgiz (2001) and Kim and Kim (2004), who report the AHBS model does not outperform other models, adopt the "relative smile" approach. That is, the type of the AHBS model seems to be important for pricing and hedging options. Jackwerth and Rubinstein (2001), Li and Pearson (2007), Kim (2009), and Choi and Ohk (2011) have found that the "absolute smile" approach shows better performance than the "relative smile" approach for pricing options. Also simpler model among the AHBS models shows better performance than other models. That is, the presence of more parameters actually cause over-fitting.

When we forecast and hedge option prices, we need to estimate the parameters to plug into each model. For one day ahead pricing and hedging, the parameters are estimated using the previous days' options data. For one week ahead pricing and hedging, the options data before seven days are used. In general trading dates, there is no complicate problems. However, it is standard to eliminate the nearest option contracts with expiries less than 7 days, and use the next-to-nearest option contracts with expiries less than 7 days plus 1 month for the empirical study. When forecasting the parameters for the next-to-nearest option contracts with expiry less than 7 days plus 1 month, we have the problems about the roll-over strategies of the parameter. One can use either the nearest contracts with expiry greater than 6 days (the nearest-to-next strategy) or the next-to-nearest contracts with expiry greater than 6 days plus 1 month (the next-to-next strategy). Choi and Ohk (2011) have shown that the next-to-next roll-over strategy can mitigate the over-fitting problems of AHBS models and can make the AHBS models with more parameters the better model than the AHBS model with less parameters.

The next-to-next roll-over strategy of the parameters can be useful. Is this strategy functioned with only the AHBS models? Or is this strategy also functioned with mathematically completed models, the stochastic volatility (henceforth SV) and stochastic volatility with jump (henceforth SVJ) models? In this paper, we examine the empirical performance of several options pricing models with respect to the roll-over strategies of parameters. Not only the traders' rules, AHBS-type models, but also the SV model and the SVJ model are considered for a horse race competition. We compare the pricing and hedging performances of several models using the traditional roll-over strategy of the parameters, the nearest-to-next approach, with those using the new roll-over strategy, the next-to-next approach. We examine that new roll-over strategy of the parameters can be functioned not only the AHBS-type models but also the mathematically complicated models, the SV and SVJ models. After considering the new roll-over strategy of the parameters, we find out the best options pricing model.

We fill the gaps that have not been resolved in previous researches. First, when the roll-over strategies of the parameters are examined, Choi and Ohk (2011) and Choi, Jordan, and Ohk (2012) do not consider the mathematically complicated models that are shown to be competitive options pricing models. In this paper, it is examined whether the roll-over strategies of the parameters for the SV and the SVJ models is functioned. Second, in previous researches, the new roll-over strategies of the parameters, the next-to-next strategy, is not considered for hedging performance. When we find out the best options pricing model, both pricing and hedging performance are considered. Pricing performance measures the ability to forecast the level of options price, but hedging performance does the ability to forecast the variability of options prices. If a specific model shows better performance than other models for both measures, that model can be truly the best options pricing model. Third, Choi and Ohk (2011) and Choi, Jordan, and Ohk (2012) consider the sample period with a span of two years. For two years, the dates that need the roll-over of the parameters are twenty four days when we examine the one day ahead out-of-sample pricing performance. The effect of the roll-over strategy can be exaggerated because of small sample. In this paper, we examine the roll-over strategy using a sample date with a span of 13 years. If the roll-over strategy is worked well even for the long sample period, we can conjecture that there is the structural change of the parameters when the maturity of options is roll-overed. Fourth, recent detailed researches about the AHBS-type models examined KOSPI 200 options, one of emerging markets. Although KOSPI 200 options are the biggest derivatives product in terms of trading volumes, that product is traded in the emerging market. We use S&P 500 (OEX) option price for our empirical work. S&P 500 options have been the focus of many existing investigations including, among others, Bakshi, Cao, and Chan (1997), Bates (1996), Dumas, Fleming, and Whaley (1995). Also, the roll-over strategies of the parameter is not examined in S&P 500 options market. If the new roll-over strategy is well functioned for OEX options, we can expect that it is not only fit to emerging markets but also generally can be applied into advanced options markets.

It is found that when we use the traditional estimation method, the nearest-to-next strategy, the SVJ and SV models show better performance than the AHBS-type models for pricing options. Among AHBS-type models, simpler model with less parameter shows better performance than other models. That is, for the AHBS-type models, the presence of more parameters actually cause over-fitting but that does not cause over-fitting problem for the mathematically complicated models. For the hedging performance, the AHBS-type models show better performance than the mathematically complicated models but, the differences among the models are not significant. When we use the next-to-next strategy, the results are changed. The next-to-next strategy decreases the errors of all options pricing models. The pricing errors of the AHBS-type models are decreased largely by the next-to-next strategy. AHBS-type models show better performance than the mathematically complicated models for pricing options. That is, the next-to-next strategy mitigate over-fitting problem of AHBS-type models. On the other hand, the improvement of the mathematically complicated models including the BS model using the next-to-next strategy is not much.

The outline of this paper is as follows. The AHBS models, the stochastic volatility with jumps model and the roll-over strategies of the parameters are reviewed in Section 2. The data used for analysis are described in Section 3. Section 4 describes parameter estimates of each model and evaluates pricing and hedging performances of alternative models. Section 5 concludes our study by summarizing the results.

II. Model

1. Ad Hoc Black-Scholes Model

Despite its significant pricing and hedging biases, the Black and Scholes (1973) model (henceforth the BS model) continues to be widely used by market practitioners. However, when practitioners apply the BS model, they commonly allow the volatility parameter to vary across strike prices and maturities of options, to fit the volatility to the observed smile pattern. As Dumas, Fleming, and Whaley (1998) show, this procedure can circumvent some of the biases associated with the BS model's constant volatility assumption.

We have to construct the AHBS model in which each option has its own implied volatility depending on a strike price and the time to maturity. Specifically, the spot volatility of the asset that enters the BS model is a function of the strike price and the time to maturity or a combination of both. However we only consider the function of the strike price because the liquidity of the KOPSI 200 index options market is concentrated in the nearest expiration contract. Dumas, Fleming, and Whaley (1998) show that the specification that includes a time parameter does worst of all, indicating that the time variable is an important cause of overfitting problem at the estimation stage.

There are two versions of the ad hoc approach. In the "relative smile" approach, the implied volatility skew is treated as a fixed function of moneyness, S/K and the implied volatility for a fixed strike K varies as the stock index S varies. This is also known as the "sticky volatility" method. In the "absolute smile" approach, the implied volatility is treated as a fixed function of the strike price K and the implied volatility for a fixed strike does not vary with S. This is also known as the "sticky delta" method. These models are so called the ad hoc Black-Scholes model (henceforth AHBS). Dumas, Fleming and Whaley (1998), Jackwerth and Rubinstein (2001) and Li and Pearson (2007), Kim (2009) and Choi and Ohk (2011), Choi, Jordan, and Ohk (2012) who report the AHBS model outperforms other models, adopt the "absolute smile" approach. On the other hand, Kirgiz (2001) and Kim and Kim (2004), who report the AHBS model does not outperform other models, adopt the "relative smile" approach. That is, the type of the AHBS model seems to be important for pricing and hedging options.

In the "relative smile" approach, the implied volatility skew is treated as a fixed function of moneyness, S/K and the implied volatility for a fixed strike K varies as the stock index S varies. In the "absolute smile" approach, the implied volatility skew is treated as a fixed function of the strike price K and the implied volatility for a fixed strike does not vary with S. Specifically we adopt the following six specifications for the BS implied volatilities:

$$\text{R1: } \sigma_i = \beta_1 + \beta_2 \cdot (S / K_i) \tag{1}$$

$$\text{R2: } \sigma_i = \beta_1 + \beta_2 \cdot (S / K_i) + \beta_3 \cdot (S / K_i)^2 \tag{2}$$

$$\text{R3: } \sigma_i = \beta_1 + \beta_2 \cdot (S / K_i) + \beta_3 \cdot (S / K_i)^2 + \beta_4 \cdot (S / K_i)^3 \tag{3}$$

$$\text{A1: } \sigma_i = \beta_1 + \beta_2 \cdot K_i \tag{4}$$

$$\text{A2: } \sigma_i = \beta_1 + \beta_2 \cdot K_i + \beta_3 \cdot K_i^2 \tag{5}$$

$$\text{A3: } \sigma_i = \beta_1 + \beta_2 \cdot K_i + \beta_3 \cdot K_i^2 + \beta_4 \cdot K_i^3 \tag{6}$$

where σ_i is the implied volatility for an i th option of strike K_i and spot price S .

From first to third models are the "relative smile" approaches using the moneyness as the independent variables. From fourth to the last models are the "absolute smile" approaches using the strike prices as the independent variables. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variables. R2 is the ad hoc Black-

Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variables. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variables. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variables. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variables. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variables. Up to now, previous studies do not consider the third power of the moneyness and the strike price. In this paper, the performances of the AHBS models with higher degrees are examined for the first time.

