Do Implied Put and Call Sneers Contain Different Information?

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Abstract

The ad hoc Black-Scholes model is one of the most widely used models for forecasting implied volatility. In this paper, we propose a methodology that provides more accurate out-of-sample implied volatility forecasts. Standard approaches estimate the whole volatility smile using both out-of-the-money puts and calls. The improvements from our method are obtained by taking advantage of information contained in the asymmetric slopes of the put and call implied volatility sneers that result in a discontinuity when moneyness is equal to 1. These improvements in out-of-sample implied volatility forecasts are large and significant. Our results are robust across several dimensions, including: time period, forecast horizon, moneyness, and model specification.

Keywords: Ad Hoc Black-Scholes (AHBS), asymmetric volatility sneer, data usage, implied volatility.

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Abstract

The ad hoc Black-Scholes model is one of the most widely used models for forecasting implied volatility. In this paper, we propose a methodology that provides more accurate out-of-sample implied volatility forecasts. Standard approaches estimate the whole volatility smile using both out-of-the-money puts and calls. The improvements from our method are obtained by taking advantage of information contained in the asymmetric slopes of the put and call implied volatility sneers that result in a discontinuity when moneyness is equal to 1. These improvements in out-of-sample implied volatility forecasts are large and significant. Our results are robust across several dimensions, including: time period, forecast horizon, moneyness, and model specification.

I Introduction

There is a huge effort by practitioners and academics to make accurate out-of-sample (OOS) forecasts for implied volatility. Having an accurate OOS forecast of implied volatility is important. First it is a basic input in option pricing models that are used in trading strategies. Second, accurate hedge positions can only be obtained when the implied volatility is accurately estimated and forecast. Given the magnitude of trading in derivative contracts, the ability to accurately make OOS forecasts of implied volatility is critical. This paper develops a new methodology that improves implied volatility OOS forecasts.

Typically implied volatility is estimated using the whole cross-section of out-of-the-money (OTM) put and call options. However, this approach to simultaneously using OTM-puts and OTM-calls in the estimation imposes hidden constraints. Using both put and call contracts constrains the implied volatility smile to be continuous at unit moneyness. That is, the OTM-call and the OTM-put volatility sneer curves must be continuous and differentiable at $S/K = 1$. Another constraint is there must be symmetry in the slopes of the call and put sneers. However, neither condition is typical in real option data. We have observed that the OTM-call and OTM-put sneers are almost always discontinuous (see Figure 1). This discontinuity contains valuable information that, to date, has not been incorporated into implied volatility forecasts. We develop a new data usage methodology in order to take advantage of the information in the volatility smile discontinuity that allows us to make significant improvements in OOS forecasts of implied volatility.

Figure 1 about here.

There is a simple economic intuition for what information is contained in the curvature and slope of the call and put sneers. This information is reflected in the asymmetric slopes of the put and call sneers, which leads to the observed discontinuity in implied volatility at-the-money (ATM). It is instructive to look at an example of an up-trending market. As the underlying index increases, on the one hand, OTM call options increase in value as the index price approaches the OTM strike price. On the other hand, OTM puts become more OTM and thus their value decreases slower than the OTM call value increases. Implied volatilities derived from these instruments will reflect this asymmetric response. The volatility in the OTM call will be high compared to the volatility in the OTM put. Also, near-the-money (NTM) calls will become in-the-money (ITM). At this point, the price change is close to linear in the index price. NTM puts will lose value at a faster rate, leading to a higher implied volatility compared to the NTM calls. That is, the relative value of implied volatility is reversed for NTM puts and calls when compared to OTM puts can calls. This differential in relative values creates two effects: (i) the call sneer should be steeper than the put sneer, and (ii) the ATM gap will be positive, i.e., ATM put implied volatility is greater than ATM call implied volatility. This two differences will change with the speed of price, i.e., the slope of the market trend line. Similar intuition holds for down- and side-trending markets. Thus, one can conclude that important information on market trend and trend speed is incorporated in the differences between the call and put sneers. If market price level and return are related to expected implied volatility, utilizing a methodology to specifically calculate the difference should incorporate important information and thus lead to better parameter estimates, which will lead to better implied volatility OOS forecasts.