For the implementation, we follow a four-step procedure. First, we abstract the BS implied volatility from each option. Second, we set up the implied volatilities as the dependent variable and the moneyness or the strike price as the independent variables. And we estimate the $\beta_i (i = 1,2,3,4)$ by ordinary least squares. Third, using estimated parameters from the second step, we plug each option's moneyness or the strike price into the equation, and obtain the model-implied volatility for each option. Finally, we use volatility estimates computed in the third step to price options with the following BS formula.

$$C(t,T;K) = S(t)N(d_1) - Ke^{-r(T-t)}N(d_2) \tag{7}$$

$$P(t,T;K) = Ke^{-r(T-t)}N(-d_2) - S(t)N(-d_1) \tag{8}$$

$$d_1 = \frac{\ln[S(t)/K] + (r + \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}, \quad d_2 = d_1 - \sigma\sqrt{T-t} \tag{9}$$

where $N(\cdot)$ is the cumulative standard normal density. The AHBS model, although theoretically inconsistent, can be a more challenging benchmark than the simple BS model for any competing option valuation model.

2. Stochastic Volatility with Jumps Model

Bakshi, Cao, and Chan (1997) derived a closed-form option pricing model that incorporates stochastic volatility and random jumps. Under the risk neutral measure, the underlying nondividend-paying stock price $S(t)$ and its components for any time t are given by

$$\frac{dS(t)}{S(t)} = [R(t) - \lambda\mu_J]dt + \sqrt{V(t)}dZ_S(t) + J(t)dq(t) \tag{10}$$

$$dV(t) = [\theta_v - K_v V(t)]dt + \sigma_v \sqrt{V(t)}dZ_v(t) \tag{11}$$

$$\ln[1 + J(t)] \sim N(\ln[1 + \mu_J] - 1/2\sigma_J^2, \sigma_J^2) \tag{12}$$

where $R(t)$ is the instantaneous spot interest rate at time t, λ is the frequency of jumps per year and $V(t)$ is the diffusion component of return variance (conditional on no jump occurring). $Z_S(t)$ and $Z_v(t)$ are standard Brownian motions, with $Cov_t[dZ_S(t), dZ_v(t)] = \rho dt$. $J(t)$ is the percentage jump size (conditional on a jump occurring) that is lognormally, identically, and independently distributed over time, with unconditional mean, μ_J. The standard deviation of $\ln[1 + J(t)]$ is σ_J. $q(t)$ is a Poisson jump counter with intensity λ, that is, $\Pr[dq(t) = 1] = \lambda dt$ and $\Pr[dq(t) = 0] = 1 - \lambda dt$. κ_v, θ_v / κ_v, and σ_v are the speed of adjustment, long-run mean, and variation coefficient of the diffusion volatility $V(t)$, respectively. $q(t)$ and $J(t)$ are uncorrelated with each other or with $Z_S(t)$ and $Z_v(t)$.

For a European call option written on the stock with strike price K and time to maturity τ, the closed form formula for price $C(t, \tau)$ at time t is as follow.

$$C(t,\tau)=S(t)P_1(t,\tau;S,R,V)-Ke^{-R\tau}P_2(t,\tau;S,R,V) \tag{13}$$

where the risk neutral probabilities, P_1 and P_2, are computed from inverting the respective characteristic functions of the following:

$$P_j(t,\tau;S(t),R(t),V(t))$$

$$=\frac{1}{2}+\frac{1}{\pi}\int_0^\infty \mathrm{Re}\left[\frac{\exp(-i\phi \ln K)f_j(t,\tau,S(t),R(t),V(t);\phi)}{i\phi}\right] \quad (j=1,2) \tag{14}$$

The characteristic functions, f_j, are given in equations (A-1) and (A-2) of the Appendix. The price of a European put on the same stock can be determined from the put-call parity.

The option valuation model in equation (13) and (14) contains the most existing models as special cases. For example, we obtain (i) the BS model by setting $\lambda=0$ and $\theta_v=\kappa_v=\sigma_v=0$; and (ii) the SV model by setting $\lambda=0$, where to derive each special case from equation (14) one may need to apply L'Hopital's rule.

In applying option pricing models, one always encounters the difficulty that spot volatilities and structural parameters are unobservable. As estimated in the standard practice, we estimate the parameters of each model every sample day. Since closed-form solutions are available for an option price, a natural candidate for the estimation of parameters in the pricing and hedging formula is a non-linear least squares procedure, involving a minimization of the sum of percentage squared errors between the model and the market prices. Estimating parameters from the asset returns can be an alternative method, but historical data reflect only what happened in the past. Furthermore, the procedure using historical data is not capable of identifying risk premiums, which must be estimated from the options data conditional on the estimates of other parameters. The important advantage of using option prices to estimate parameters is to allow one to use the forward-looking information contained in the option prices.

Let $O_i^*(t,\tau;K)$ denote the model price of the option i on day t and $O_i(t,\tau;K)$ denote the market price of option i on day t. To estimate parameters for each model, we minimize the sum of percentage squared errors between the model and the market prices:

$$\min_{\phi_t}\sum_{i=1}^{N}\left[\frac{O_i^*(t,\tau;K)-O_i(t,\tau;K)}{O_i(t,\tau;K)}\right]^2 \quad (t=1,\Lambda\ ,T) \qquad (15)$$

where N denotes the number of options on day t, and T denotes the number of days in the sample. Conventionally, the objective function to minimize the sum of squared errors is used. However, we adopt the above function since the conventional method that gives more weight to relatively expensive in-the-money options makes the worse fit for out-of-the-money options.[1]

3. Rollover Strategies

When we forecast and hedge option prices, we need to estimate the parameters to plug into each model. For one day ahead pricing and hedging performance, the parameters are estimated using the previous days' options data. For one week ahead pricing and hedging performance, the options data seven days ago are used. In general trading dates, there is no complicate problems to implement this methodology. However, it is standard to eliminate the nearest option contracts with expiries less than 7 days, and use the next-to-nearest option contracts with expiries less than 7 days plus 1 month for the empirical study because of the liquidity problems of options contract. When forecasting the parameters for the next-to-nearest option contracts with expiry less than 7 days plus 1 month, one can use either the nearest contracts with expiry

[1] In our sample, there was no large difference between the results using the sum of squared errors and those using the sum of squared percentage errors.

greater than 6 days or the next-to-nearest contracts with expiry greater than 6 days plus 1 month. The information content of these two contracts may differ and the rollover procedure may be important to the accuracy of the parameter forecasting. Choi and Ohk (2011) consider two rollover strategies from then on the day of rollover from the nearest contract to next contract: the nearest-to-next strategy and the next-to-next strategy. Specifically, when the nearest contract's expiry is less than 7 days, the next-to-next strategy uses the next-to-nearest contracts on the previous day(s), whereas the nearest-to-next one uses the nearest-term contracts. These two strategies are different only on the day(s) when the expiry of nearest-term option contracts is less than seven days. In this paper, the performances of the nearest-to-next strategy and the next-to-next strategy are compared.

III. Data

The SPX option data used in this paper come from Option Metrics LLC. The data include end-of day bid and ask quotes, implied volatilities, open interest, and daily trading volume for the SPX (S&P 500 index) options traded on the Chicago Board Options Exchange from January 4, 1996 through December 31, 2008. The data also include daily index values and estimates of dividend yields, as well as term structures of zero-coupon interest rates constructed from LIBOR quotes and Eurodollar futures prices. We use the bid-ask average as our measure of the option price.

The following rules are applied to filter data needed for the empirical test. We use out-of-the-money options for calls and puts. First of all, since there is only a very thin trading volume for the in-the-money (henceforth ITM) option, the reliability of price information is not entirely satisfactory. Therefore, we use price data regarding both put and call options that are near-the-money and out-of-the-money (henceforth OTM). Second, if both call and put option prices are used, ITM calls and OTM puts which are equivalent according to the put-call parity are used to estimate the parameters. Third, as Huang and Wu (2004) mention, "the Black-Scholes model has been known to systematically misprice equity index options, especially those that are out-of-the-money (OTM)." We recognize the need for alternative option pricing model to mitigate this effect. As options with less than 7 days to expiration may induce biases due to low prices and bid-ask spreads, they are excluded from the sample. Because the liquidity is concentrated in the nearest expiration contract, we only consider options with the nearest maturity. To mitigate the impact of price discreteness on option valuation, prices lower than 0.4 are not included. Prices not satisfying the arbitrage restriction are excluded.