Indeed, papers document that implied volatility is related to price and return of the underlying index. Combined results of Bali and Hovakimian (2009) and Bakshi and Kapadia (2003a,b) show that implied volatility is greater than realized volatility and this difference, i.e., the implied volatility spread, is related to returns. From this one can conclude that part of implied volatility can be explained by return. Choi, Jordan, and Ok (2012) test this joint conjecture and document a significant relationship between implied volatility and return. Thus, it is an empirical question concerning the costs versus benefits of exploiting this relationship.

Incorporating extra information should add to the accuracy of OOS forecasts. However, to capture additional information requires an associated increase in the number of parameters in the model, thus potentially decreasing the parameter estimation accuracy. In addition, trying to capture more information may increase the technical difficulty of the technique. It is not directly obvious on how one should change the model or methodology in order to capture the additional information. Our contribution is that we develop a succinct method to incorporate the information contained in the asymmetric response of the call and put sneers. Our method requires only one more step than the conventional approach (CON) and the technical difficulty of our method is identical to CON. Our proposed method separates the implied volatility smile estimation step into two steps, one to estimate the call sneer only using OTM calls and the other to separately estimate the put sneer only using OTM puts. Our separation method (SEP) does increase the number of parameters to be estimated.[1] Thus, it is an empirical question as to whether the SEP method outperforms the CON method. We conduct extensive tests to document that SEP clearly dominates CON. The forecast accuracy gains from using SEP are large and significant.

The rest of the paper is as follows. In section 2, we review some literature. In section 3, we describe our data and provide some background information on the Korean market index and the Korean options market. In section 4, our methodology is explained. Next, we present our INS and OOS empirical findings in sections 5 and 6, respectively. In section 7, our new methodology is compared directly with the standard

[1]This is referred to as the "overfitting problem." Since we forecast 10 minutes to 1 hour, the underlying implied volatility structure does not change as much as with long-term forecasts.

methodology, which is followed by some robustness tests in section 8. Finally, in section 9 we summarize and conclude our results.

II Literature, Data, and Market Background

In this section, we review the relevant data, describe our data, and provide some background on the Korean stock and options markets.

A Literature Review

There is a large literature that attempts to use historic data in order to forecast volatility, e.g., GARCH. However, historic or realized data does not incorporate expectations. Using the Black-Scholes (BS) model in order to imply volatility from options prices incorporates market expectations. Thus, the methodology in this paper is forward looking, not backward looking.

Again, there is a large literature that attempts to estimate implied volatility models in order to predict the future underlying return. This line of literature is quite different than the focus of our paper as we concentrate on OOS forecasts on implied volatility.[2] Completely different subsets of agents would be interested in each separate line of research. Predicting returns will be of interest to traders and speculators, whereas, accurate forecasts of implied volatility, although of interest to vol-traders, will be mostly used by hedgers. For example, if an exact forecast of implied volatility could be made at the desired hedging horizon, a hedger who will hold the position to expiry would have no need to rebalance. Thus, accurate implied volatility forecasts are an important calculation to most businesses with future obligations.

The research on predicting volatility can be broken down into several approaches, e.g., deterministic volatility function and GARCH option valuation. There is, however, extensive research that demonstrates the superiority of the AHBS method compared to these alternative and more sophisticated methods.[3] It is for this reason that the AHBS model is the model most used by practitioners. Thus, we focus our efforts and only consider the AHBS model from this point on.