We divide the option data into several categories according to the moneyness, S/K. Table 1 describes certain sample properties of the OEX option prices used in the study. Summary statistics are reported for the option price and the total number of observations, according to each moneyness-option type category. Table 2 presents the "volatility smiles" effects for 26 consecutive sub-periods. We employ six fixed intervals for the degree of moneyness, and compute the mean over alternative subperiods of the implied volatility. OEX options market seems to be "sneer" independent of the subperiods employed in the estimation. As the S/K increase, the implied volatilities decrease to near-the-money but, after that, increase to out-of-the-money put options. The implied volatility of deep out-of-the-money puts is larger than that of deep out-of-the-money calls. That is, a volatility smile is skewed towards one side. The skewed volatility smile is sometimes called a 'volatility smirk' because it looks more like a sardonic smirk than a sincere smile. In the equity options market, the volatility smirk is often negatively skewed where lower strike prices for out-of-the money puts have higher implied volatilities and, thus, higher valuations.[2] This is consistent with Rubinstein (1994), Derman (1999), Bakshi, Kapadia, and Madan (2001), and Dennis and Mayhew (2002). As the smile evidence is indicative of negatively-skewed implicit return distribution with excess kurtosis, a better model must be based on a distributional assumption that allows for negative skewness

[2] See Rubinstein(1994) and Bakshi, Cao, and Chan(1997).

and excess kurtosis.

IV. Empirical Results

In this section, we compare empirical performances of each model with respect to in-sample pricing, out-of-sample pricing and hedging performance. The analysis is based on two measures: mean absolute percentage errors (henceforth MAPE), and root mean squared errors (henceforth RMSE) as follows.

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N}\sum_{i=1}^{N}\left|\frac{O_i(t,\tau;K)-O_i^*(t,\tau;K)}{O_i(t,\tau;K)}\right| \tag{16}$$

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\frac{1}{N}\sum_{i=1}^{N}\left[O_i(t,\tau;K)-O_i^*(t,\tau;K)\right]^2} \tag{17}$$

where, $O_i^*(t,\tau;K)$ denote the model price of the option i on day t and $O_i(t,\tau;K)$ denote the market price of option i on day. N denotes the number of options on day t, and T denotes the number of days in the sample. MAPE measures the magnitude of pricing errors, while RMSE measures the volatility of errors.

1. In-sample Pricing Performance

Table 3 reports the mean and the standard error of the parameter estimates for each model. R^2 values for each model are reported. For the AHBS-type models, each parameter is estimated by the ordinary least squares every day. For the BS, SV, and SVJ models, each parameter is estimated by minimizing the sum of percentage squared errors between model and market option prices every day. First, the estimates of each model's parameters have excessive standard errors of daily parameters. However, such estimation will be valuable for the following reasons.

The estimated parameters can be generated by indicating market sentiment on a daily basis and the estimated parameters may suggest the future specification of more complicated dynamic models. Because this ad hoc Black-Scholes method is based on not theoretical backgrounds but the traders' rule, it is not a fatal problem. Second, as expected, the models (R3 andA3) that have four independent variables show higher R^2 values than other models do. So, it is necessary to check over-fitting problem by examining the out-of-sample pricing performance. Third, the implied correlation of the SV and SVJ models has negative values. The negative estimate indicates that the implied volatility and the index returns are negatively correlated and the implied distribution perceived by option traders is negatively skewed. This is consistent with the volatility sneer pattern shown in table 2.

We evaluate the in-sample pricing performance of each model by comparing market prices with model's prices computed by using the parameter estimates from the current day. Table 4 reports in-sample valuation errors for the alternative models computed over the whole sample of options. The SVJ model shows the best performance closely followed by the A3 model for MAPE and the A3 model outperforms other models for RMSE. In a rough way, the SVJ and the A3, the complex models, are the best models for in-sample pricing. This is a rather obvious result when the use of larger number of parameters in the SVJ and A3 model is considered. Surprisingly, although the SV model has five parameters, the SV model does not show better performance than the A3 and the R3 model with four parameters. The in-sample pricing performance is not simply contingent on the number of free parameters. Lastly, all models show moneyness-based valuation errors. The models exhibit the worst fit for the out-of-the-money options. The fit, as measured by MAPE, steadily improves as we move from out-of-the-money to near-the-money options. Overall, all AHBS-type models and mathematically complicated models show better performance than the BS model. Also the traders' rule can explain the current market price in the options market although it is not rooted in rigorous theory.

2. Out-of-sample Pricing Performance

In-sample pricing performance can be biased due to the potential problem of over-fitting to the data. A good in-sample fit might be a consequence of having an increasingly larger number of parameters. To lower the impact of this connection to inferences, we turn to examining the model's out-of-sample cross-sectional pricing performance. In the out-of-sample pricing, the presence of more parameters may actually cause over-fitting and have the model penalized if the extra parameters do not improve its structural fitting. This analysis also has the purpose of assessing the stability of each model's parameter over time. To control the parameters' stability over alternative time periods, we analyze out-of-sample valuation errors for the following day (week). We use the current day's estimated structural parameters to price options for the following day (week).

Table 5 and table 6 respectively report one-day and one-week ahead out-of-sample valuation errors for alternative models computed over the whole sample of options. First of all, we examine the pricing performance using the nearest-to-next roll-over strategy. Panel A of table 5 and table 6 represents the results using the nearest-to-next roll-over strategy. For one day ahead out-of-sample pricing, the SVJ model shows the best performance, closely followed by the SV model. The SVJ and the SV models also exhibit better fit for the one week ahead out-of-sample pricing. For the in-sample pricing performance, the AHBS-type models are competitive. However, for the out-of-sample pricing performance, the mathematically complicated models show better performance than AHBS-type models. That is, the presence of more parameters of the SVJ and SV models actually does not cause over-fitting. Contrary to Jackwerth and Rubinstein (2001), Li and Pearson (2007) and Kim (2009), the traders' rules do not dominate mathematically more sophisticated model, the SVJ and the SV models, although the traders' rules is not far behind. With respect to moneyness-based errors, similar to the case of in-sample pricing, MAPE steadily decreases as we move from deep out-of-the-money to near-the-money options for all models. Generally, the SVJ model outperforms all the other models.

Pricing errors increase from in-sample to out-of-sample pricing. The average of MAPE of all the models is 0.1334 for the in-sample pricing, and grows to 0.4022 for one-day ahead out-of-sample pricing. One-week ahead out-of-sample pricing errors grow to 0.6953 almost five times as much as in-sample pricing errors. The relative margin of performance is significantly changed when compared to that of the in-sample pricing case. The difference of the BS and the best model, the SVJ model, becomes smaller in the out-of-sample pricing. The ratio of the BS model to the SVJ model for MAPE is 8.2279 for in-sample pricing errors. The ratio of the BS model to the SVJ model decreases to 2.5267 and to 1.4218 for one-day ahead and one-week ahead out-of-sample errors, respectively. As the term of the out-of-sample pricing gets longer, the difference between the BS model and the SVJ model, becomes smaller. The pricing performance of the SVJ model that is the best model for in-sample pricing is maintained as the term of out-of-sample pricing gets longer, implying that the presence of more parameters actually does not cause over-fitting. However, for the AHBS-type models, the A3 and R3 model, the best models among them for in-sample pricing, do not remain their position for one day and one week ahead out-of-sample pricing. For out-of-sample pricing, the A3 and the R3 models are changed into the very last implying that the presence of more parameters actually cause over-fitting. This result is consistent with the result of Jackwerth and Rubinstein (2001), Li and Pearson (2007) and Kim (2009). As a result, the mathematically complicated models do not have over-fitting problems and the AHBS-type models have those when the nearest-to-next roll-over strategy is used. To mitigate these problems, we need to consider the new roll-over strategy, the next-to-next strategy.

Second, we examine the pricing performance for the next-to-next roll-over strategy suggested by Choi and Ohk (2011). Panel B of table 5 and table 6 represents the results for the next-to-next roll-over strategy. Above all, the next-to-next roll-over strategy decreases the errors of all options pricing models. After using the next-to-next strategy, the averages of the MAPEs of all options pricing models are decreased from 0.4022 (0.6953) to 0.2557 (0.3485) for one day (one week) ahead out-of-sample pricing. Panel A and panel B of Figure 1 represent the MAPE of each options pricing model for both the nearest-to-next and the next-to-next roll-over strategies, respectively. The pricing errors of the AHBS-type models are decreased largely by the next-to-next strategy. Among them, the models with more parameters, the R3 and A3 model are favored the most. On the other hand, the improvement of the mathematically complicated models including the BS model is not much. Using the next-to-next strategy, the averages of the MAPEs of all AHBS-type models are decreased from 0.4426 (0.7968) to 0.2321 (0.2321), but those of the mathematically complicated models are from 0.2176 (0.4480) to 0.1924 (0.3342) for one day (one week) ahead out-of-sample pricing, respectively. For one day ahead out-of-sample pricing, the A2 model generally shows the best performance, closely followed by the SV model. The A3 models exhibit better fit for the one week ahead out-of-sample pricing, closely followed by the SV model. Using the nearest-to-next roll-over strategy, the SVJ model shows better performance than other models. However, using next-to-next strategy, AHBS-type models show better performance than the mathematically complicated models. As a result, after the next-to-next roll-over strategy is applied, the A2 or A3 model outperforms all the other models.