There is a developing literature that studies the use of AHBS implied volatility models to make OOS forecasts of future implied volatility. Choi and Ok (2011) demonstrate that forecast accuracy can be significantly increased by adjusting the rollover strategy. Choi, Jordan, and Ok (2012) show that large reductions in forecast accuracy is realized when expectations are incorporated into dividend estimates. Our paper is most similar to this literature in that we document a new methodology to estimate the implied volatility curve. The gains from our proposed methodology are above and beyond those documented in the prior literature as we incorporate all suggested improvements in our methodological implementation.

[2]See Cremers and Weinbaum (2010) for a summary of this literature.

[3]For example, see Dumas, Fleming, and Whaley (1998); Jackwerth and Rubinstein (2001); Brandt and Wu (2002); and Christoffersen and Jacobs (2004a).

B Data

We use minute-by-minute intraday data from the Korean Exchange (KRX). That is, our data includes minute-by-minute put and call option prices on the KOSPI 200 index for January 1, 2007 to December 31, 2009. The last reported price is the last transaction prior to 2:50 p.m. We exclude the first 10 minutes of the data due to unusual activity of the opening process. For each option contract, we have the underlying asset price, the strike price, and whether the option is a put or call. We restrict our analysis to nearest-expiry, OTM contracts.

In order to improve the information environment of our data, we exclude certain subsets of data. For example, options with prices lower than 0.02 are excluded. Prices not satisfying the arbitrage restriction are excluded, e.g., put-call pairs not satisfying put-call parity are excluded. We only use OTM options for both calls and puts, because there tends to be low trading volume for ITM options. Finally, options with less than 7 days to expiration are excluded. Options with less than 7 days to expiration may induce biases due to low prices and bid-ask spreads. Instead, the nearest options with greater than 6 days to expiration are chosen.

Owing to liquidity problems of the Korean Treasury bill market, the three-month CD rates are used as risk-free interest rates in spite of the mismatch of maturity between options and spot rates. For the empirical analysis, the last reported transaction price prior to 2:50pm of each option is selected to resolve the synchronization issues between the stock and options markets mentioned in Dumas et al. (1998). The cut at 2:50pm is used since there are simultaneous bids and offers from 2:50pm. That is, because the recorded KOPSI 200 index values are not equivalent to the daily closing index levels, there is no nonsynchronous price issue, except the KOSPI 200 index level itself may contain stale component stock prices at each point in time.

C Korean stock market

We present a figure of the KOSPI 200 market index for 2007, 2008, and 2009 in order to compare the market characteristics pre-, during-, and post-the-liquidity crisis. These three different market types provide a robustness test to the stability of our results. In 2007, Figure 2 shows there was a strong up trend in the market with high volatility in the second half of the year. Of course, 2008 was the year of the liquidity crisis and thus there is both a strong downward trend and high volatility throughout the year. Finally, there is an upward trend with medium, but steady, volatility in 2009. We use 2007 as our base year. Thus, years 2008 and 2009 will provide an out-of-sample robustness tests.

[Figure 2 about here.]

D Korean options market

Since the KOSPI 200 was introduced by the KSE (Korea Stock Exchange) on July 7, 1997, the KOSPI 200 options market, despite its short history, has become one of the fastest-growing markets in the world. Three consecutive near-term delivery months and one additional month from the quarterly cycle (March, June, September, and December) make up four contract months. Options expire on the second Thursday of each contract month. Each contract month has at least five strike prices. The number of strike prices may increase depending on the price movement. The trading of KOSPI 200 index options is fully automated. The style of exercising KOSPI 200 options is European, and thus, contracts can be exercised only on expiration dates. Hence, our test results are not affected by complications associated with the early exercise feature of U.S. options. Moreover, liquidity is concentrated in the nearest expiration contract.

III Methodology

In this section, we develop the methodology used to calculate implied volatility.

A Ad hoc Black-Scholes models

Due to its simplicity and excellent performance compared to more sophisticated models, the AHBS model is a popular option valuation models among practitioners. In the AHBS model, implied volatility skew is modeled as a polynomial function and estimated by OLS. There are three standard versions of the AHBS model, which differ by the definition used for implied volatility: (i) the relative smile (R3) approach defines implied volatility as a function of moneyness, "S/K", (ii) the absolute smile (A3) approach defines implied volatility as a fixed function of strike price , "K", and (iii) the forward moneyness (F3) approach defines implied volatility as a fixed function of the logarithm of the strike price over the forward price, normalized by the standard deviation of expected return on maturity. Choi, Jordan, and Ok (2012) investigate the performance of six different AHBS models, i.e., a linear and a quadratic version of A3, R3, and F3, and three dividend estimation schemes. For OOS forecasts, the A3 model utilizing the implied-forward dividend scheme is the best pair under three of the four error measure/dividend scheme combinations. It is a very close second in the remaining category. Given the consistent superior performance of the AHBS$_{A3}$ model that utilizes the implied-forward dividend scheme for INS, one-day OOS forecasts, and one-week OOS forecasts, we shall concentrate on this combination in the rest of the paper.[4] We utilize both a quadratic and cubic specification for the market's implied Black-Scholes volatilities.[5]

$$\text{(1)} \qquad \text{AHBS}_{Aq} : \sigma_i^{im} = \beta_0 + \beta_1 \cdot K_i + \beta_2 \cdot K_i^2$$

$$\text{(2)} \qquad \text{AHBS}_{Ac} : \sigma_i^{im} = \beta_0 + \beta_1 \cdot K_i + \beta_2 \cdot K_i^2 + \beta_3 \cdot K_i^3$$

where σ_i^{im} is the implied volatility for an option with the strike price K_i and the spot price S. The subscripts q and c refer to a quadratic and cubic polynomial model, respectively.

The innovation in this paper is that rather than calculating the whole implied volatility smile simultaneously using puts and calls, we individually estimate the call sneer, i.e., the downward sloping left curve of

[4] We refer to the AHBS$_{A3}$ model of Choi, Jordan, and Ok (2012) as AHBS$_{Aq}$.

[5] We extend our study to include a cubic model as we focus on short-horizon forecasts. Thus, the overfitting problem is not severe, implying there may be gains to increasing the order of the estimated polynomial.

the volatility smile, and the put sneer, i.e., the upward sloping right half of the volatility smile. We estimate the call sneer using only OTM calls for $S/K < 1$. Likewise, we calculate the put sneer using only OTM puts for $S/K > 1$.

B Forward-implied dividend calculation

For our implied dividend calculations, we use a four-step procedure. We first calculate the forward price from option prices and from these forward prices we then calculate the expected dividend yield. An important advantage is that this method estimates expectations on dividends directly. Most methods use realized dividends to estimate expected dividends, but past research has shown this approach can result in misleading conclusions. To calculate expected dividends, we utilize the forward price as the underlying asset in the BS model and we utilize the risk-free rate as the appropriate discount rate.

For our implied dividends, we use options prices in order to calculate the forward price and from this the expected dividend yield. The advantage of this strategy is that it incorporates implied market expectations rather than realizations on the dividend stream. As asset pricing theory is based on expectations, this method should provide some advantage. In this scenario, the underlying asset in the Black-Scholes formula is changed from the stock price to the forward price and the dividend yield is changed to the risk-free rate. This method is developed by Carr and Wu (2003) and further explored in Zhang and Xiang (2008).[6]

Step 1. Compute implied volatility σ_i^{im} satisfying BS formula:

$$\begin{aligned} c &= c(t, F; T, K, \sigma) = Fe^{-r\tau}N(d_1) - Ke^{-r\tau}N(d_2) \\ p &= p(t, F; T, K, \sigma) = Ke^{-r\tau}N(-d_2) - Fe^{-r\tau}N(-d_1) \end{aligned} \tag{3}$$

with

$$\begin{aligned} d_1 &= \frac{\ln(F/K) + (\sigma^2/2)\tau}{\sigma\sqrt{\tau}} \\ d_2 &= d_1 - \sigma\sqrt{\tau}, \qquad \tau = T - t, \end{aligned}$$

where F is the implied forward price from the contemporaneous option prices.