Finally, we consider the relative strength of the absolute and relative smile models for pricing options. For in-sample pricing, the averages of the MAPEs of relative smile and absolute smile approaches are 0.0969 and 0.1005, respectively. Using the nearest-to-next strategy, for one day (one week) ahead out-of-sample pricing, the average MAPEs of alternative relative smile and absolute smile approaches are 0.4724 (0.8628) and 0.4128 (0.7308), respectively. Using the next-to-next strategy, for one day (one week) ahead out-of-sample pricing, the averages of the MAPEs of alternative relative smile and absolute smile approaches are 0.2462 (0.3518) and 0.2180 (0.2836), respectively. In other words, the effects of the reduction of pricing errors using the absolute smile approach are much better compared with those using the relative smile approach. This result is consistent with that of Jackwerth and Rubinstein (2001), Li and Pearson

(2007), Kim (2009), and Choi and Ohk (2011) who report that the "absolute smile" model beats the "relative smile" model in predicting prices. The result can be explained by the fact that the absolute smile model implicitly adjusts for the negative correlation between the index level movement and the level of implied volatilities. Because the absolute model treats the skew as a fixed function of the strike instead of the moneyness S/K, it makes out a smaller implied volatility than the relative smile model when there is an increase in the stock price.

3. Hedging Performance

Hedging performance is important to gauge the forecasting power of the volatility of underlying assets. We examine hedges in which only a single instrument (i.e., the underlying asset) can be employed. In practice, option traders usually focus on the risk due to the underlying asset price volatility alone, and carry out a delta-neutral hedge, employing only the underlying asset as the hedging instrument.

We implement hedging with the following method. Consider hedging a short position in an option, $O(t,\tau;K)$ with τ periods to maturity and strike price of K. Let $\Delta_S(t)$ be the number of shares of the underlying asset to be purchased, and $\Delta_0(= O(t,\tau;K) - \Delta_S(t)S_t)$ be the residual cash positions. We consider the delta hedging strategy of $\Delta_S = \partial O(t,\tau;K)/\partial S_t$ and $\Delta_0(t)$.

To examine the hedging performance, we use the following steps. First, on day t, we short an option, and construct a hedging portfolio by buying $\Delta_S(t)$ shares of the underlying asset[3], and investing $\Delta_0(t)$ in a risk-free bond. To compute $\Delta_S(t)$, we use estimated parameters from the previous trading day and the current day's asset price. For the SV model, we use estimated instantaneous volatility from the previous day. For the AHBS model, the volatility parameter necessary to compute the delta position is obtained by plugging the option specific strike price

[3] The delta, for a put option, is negative, which means that a short position in put options should be hedged with a short position in the underlying stock.

into the regression equation along with the previous day's parameter estimates. Second, we liquidate the position after the next trading day or the next week. Then we compute the hedging error as the difference between the value of the replicating portfolio and the option price at the time of liquidation:

$$\varepsilon_t = \Delta_S \cdot S_{t+\Delta t} + \Delta_0 e^{r\Delta t} - O(t+\Delta t, \tau - \Delta t; K). \qquad (18)$$

Table 7 and table 8 present one day and one week hedging errors over alternative moneyness categories respectively. First, using the nearest-to-next roll-over strategy, the A1 model has the best hedging performance for one day and one week. Except the BS model, the SV or the SVJ model is the worst performer. For the hedging performance, the AHBS-type models show better performance than the other models. However the difference among models is not so large. This result is consistent with Kim (2009). The ratio of the BS model to the A1 model which is the best performers is 1.1724 and 1.0967 for one-day ahead and one-week ahead hedging errors, respectively. In each moneyness category, the hedging errors are highest for ATM options and get smaller as we move to OTM options. This pattern is true for every model and for each rebalancing frequency. Second, we examine the hedging results using the next-to-next roll-over strategy. In Panel A and Panel B of Figure 2, the errors of all models are decreased and the AHBS-type models are favored the most, similar to the pricing results. The A3 is the best performer for both one day and one week ahead hedging errors. However, the next-to-next strategy does not make extreme decreases. For hedging performance, the impact of the next-to-next roll-over strategy is not much.

V. Conclusion

For the OEX options, we implement a horse race competition among several options pricing models. We examine the traders' rules to predict future implied volatilities by applying simple ad hoc rules to the observed current implied volatility function and the mathematically complicated models, the SV and the SVJ model, for pricing and hedging options. The roll-over strategies of the parameters for each options pricing model are also examined. In the nearest-to-next strategy, the options data of the nearest term contract on day $t - k$ is used to estimate the parameters of the next-to-nearest contract on day t, whereas in the next-to-next, the next-to-nearest contract on day $t - k$ is used to estimate the parameter of the next-to-nearest contract on day t.

It is found that when we use the traditional estimation method, the nearest-to-next strategy, the SVJ and SV models show better performance than the AHBS-type models for pricing options. Among AHBS-type models, simpler model with less parameter shows better performance than other models. That is, for the AHBS-type models, the presence of more parameters actually cause over-fitting but that does not cause over-fitting problem for the mathematically complicated models, the SV and SVJ models. For the hedging performance, the AHBS-type models show better performance than the mathematically complicated models but, the differences among the models are not significant. When we use the next-to-next strategy, the results are changed. The next-to-next strategy decreases the errors of all options pricing models. The pricing errors of the AHBS-type models are decreased largely by the next-to-next strategy. AHBS-type models show better performance than the mathematically complicated models for pricing options. That is, the next-to-next strategy mitigate over-fitting problem of AHBS-type models. On the other hand, the improvement of the mathematically complicated models including the BS model using the next-to-next strategy is not much. Also, the "absolute smile" approach shows better performance than the "relative smile" approach.

As a result, when the nearest-to-next strategy is considered, the SVJ model shows better performance than the AHBS-type models. However, after considering the next-to-next strategy, the AHBS-type model has the advantage of simplicity and can be competitive model for pricing and hedging S&P 500 index options.

Appendix

The characteristic functions $\hat{f}_j$ for the SVJ model are respectively given by

$$\hat{f}_1 = \exp\left[-i\phi \ln[B(t,\tau)] - \frac{\theta_v}{\sigma_v^2}\left[2\ln\left(1 - \frac{[\xi_v - \kappa_v + (1+i\phi)\rho\sigma_v](1-e^{-\xi_v\tau})}{2\xi_v} \right)\right]\right.$$

$$- \frac{\theta_v}{\sigma_v^2}[\xi_v - \kappa_v + (1+i\phi)\rho\sigma_v]\tau + i\phi\ln[S(t)]$$

$$+ \lambda(1+\mu_J)\tau\left[(1+\mu_J)^{i\phi} e^{(i\phi/2)(1+i\phi)\sigma_J^2} - 1\right] - \lambda i\phi\mu_J\tau$$

$$\left. + \frac{i\phi(i\phi+1)(1-e^{-\xi_v\tau})}{2\xi_v - [\xi_v - \kappa_v + (1+i\phi)\rho\sigma_v](1-e^{-\xi_v\tau})} V(t) \right], \tag{A-1}$$

and

$$\hat{f}_2 = \exp\left[-i\phi \ln[B(t,\tau)] - \frac{\theta_v}{\sigma_v^2}\left[2\ln\left(1 - \frac{[\xi_v^* - \kappa_v + i\phi\rho\sigma_v](1-e^{-\xi_v^*\tau})}{2\xi_v} \right)\right]\right.$$

$$- \frac{\theta_v}{\sigma_v^2}[\xi_v^* - \kappa_v + i\phi\rho\sigma_v]\tau + i\phi\ln[S(t)]$$

$$+ \lambda(1+\mu_J)\tau\left[(1+\mu_J)^{i\phi} e^{(i\phi/2)(i\phi-1)\sigma_J^2} - 1\right] - \lambda i\phi\mu_J\tau$$

$$\left. + \frac{i\phi(i\phi-1)(1-e^{-\xi_v^*\tau})}{2\xi_v^* - [\xi_v^* - \kappa_v + i\phi\rho\sigma_v](1-e^{-\xi_v^*\tau})} V(t) \right], \tag{A-2}$$

where

$$\xi_v = \sqrt{[\kappa_v - (1+i\phi)\rho\sigma_v]^2 - i\phi(1+i\phi)\sigma_v^2}$$

$$\xi_v^* = \sqrt{[\kappa_v - i\phi\rho\sigma_v]^2 - i\phi(i\phi-1)\sigma_v^2}$$

The characteristic functions for the SV model can be obtained by setting $\lambda = 0$ in (A-1) and (A-2).

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Table 1: Options Data

This table reports average option price, and the number of options, which are shown in parentheses, for each moneyness and type (call or put) category. The sample period is from January 4, 1996 to December 31, 2008. Last bid-ask average of each option contract is used to obtain the summary statistics. Moneyness of an option is defined as S/K where S denotes the spot price and K denotes the strike price.

Call Options			Put Options		
Moneyness	Price	Number	Moneyness	Price	Number
S/K<0.94	2.7833	10,033	1.00<S/K<1.03	13.0104	17,966
0.94<S/K<0.96	4.8054	13,580	1.03<S/K<1.06	6.5072	15,149
0.96<S/K<1.00	12.2916	18,783	S/K>1.06	3.0967	31,201
Total	7.6435	42,396	Total	6.6693	64,316

Table 2: Implied Volatility

This table reports the implied volatilities calculated by inverting the Black-Scholes model separately for each moneyness category. The implied volatilities of individual options are then averaged within each moneyness category and across the days in the sample. Moneyness is defined as S/K where S denotes the spot price and K denotes the strike price. 1996 01-06 is the period from January, 1996 to June, 1996.

	$S/K < 0.94$	$0.94 < S/K < 0.97$	$0.97 < S/K < 1.00$	$1.00 < S/K < 1.03$	$1.03 < S/K < 1.06$	$S/K > 1.06$
1996 01-06	0.1308	0.1204	0.1207	0.1553	0.1841	0.2249
1996 07-12	0.1413	0.1243	0.1289	0.1606	0.1884	0.2332
1997 01-06	0.1626	0.1579	0.1636	0.1895	0.2108	0.2516
1997 07-12	0.1920	0.1867	0.1957	0.2223	0.2477	0.3092
1998 01-06	0.1517	0.1491	0.1588	0.1917	0.2226	0.2872
1998 07-12	0.2364	0.2037	0.2139	0.2406	0.2709	0.3492
1999 01-06	0.1831	0.1851	0.2011	0.2267	0.2511	0.3132
1999 07-12	0.1626	0.1658	0.1774	0.2035	0.2267	0.2887
2000 01-06	0.1922	0.1840	0.1969	0.2238	0.2417	0.3025
2000 07-12	0.2095	0.1844	0.1891	0.2070	0.2259	0.2841
2001 01-06	0.2120	0.1962	0.2040	0.2269	0.2391	0.2996
2001 07-12	0.2159	0.1977	0.2115	0.2401	0.2638	0.3525
2002 01-06	0.1781	0.1694	0.1740	0.1993	0.2256	0.2889
2002 07-12	0.2711	0.2683	0.2787	0.3070	0.3270	0.3850
2003 01-06	0.2427	0.2248	0.2208	0.2325	0.2504	0.2951
2003 07-12	0.1563	0.1459	0.1446	0.1689	0.1911	0.2444
2004 01-06	0.1464	0.1262	0.1243	0.1504	0.1768	0.2281
2004 07-12	0.1227	0.1127	0.1121	0.1354	0.1589	0.2036
2005 01-06	0.1197	0.1025	0.0986	0.1233	0.1510	0.1994
2005 07-12	0.1628	0.0902	0.0926	0.1205	0.1472	0.1958
2006 01-06	0.1205	0.0968	0.0981	0.1289	0.1562	0.2131
2006 07-12	0.2184	0.0875	0.0903	0.1201	0.1480	0.1954
2007 01-06	0.1666	0.0945	0.0955	0.1301	0.1618	0.2236
2007 07-12	0.1809	0.1548	0.1713	0.2124	0.2386	0.2917
2008 01-06	0.1902	0.1771	0.1942	0.2284	0.2471	0.2893
2008 07-12	0.3975	0.3296	0.3435	0.3754	0.4017	0.4722

Table 3: Parameters

The table reports the mean and the standard error of the parameter estimates for each model. The mean and the standard deviation of R^2s for each model are reported. For the AHBS-type models, each parameter is estimated by the ordinary least squares every day. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variable. R2 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variable. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variable. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variable. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variable. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variable. BS is the Black-Scholes (1973) option pricing model. SV is the option pricing model considering the continuous-time stochastic volatility. SVJ is the option pricing model considering the continuous-time stochastic volatility and the jumps. For the BS, SV, and SVJ models, each parameter is estimated by minimizing the sum of percentage squared errors between model and market option prices every day.

Panel A: AHBS-type Models

	β_0	β_1	β_2	β_3	R^2
R1	-0.6097 (0.0052)	0.8006 (0.0046)			0.9326 (0.1124)
R2	1.7984 (0.0631)	-3.9174 (0.1255)	2.3059 (0.0621)		0.9720 (0.0427)
R3	26.9431 (1.0340)	-77.5085 (3.0511)	73.9906 (2.9996)	-23.2409 (0.9828)	0.9833 (0.0289)
A1	1.0360 (0.0048)	-0.0008 (0.0000)			0.9152 (0.1202)
A2	4.3900 (0.0656)	-0.0071 (0.0001)	0.0000 (0.0000)		0.9761 (0.0377)
A3	-17.1892 (1.0140)	0.0559 (0.0030)	-0.0001 (0.0000)	0.0000 (0.0000)	0.9847 (0.0285)

Panel B: Other Models

	σ
BS	0.1699 (0.0012)

	λ	μ_J	σ_J	κ	θ	σ_v	ρ	v_t
SV				5492.2986 (5200.8240)	6.3328 (0.4005)	140.5703 (127.4397)	-0.5426 (0.0023)	6.5856 (6.3503)
SVJ	2.4129 (0.1533)	0.0084 (0.0268)	2.2860 (04780)	5814.9122 (3853.0067)	0.4964 (0.0287)	2.2812 (0.3920)	-0.2469 (0.0119)	25.9249 (23.5741)

Table 4: In-Sample Pricing Errors

This table reports in-sample pricing errors with respect to moneyness. S/K is defined as moneyness where S denotes the asset price and K denotes the strike price. Each model is estimated every day during the sample period and in-sample pricing errors are computed using estimated parameters from the current day. MAPE denotes mean absolute percentage errors and RMSE denotes root mean squared errors. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variables. R2 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variables. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variables. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variables. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variables. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variables. BS is the Black-Scholes (1973) option pricing model. SV is the option pricing model considering the continuous-time stochastic volatility. SVJ is the option pricing model considering the continuous-time stochastic volatility and jumps.

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	0.2780	0.3521	0.2537	0.1337	0.4723	0.2116	0.1089	0.1186	0.0984
	0.94<S/K<0.96	0.2145	0.2268	0.1546	0.0915	0.2555	0.1431	0.0769	0.0561	0.0467
	0.96<S/K<1.00	0.1328	0.1090	0.0854	0.0615	0.1169	0.0800	0.0565	0.0561	0.0442
	1.00<S/K<1.03	0.2987	0.0655	0.0425	0.0480	0.0720	0.0436	0.0471	0.0586	0.0516
	1.03<S/K<1.06	0.6453	0.0749	0.0469	0.0384	0.0879	0.0461	0.0357	0.0566	0.0448
	S/K>1.06	0.9065	0.0957	0.0739	0.0590	0.1148	0.0691	0.0566	0.0702	0.0712
	Total	0.4838	0.1308	0.0940	0.0658	0.1557	0.0863	0.0595	0.0666	0.0588
RMSE	S/K<0.94	0.8478	0.6683	0.4764	0.2383	2.8438	0.3796	0.2173	0.3040	0.4919
	0.94<S/K<0.96	1.3162	0.9581	0.6833	0.3747	1.0699	0.7589	0.3370	0.5302	0.6625
	0.96<S/K<1.00	2.3751	1.3847	1.1295	0.8592	1.5330	1.0672	0.8222	0.9734	1.1253
	1.00<S/K<1.03	4.7693	1.0109	0.8813	0.9327	1.0172	0.9080	0.8887	1.1914	1.5422
	1.03<S/K<1.06	4.7025	0.5752	0.5852	0.3648	0.5569	0.5734	0.3191	0.5246	1.3276

	S/K>1.06	3.6577	0.3225	0.3329	0.2059	0.3643	0.3000	0.1828	0.2238	1.2709
	Total	3.4873	0.8635	0.7191	0.5752	1.2557	0.7065	0.5432	0.7100	1.1934

Table 5: One Day Ahead Out-of-Sample Pricing Errors

This table reports one day ahead out-of-sample pricing errors with respect to moneyness. S/K is defined as moneyness where S denotes the asset price and K denotes the strike price. Each model is estimated every day during the sample period and one day ahead out-of-sample pricing errors are computed using estimated parameters from the previous trading day. MAPE denotes mean absolute percentage errors and RMSE denotes root mean squared errors. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variables. R2 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variables. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variables. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variables. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variables. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variables. BS is the Black-Scholes (1973) option pricing model. SV is the option pricing model considering the continuous-time stochastic volatility. SVJ is the option pricing model considering the continuous-time stochastic volatility and jumps.