Step 2. Use the ordinary least square method to estimate the parameters $\{\beta_k\}_{k=0}^2$ in Equation 1 and $\{\beta_k\}_{k=0}^3$ in Equation 2. For AHBS$_{Aq}$, the parameters β_0, β_1, and β_2 are estimated by minimizing the equally-weighted mean squared error:

$$\Sigma_i[\sigma_i^{im} - (\beta_0 + \beta_1 K_i + \beta_2 K_i^2)]^2.$$

Step 3. Use the estimated parameters from Step 2 to compute the model implied volatility for each option at time $t+k$, i.e., compute $\hat{\sigma}_{i,t+k}$ for $k = 1, 2, \ldots$.

[6]When using the underlying stock, one needs to buy $\exp(-q(T-t))$ units of the underlying at time t to have one unit of the underlying asset at time T. However, if one uses the underlying forward, then one needs to buy $\exp(-r(T-t))$ units of the underlying forward at time t to have one unit of the underlying asset at time T.

Step 4. From the BS formula with F as the underlying, i.e., Equation 3, use the model implied volatility estimates from Step 3 to price options, $V^*_{i,t+k} = V^*(t+k, F_{t+k}; T, K_i, \hat{\sigma}_{i,t+k})$.

C Error measures

We use the following two error measures as our metric of OOS forecast fit. First we use the root mean square valuation error (RMSVE) and the mean absolute error (MAE).

$$\text{RMSVE} = \frac{1}{T}\sum_{t=1}^{T}\sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}\left[V(t,S;K_i) - V^*(t,S;K_i)\right]^2} \tag{4}$$

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t}\left|V(t,S;K_i) - V^*(t,S;K_i)\right| \tag{5}$$

where $V^*(t,S,K_i)$ denotes the model price of option i on day t and $V(t,S,K_i)$ denotes the market price of option i on day t. N_t denotes the number of traded OTM calls and puts to differences in strike prices on day t, and T denotes the number of days in the sample. MAE measures the magnitude of pricing errors, whereas the RMSVE measures the volatility of errors.

D Parameter estimation

At each minute t, we use the cross-section of option prices (either OTM calls or OTM puts) to estimate the coefficients of either the quadratic or cubic AHBS$_A$ model. Using these coefficients, we then forecast the implied volatility at time $t+10$ for the 10-minute forecast horizon and calculate our error metric. Table 1 presents the mean and standard error of the estimated parameters for both the quadratic and cubic AHBS$_A$ models. Each parameter is estimated by minimizing the trade equally-weighted mean squared error for each trading day. Panels A, B, and C of Table 1 give parameter estimates using only calls (superscript $Call$), only puts (superscript Put), and both calls and puts (superscript All), respectively.

Table 1 about here.

The signs of the parameters for each model are consistent across all three years. However, the coefficient magnitudes can change substantially. For example, β_1 in the AHBS$^{Call}_{Ac}$ model changes from 44.357 in 2007 down to 8.2408 in 2008 and then back up to 14.4263 in 2009.

IV INS Empirical Results

In Table 2, we investigate the in-sample (INS) fit of the AHBS model by moneyness, i.e., by S/K, and by forecast horizon. We compare the accuracy between the CON and SEP methodologies. Panels A and B give the results for the AHBS$_{Aq}$ model, while Panels C and D give the forecast errors for the AHBS$_{Ac}$ model under RMSVE and MAE, respectively. The standard AHBS methodology (CON) estimates the implied volatility smile using both OTM puts and OTM calls. Estimating the entire implied volatility smile at one time can be thought of as a simultaneous estimating of the call and put sneers where continuity and smoothness is imposed as constraints at $S/K = 1$, i.e., ATM. Our proposed methodology relaxes both constraints. Instead, we propose to estimate the call and put sneers separately (SEP) using OTM calls and OTM puts, respectively.