Panel A: Nearest-to-Next

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	0.5341	1.5407	0.9417	1.5318	1.9915	0.9234	1.6504	0.5778	0.4373
	0.94<S/K<0.96	0.3247	0.3937	0.3218	0.3152	0.4314	0.2639	0.2966	0.2566	0.2623
	0.96<S/K<1.00	0.1802	0.1765	0.1610	0.1461	0.1558	0.1315	0.1182	0.1412	0.1474
	1.00<S/K<1.03	0.3000	0.1205	0.1059	0.1072	0.1048	0.0868	0.0888	0.1241	0.1177
	1.03<S/K<1.06	0.6398	0.1673	0.1545	0.1574	0.1455	0.1297	0.1288	0.1831	0.1701
	S/K>1.06	0.9048	0.2719	0.6004	1.5192	0.2345	0.4619	1.0370	0.2295	0.2221
	Total	0.5291	0.3496	0.3731	0.6945	0.3765	0.3116	0.5502	0.2258	0.2094
MSE	S/K<0.94	3.1253	9.8866	6.9483	11.2266	12.1547	7.4598	11.6676	10.2350	1.8681
	0.94<S/K<0.96	2.2157	2.5736	2.2606	2.2050	2.8509	1.9258	1.8610	4.5890	2.0238
	0.96<S/K<1.00	2.9984	2.6426	2.3948	2.3005	2.3494	1.9160	1.7958	4.1612	2.5945
	1.00<S/K<1.03	4.9140	2.2118	2.1536	2.1869	1.8059	1.7111	1.7057	4.1129	2.6332
	1.03<S/K<1.06	4.7668	1.7302	1.7318	1.8537	1.3526	1.3127	1.2769	3.6266	2.1428

	S/K>1.06	3.7063	1.6942	3.1487	12.5589	1.3521	2.3913	9.4232	4.0781	1.7147
	Total	3.7990	3.6539	3.2101	7.7982	4.1522	2.9598	6.3635	5.0155	2.1709

Panel B: Next-to-Next

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	0.4918	0.9766	0.6284	1.0934	1.0709	0.5456	0.9756	0.4143	0.4069
	0.94<S/K<0.96	0.3204	0.3412	0.3045	0.2646	0.3045	0.2433	0.2133	0.2340	0.2397
	0.96<S/K<1.00	0.1795	0.1688	0.1563	0.1415	0.1469	0.1260	0.1123	0.1322	0.1381
	1.00<S/K<1.03	0.2992	0.1163	0.1008	0.1021	0.0999	0.0811	0.0831	0.1121	0.1091
	1.03<S/K<1.06	0.6390	0.1612	0.1447	0.1450	0.1392	0.1213	0.1202	0.1661	0.1592
	S/K>1.06	0.9042	0.2016	0.1865	0.1906	0.1865	0.1573	0.1591	0.1954	0.2018
	Total	0.5241	0.2664	0.2174	0.2549	0.2564	0.1813	0.2162	0.1916	0.1931
MSE	S/K<0.94	2.0566	6.5118	4.4744	9.9655	7.7868	4.2148	10.1036	2.0878	1.9821
	0.94<S/K<0.96	2.0071	1.9145	1.8257	1.7539	1.5357	1.3176	1.2002	1.8637	1.7718
	0.96<S/K<1.00	2.9282	2.3118	2.1726	2.0654	1.9846	1.6376	1.4830	2.1965	2.1697
	1.00<S/K<1.03	4.9063	1.9392	1.8888	1.9098	1.4814	1.3808	1.3534	2.0800	2.2010
	1.03<S/K<1.06	4.7669	1.4731	1.4869	1.4545	1.0535	1.0306	0.9614	1.5444	1.8706
	S/K>1.06	3.6934	1.1429	1.1481	1.1399	0.8229	0.7548	0.7765	1.1771	1.6165
	Total	3.6995	2.5918	2.1065	3.4315	2.7239	1.7325	3.2841	1.7813	1.9167

Table 6: One Week Ahead Out-of-Sample Pricing Errors

This table reports one week ahead out-of-sample pricing errors for the KOSPI 200 option with respect to moneyness. S/K is defined as moneyness where S denotes the asset price and K denotes the strike price. Each model is estimated every day during the sample period and one week ahead out-of-sample pricing errors are computed using estimated parameters from one week ago. MAPE denotes mean absolute percentage errors and RMSE denotes root mean squared errors. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variables. R2 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variables. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variables. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variables. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variables. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variables. BS is the Black-Scholes (1973) option pricing model. SV is the option pricing model considering the continuous-time stochastic volatility. SVJ is the option pricing model considering the continuous-time stochastic volatility and jumps.

Panel A: Nearest-to-Next

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	0.8617	1.9879	2.0170	3.0647	2.6419	2.0196	3.6512	1.3913	0.7470
	0.94<S/K<0.96	0.4497	0.5460	0.4920	0.4991	0.5954	0.4316	0.5740	0.5209	0.5237
	0.96<S/K<1.00	0.2190	0.2455	0.2304	0.2148	0.2103	0.1795	0.1709	0.2549	0.2709
	1.00<S/K<1.03	0.3069	0.1766	0.1677	0.1667	0.1433	0.1316	0.1333	0.2247	0.2172
	1.03<S/K<1.06	0.6341	0.2672	0.2738	0.2784	0.2119	0.2234	0.2277	0.3665	0.3355
	S/K>1.06	0.8970	0.5984	1.4879	2.7130	0.4559	1.1021	1.6741	0.5318	0.4778
	Total	0.5808	0.5424	0.7952	1.2507	0.5488	0.6527	0.9910	0.4874	0.4085
MSE	S/K<0.94	4.2860	11.7077	12.6689	15.3663	14.5579	11.5353	15.0424	12.9565	2.7126
	0.94<S/K<0.96	2.9367	3.4075	3.4598	3.3580	3.6598	2.6120	3.1233	6.5186	3.1778
	0.96<S/K<1.00	3.6061	3.6611	3.4406	3.3757	3.0477	2.5708	2.5055	6.3450	4.1884
	1.00<S/K<1.03	5.1224	3.3300	3.3049	3.3273	2.5613	2.4069	2.4213	6.3463	4.2508
	1.03<S/K<1.06	4.8038	2.7604	2.7448	2.8641	2.1222	2.0400	2.2054	5.7462	3.3905

	S/K>1.06	3.6253	2.5126	4.1344	15.3676	2.0307	3.4903	11.2947	5.6007	2.6057
	Total	4.0802	4.6395	5.1587	9.8868	5.1212	4.4360	7.9132	6.9945	3.4238

Panel B: Next-to-Next

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	0.6769	1.0920	1.1717	0.8539	0.9536	0.9828	0.6170	0.5046	0.7284
	0.94<S/K<0.96	0.4182	0.4678	0.4482	0.4071	0.3642	0.3345	0.3078	0.3604	0.4830
	0.96<S/K<1.00	0.2159	0.2419	0.2340	0.2157	0.1933	0.1758	0.1600	0.2083	0.2569
	1.00<S/K<1.03	0.3104	0.1707	0.1601	0.1581	0.1306	0.1155	0.1169	0.1727	0.1984
	1.03<S/K<1.06	0.6392	0.2405	0.2361	0.2382	0.1869	0.1863	0.1881	0.2892	0.3231
	S/K>1.06	0.9025	0.3294	0.3274	0.3285	0.2926	0.2784	0.2793	0.3076	0.4234
	Total	0.5618	0.3640	0.3647	0.3266	0.3042	0.2932	0.2534	0.2901	0.3783
MSE	S/K<0.94	2.7911	7.3373	8.4343	5.7274	7.4183	8.2250	3.0896	2.2932	2.8595
	0.94<S/K<0.96	2.7126	2.7285	2.6666	2.5978	2.0137	1.8453	1.7212	2.3140	2.7989
	0.96<S/K<1.00	3.6344	3.2995	3.2114	3.1088	2.5312	2.2361	2.0776	3.0648	3.4921
	1.00<S/K<1.03	5.3199	3.0122	2.9683	2.9811	2.0871	1.9427	1.9221	3.0605	3.3834
	1.03<S/K<1.06	5.0098	2.4232	2.4145	2.4438	1.6461	1.5466	1.5552	2.3768	2.8596
	S/K>1.06	3.8287	1.8045	1.8136	1.8225	1.3018	1.1693	1.2655	1.5868	2.2649
	Total	4.0749	3.3527	3.5615	2.9933	2.9041	3.0086	1.8623	2.4379	2.9154

Table 7: One Day Ahead Hedging Errors

This table reports one day ahead hedging error with respect to moneyness. Only the underlying asset is used as the hedging instrument. Parameters and spot volatility implied by all options of the previous day are used to establish the current day's hedge portfolio, which is then liquidated the following day. For each option, its hedging error is the difference between the replicating portfolio value and its market price. MAPE denotes mean absolute percentage errors and RMSE denotes root mean squared errors. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variables. R2 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variables. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variables. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variables. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variables. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variables. BS is the Black-Scholes (1973) option pricing model. SV is the option pricing model considering the continuous-time stochastic volatility. SVJ is the option pricing model considering the continuous-time stochastic volatility and jumps.