Our results indicate that using SEP always results in a more accurate OOS forecast (i.e., a smaller forecast error) than using CON. This is true for any moneyness and for all forecast horizons. For example, for a cubic AHBS model with moneyness $1.03 < S/K < 1.06$ and a 60-minute horizon, the RMSVE is 0.0364 if CON is used, while it is 0.0187 if SEP is used. Thus, there is a 48.6% increase in forecast accuracy if the SEP method is implemented rather than the CON method. The conclusions are identical under a cubic AHBS as it is for the quadratic AHBS. In every combination of moneyness and forecast horizon, there is significant improvement in forecast accuracy when the SEP methodology is chosen over the CON methodology.

Table 2 about here.

V OOS Empirical Results

In our OOS tests, we investigate the OOS forecast accuracy by moneyness, i.e., by S/K, and by forecast horizon. We conduct such tests under both the CON and SEP methodologies to facilitate comparison. Finally, we conduct tests between the AHBS$_{Aq}$ model and the AHBS$_{Ac}$ model.

A CON vs. SEP methodology

Table 3 provides a comparison of CON and SEP. Panels A and B give the forecast errors for the AHBS$_{Aq}$ model under RMSVE and MAE, respectively. Using SEP always results in a more accurate OOS forecast (i.e., a smaller forecast error) than using CON. This is true for any moneyness and for all forecast horizons. For example, for a quadratic AHBS model with moneyness $0.94 < S/K < 0.97$ and a 10-minute horizon, the RMSVE is 0.0703 if CON is used, while it is 0.0375 if SEP is used. Thus, there is a 46.7% increase in forecast accuracy if the SEP method is implemented rather than the CON method. Panels C and D give the forecast errors for the AHBS$_{Ac}$ model under RMSVE and MAE, respectively. The conclusions are identical under a cubic AHBS as it is for the quadratic AHBS. Again, in every combination of moneyness and forecast horizon, there is significant improvement in forecast accuracy if the SEP methodology is chosen over the CON methodology.

[Table 3 about here.]

For the quadratic AHBS model (AHBS$_{Aq}$), Figure 3 visually compares the forecast error between the CON and SEP methodology for each forecast period. That is, each bar represents the improvement (positive) or loss (negative) in forecast performance realized by using the SEP in place of the CON methodology. This gain is calculated as:

$$\frac{MAE_{CON} - MAE_{SEP}}{MAE_{CON}} \tag{6}$$

The forecast gain is shown across six different moneyness classes. Panel A gives the results for the RMSVE error measure, while Panel B gives the results for the MAE error measure. The first observation is that regardless of forecast horizon or moneyness, the forecast error is always reduced by using the SEP methodology rather than the CON methodology. The second observation is that as the forecast horizon increases, the gain in forecast accuracy achieved by using the SEP over the CON methodology decreases. This is reflected in the fact that for any group of three bars, the differential (height of the bar) drops as the forecast horizon increases (move to the right). The third observation is that as the price of the underlying asset moves from a deep-out-of-the-money call option (D-OTMc) to a near-out-of-the-money call option (N-OTMc) the gain from using the SEP methodology decreases. This is true for all forecast horizons. Finally, as the price of the underlying asset moves from a deep-out-of-the-money put option (D-OTMp) to a near-out-of-the-money call option (N-OTMp) the gain from using the SEP methodology generally decreases, but not monotonically. Overall, one can conclude from this figure that it is always better to use the SEP instead of the CON methodology, regardless of the moneyness or forecast time horizon. Figure 4 provides the same comparison for the cubic AHBS model (AHBS$_{Ac}$) as Figure 3 does for the AHBS$_{Aq}$. The conclusions are remarkably similar.

[Figure 3 about here.]