Panel A: Nearest-to-Next

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	0.6677	0.6652	0.6888	0.6885	0.6857	0.6876	0.6910	0.6703	0.6762
	0.94<S/K<0.96	0.3542	0.3337	0.3376	0.3420	0.3281	0.3357	0.3414	0.3632	0.3901
	0.96<S/K<1.00	0.1526	0.1463	0.1484	0.1475	0.1461	0.1484	0.1473	0.1623	0.1723
	1.00<S/K<1.03	0.1270	0.1170	0.1160	0.1158	0.1165	0.1155	0.1153	0.1383	0.1335
	1.03<S/K<1.06	0.2082	0.1751	0.1717	0.1725	0.1740	0.1696	0.1699	0.1883	0.1869
	S/K>1.06	0.3019	0.2052	0.2205	0.2485	0.2003	0.2135	0.2358	0.2171	0.2196
	Total	0.2748	0.2351	0.2420	0.2509	0.2344	0.2391	0.2467	0.2511	0.2566
RMSE	S/K<0.94	2.5132	2.7778	2.7379	2.6767	2.8555	2.7129	2.6856	3.6700	2.7955
	0.94<S/K<0.96	1.5283	1.6582	1.6308	1.5964	1.6561	1.6085	1.5817	2.1158	2.0952
	0.96<S/K<1.00	1.4958	1.5212	1.5138	1.5077	1.5224	1.5094	1.5050	1.8682	1.8283
	1.00<S/K<1.03	2.0369	1.6609	1.6735	1.6580	1.6522	1.6677	1.6542	2.1256	2.1287
	1.03<S/K<1.06	1.6514	1.2474	1.2429	1.2336	1.2429	1.2330	1.2238	1.5762	1.6345

	S/K>1.06	1.3234	0.9074	0.9160	1.0574	0.9071	0.9038	1.0349	1.1785	1.2405
	Total	1.6874	1.5366	1.5282	1.5363	1.5472	1.5159	1.5288	1.9725	1.8503

Panel B: Next-to-Next

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	0.6500	0.6197	0.6313	0.6179	0.6068	0.6257	0.6127	0.6547	0.6756
	0.94<S/K<0.96	0.3539	0.3294	0.3366	0.3337	0.3209	0.3337	0.3301	0.3611	0.3903
	0.96<S/K<1.00	0.1525	0.1459	0.1483	0.1475	0.1456	0.1483	0.1472	0.1622	0.1723
	1.00<S/K<1.03	0.1270	0.1170	0.1160	0.1158	0.1165	0.1155	0.1153	0.1383	0.1329
	1.03<S/K<1.06	0.2082	0.1750	0.1714	0.1718	0.1739	0.1694	0.1695	0.1877	0.1859
	S/K>1.06	0.3024	0.2007	0.2005	0.2010	0.1973	0.1963	0.1971	0.2133	0.2163
	Total	0.2733	0.2290	0.2306	0.2291	0.2254	0.2281	0.2265	0.2481	0.2553
MSE	S/K<0.94	2.3741	2.6121	2.5715	2.5004	2.6184	2.5213	2.4721	3.3134	2.9120
	0.94<S/K<0.96	1.5172	1.6290	1.6141	1.5843	1.6206	1.5948	1.5668	2.1139	2.0934
	0.96<S/K<1.00	1.4937	1.5120	1.5106	1.5061	1.5131	1.5073	1.5030	1.8547	1.8303
	1.00<S/K<1.03	2.0454	1.6653	1.6774	1.6626	1.6578	1.6728	1.6594	2.1289	2.1032
	1.03<S/K<1.06	1.6639	1.2526	1.2494	1.2366	1.2496	1.2411	1.2311	1.5756	1.5971
	S/K>1.06	1.3398	0.9067	0.8959	0.8978	0.9081	0.8881	0.8921	1.1397	1.2071
	Total	1.6751	1.5059	1.4970	1.4772	1.5044	1.4827	1.4676	1.9060	1.8502

Table 8: One Week Ahead Hedging Errors

This table reports one week ahead hedging error with respect to moneyness. Only the underlying asset is used as the hedging instrument. Parameters and spot volatility implied by all options of the previous day are used to establish the current day's hedge portfolio, which is then liquidated the next week. For each option, its hedging error is the difference between the replicating portfolio value and its market price. MAPE denotes mean absolute percentage errors and RMSE denotes root mean squared errors. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variables. R2 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variables. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variables. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variables. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variables. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variables. BS is the Black-Scholes (1973) option pricing model. SV is the option pricing model considering the continuous-time stochastic volatility. SVJ is the option pricing model considering the continuous-time stochastic volatility and jumps.

Panel A: Nearest-to-Next

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	2.8491	2.9664	2.9921	2.9648	2.9794	3.0041	2.9787	3.5156	3.3768
	0.94<S/K<0.96	1.1475	1.1192	1.1244	1.1293	1.1165	1.1214	1.1266	1.3321	1.3710
	0.96<S/K<1.00	0.4419	0.4281	0.4313	0.4308	0.4231	0.4293	0.4295	0.4546	0.4716
	1.00<S/K<1.03	0.3703	0.3721	0.3696	0.3701	0.3719	0.3684	0.3689	0.4033	0.3946
	1.03<S/K<1.06	0.6822	0.6543	0.6489	0.6538	0.6519	0.6440	0.6464	0.6920	0.6786
	S/K>1.06	1.0605	0.8051	0.8375	0.8674	0.7921	0.8211	0.8445	0.8481	0.8426
	Total	0.9597	0.8797	0.8919	0.9003	0.8751	0.8861	0.8924	0.9823	0.9730
MSE	S/K<0.94	6.6513	7.0792	7.0946	7.0745	7.1525	7.0756	6.9844	8.8376	8.2344
	0.94<S/K<0.96	3.1401	3.2563	3.2330	3.2005	3.2709	3.2093	3.1837	4.1987	4.1980
	0.96<S/K<1.00	3.1357	3.2304	3.2024	3.1794	3.2309	3.1813	3.1667	3.5489	3.5308
	1.00<S/K<1.03	4.1265	3.7116	3.6913	3.6902	3.7169	3.6885	3.6935	3.9930	4.0198
	1.03<S/K<1.06	3.0727	2.8233	2.8127	2.8464	2.8169	2.8002	2.8106	3.1969	3.2028

	S/K>1.06	2.5903	2.2104	2.2283	2.3903	2.1970	2.2066	2.3509	2.4710	2.4540
	Total	3.5724	3.4869	3.4816	3.5086	3.4987	3.4659	3.4768	4.1056	3.9970