[Figure 4 about here.]

VI Cubic vs. Quadratic AHBS

Figure 5 compares the forecast error improvement by going from the quadratic to a cubic AHBS$_A$ model for each forecast period. We use all three years in our estimates. Panel A gives the results for the RMSVE error measure, while Panel B gives the results for the MAE error measure. The first observation is that for any specific time period, i.e., 10 minutes, the magnitude of the error is larger under the CON methodology than it is under the SEP methodology. The second observation is that the error from the AHBS$_{Aq}$ model is always higher than that for the AHBS$_{Ac}$ model. This is true for any forecast horizon, whether CON or SEP is used. Lastly, we observe that the differential improvement from going from a quadratic to a cubic AHBS$_A$ model is greater under the CON methodology. For example, for the MAE error and the 10 minute forecast horizon, there is a 36.7% improvement in forecast accuracy under CON if AHBS$_{Ac}$ is used in place of AHBS$_{Aq}$, while the corresponding gain under SEP is 10.2%.[7] Thus, OOS forecast accuracy is improved by increasing the number of parameters from three to four. The improvement under the SEP methodology is

[7]The calculations use Equation 6, e.g., $0.367 = (0.0581 - 0.0368)/0.0581 = (MAE_{CON,q} - MAE_{CON,c})/MAE_{CON,q}$, while $0.102 = (0.0325 - 0.0292)/0.0325 = (MAE_{SEP,q} - MAE_{SEP,c})/MAE_{SEP,q}$

always small, suggesting that less is gained from going from a six-parameter to an eight-parameter model. Overall, if computing power or time is not an issue, then the best method is the AHBS$_{Ac}$ model under the SEP methodology. However, if computing or time is a constraint, the AHBS$_{Aq}$ model under the SEP methodology is an excellent substitute as little is lost in forecast performance.

[Figure 5 about here.]

What is probably the most important insight from Figure 5 is that there are improvements from two different approaches. The first improvement is from using the same data in different ways. This is represented in the figures by the difference in forecast errors using the same model, but going from CON to SEP. For any specific forecast horizon, this "data improvement" is reflected by the drop in forecast error when the SEP forecast error is compared to the CON forecast error. For example if the AHBS$_{Aq}$ model is used with a 10-minute forecast horizon, the RMSVE error goes from a 6.86% forecast error under CON to a 4.28% forecast error under SEP. The second improvement is a "model improvement." By changing the underlying model, in our case from AHBS$_{Aq}$ to AHBS$_{Ac}$, there is improvement in forecast error. This is reflected in the drop in forecast error when one compares adjacent bars, i.e., same methodology and forecast horizon. What is most important to note is that the gain in forecast accuracy is always larger when data is separated as in SEP than it is by changing the model. This can be seen in Figure 5 by comparing the CON and SEP pairs for a specific forecast horizon, e.g., 10 minutes. Specifically, the quadratic SEP10 forecast error is smaller than the cubic CON10 forecast error. This is always true whether the 10-, 30-, or 60-minute forecast horizon is used. That is, the reduction in OOS forecast error by using SEP over CON is larger than by using a cubic over a quadrati model.

VII 2008 & 2009 Robustness Tests

In this section we conduct robustness tests for our 2007 results. We conduct our analysis on OOS forecasting accuracy for minute-by-minute data for the years 2008 (liquidity crisis) and 2009 (post-liquidity crisis).

The 2008 results are displayed in Table 4. During a strong down trending market due to the crisis, the SEP methodology always outperforms the CON methodology. This is true across all moneyness categories, for all forecast horizons, and whether the RMSVE or MAE error measure is used. The results are robust across quadratic and cubic AHBS model specifications. Table 5 gives the results for 2009, the year after the liquidity crisis. Again, under all possible scenarios we test, the OOS forecast accuracy is always increased by using SEP rather than CON.

[Table 4 about here.]

[Table 5 about here.]