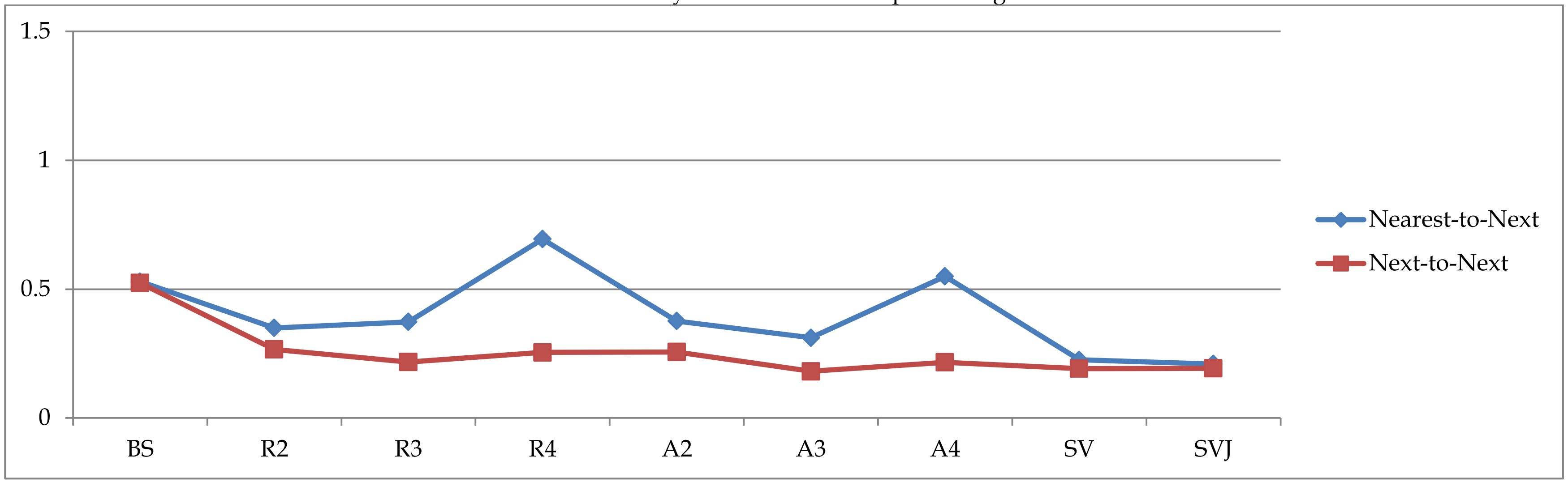
Panel B: Next-to-Next

	Moneyness	BS	R1	R2	R3	A1	A2	A3	SV	SVJ
MAPE	S/K<0.94	2.8162	2.9226	2.9128	2.8485	2.8982	2.9104	2.8508	3.4766	3.4192
	0.94<S/K<0.96	1.1432	1.1174	1.1244	1.1180	1.0969	1.1168	1.1090	1.3261	1.3721
	0.96<S/K<1.00	0.4414	0.4271	0.4314	0.4303	0.4212	0.4291	0.4284	0.4544	0.4713
	1.00<S/K<1.03	0.3703	0.3720	0.3695	0.3699	0.3717	0.3682	0.3687	0.4036	0.3942
	1.03<S/K<1.06	0.6822	0.6535	0.6470	0.6498	0.6513	0.6424	0.6444	0.6923	0.6771
	S/K>1.06	1.0629	0.7870	0.7852	0.7859	0.7783	0.7766	0.7786	0.8341	0.8305
	Total	0.9570	0.8698	0.8685	0.8628	0.8610	0.8633	0.8582	0.9739	0.9726
MSE	S/K<0.94	6.6353	7.0186	6.9674	6.8980	7.0307	6.9493	6.9083	8.8121	8.2492
	0.94<S/K<0.96	3.1257	3.2232	3.2097	3.1744	3.2071	3.1841	3.1525	4.1951	4.2015
	0.96<S/K<1.00	3.1262	3.2123	3.1997	3.1761	3.2087	3.1809	3.1627	3.5385	3.5450
	1.00<S/K<1.03	4.1231	3.7120	3.6924	3.6906	3.7175	3.6898	3.6943	3.9845	4.0072
	1.03<S/K<1.06	3.0734	2.8179	2.8049	2.8145	2.8116	2.7934	2.8023	3.1838	3.1673
	S/K>1.06	2.5988	2.1864	2.1765	2.1772	2.1762	2.1613	2.1668	2.4002	2.4054
	Total	3.5684	3.4644	3.4454	3.4270	3.4620	3.4314	3.4210	4.0830	3.9863

Figure 1: Out-of-Sample Pricing Errors

This figure shows the mean absolute percentage errors (MAPE) of out-of-sample pricing for each option pricing models with respect to the roll-over strategies. Panel A represents One-Day Ahead Out-of-Sample Pricing Errors and Panel B represents One-Week Ahead Out-of-Sample Pricing Errors. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variable. R2 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variable. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variable. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variable. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variable. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variable. BS is the Black-Scholes (1973) option pricing model. SV is the option pricing model considering the continuous-time stochastic volatility. SVJ is the option pricing model considering the continuous-time stochastic volatility and the jumps.

Panel A. One-Day Ahead Out-of-Sample Pricing Errors



Panel B. One-Week Ahead Out-of-Sample Pricing Errors

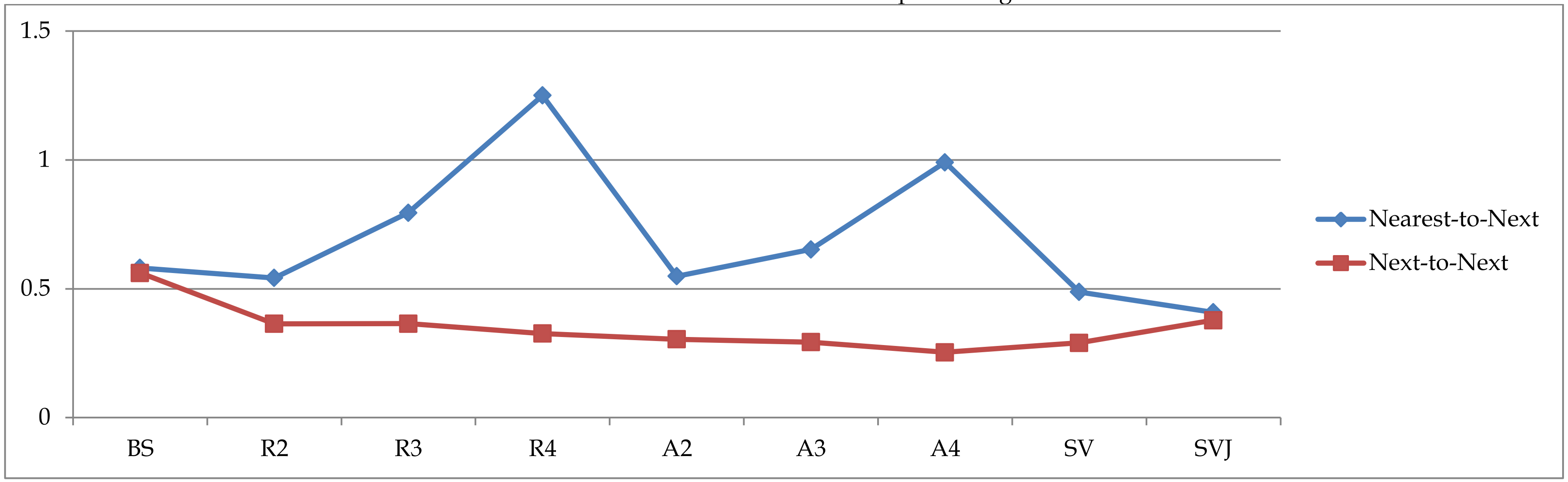
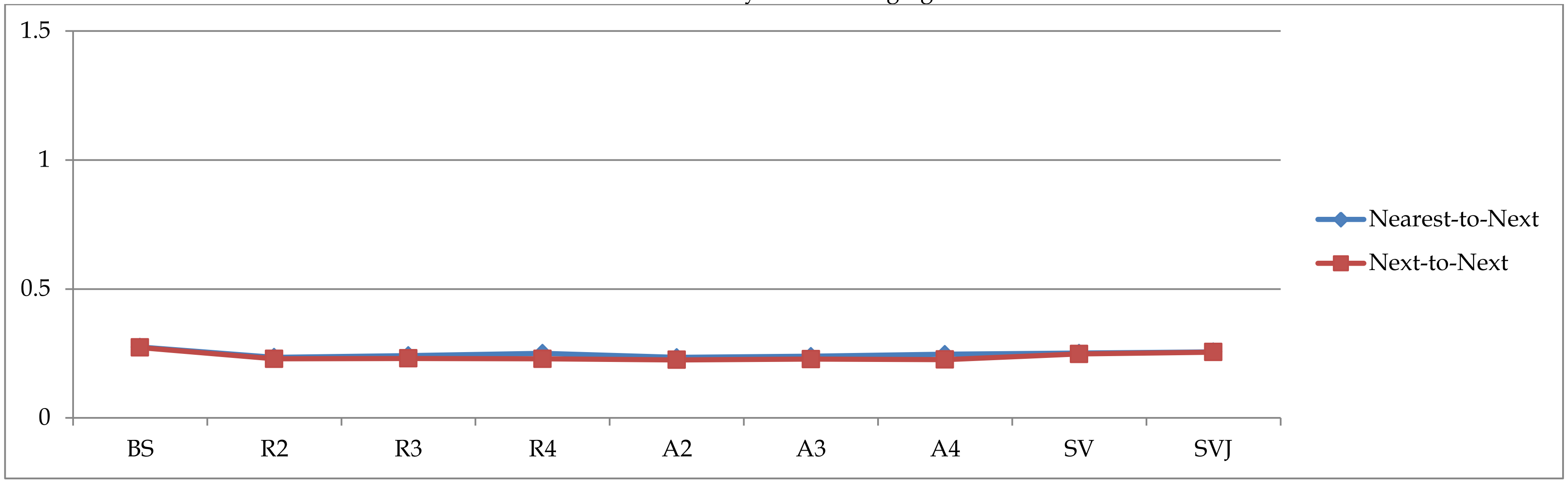


Figure 2: Hedging Errors

This figure shows the mean absolute percentage errors (MAPE) of hedging for each option pricing models with respect to the roll-over strategies. Panel A represents One-Day Ahead Hedging Errors and Panel B represents One-Week Ahead Hedging Errors. R1 is the ad hoc Black-Scholes model that considers the intercept and the moneyness as the independent variable. R2 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, and the square of the moneyness as the independent variable. R3 is the ad hoc Black-Scholes model that considers the intercept, the moneyness, the square and the third power of the moneyness as the independent variable. A1 is the ad hoc Black-Scholes model that considers the intercept and the strike price as the independent variable. A2 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square of the strike price as the independent variable. A3 is the ad hoc Black-Scholes model that considers the intercept, the strike price, and the square and the third power of the strike price as the independent variable. BS is the Black-Scholes (1973) option pricing model. SV is the option pricing model considering the continuous-time stochastic volatility. SVJ is the option pricing model considering the continuous-time stochastic volatility and the jumps.

Panel A: One-Day Ahead Hedging Errors



Panel B: One-Week Ahead Hedging Errors