We have found that no matter the moneyness and no matter the AHBS model specification, there are large OOS forecast gains to be made by estimating the call and put sneers separately, i.e., using SEP, over the standard methodology of estimating the entire implied volatility smile at the same time, i.e., using CON. Our results were based on 2007 minute-by-minute data. Figure 2 demonstrates that 2008 and 2009 have quite different dynamics than those of 2007. We thus repeat our analysis and compare SEP to CON for both years 2008 and 2009.

Figure 6 provides a visual comparison of the SEP to the CON methodology under the RMSVE error measure. Each bar represents the improvement/loss (positive/negative) in OOS forecast accuracy if the SEP methodology is used in place of the CON methodology. The conclusion that SEP is always superior to CON is robust during both 2008 and 2009. The superior performance of SEP holds across all moneyness categories, for all forecast horizons, and for both measures of forecast error.

[Figure 6 about here.]

There is an interesting relationship between the relative improvement gained from using only puts to that of using only calls. Recall from Figure 3 and Figure 4 that there was a higher OOS forecast for moneyness much less than one, i.e., D-OTM$_c$, and M-OTM$_c$, than for moneyness much greater than one, i.e., D-OTM$_p$, and M-OTM$_p$. In 2007 the market was volatile and up trending. If over-confident speculators or trend chasers were chasing returns, then puts would be subject to noise risk and thus be less accurately priced. In the crash year, 2008, where volatility remained high but the trend reversed, fear (or over pessimism) would create more noise in calls relative to puts. Interestingly, in 2008, we see that the forecast error improvement is relatively higher for calls than for puts. In 2009, when volatility is not as prominent as in 2007 and 2008, the magnitude of error for puts and calls are in line.

Figure 7 provides a visual comparison of the SEP to the CON methodology under the MAE error measure. The results are identical to those under the RMSVE error measure. There are always gains to switching to the SEP from the CON. This is true across moneyness, forecast horizons, and across different market types.

[Figure 7 about here.]

VIII Discussion and Conclusion

We carefully consider the method of incorporating information contained in OTM calls and puts into the parameter estimates from various AHBS models. The standard approach is to use both OTM calls and puts and estimate the volatility smile simultaneously. We make the empirical observation that typically the call and put sneers are discontinuous ATM and have different slopes. This empirical fact directly violates constraints imposed by the CON implied volatility smile estimation methodology. We propose a simple methodology to estimate the call and put sneers separately and investigate its effect on OOS forecast errors. We demonstrate that our "Put-Call Sneer" methodology produces more consistent estimates both in-sample market and out-of-sample.

Our results are robust across several dimensions. We conduct our tests using minute-by-minute data for three different years that have very different characteristics. That is, we conduct tests for the 2007 (pre-liquidity crisis year), 2008 (liquidity-crisis year), and 2009 (post–liquidity crisis year). We also conduct our tests for three different forecast horizons, 10-minutes, 30-minutes, and 1-hour. We also subject our tests across six different moneyness categories. Our basic finding that separately incorporating the information contained in OTM calls and OTM puts produces superior OOS forecasts is robust across all scenarios we test.

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Table 1: Parameter Estimates

Panel A: Year = 2007

	β_0 (s.e)	β_1 (s.e)$\times 10^2$	β_2 (s.e)$\times 10^4$	β_3 (s.e)$\times 10^6$
$\text{AHBS}_{Aq}^{\text{Call}}$	8.6638 (0.2508)	-7.7984 (0.2260)	1.8322 (0.0517)	
$\text{AHBS}_{Ac}^{\text{Call}}$	-30.219 (10.310)	44.357 (13.888)	-21.710 (6.3374)	3.5737 (0.9790)
$\text{AHBS}_{Aq}^{\text{Put}}$	3.0038 (0.0956)	-2.3925 (0.1004)	0.5242 (0.0266)	
$\text{AHBS}_{Ac}^{\text{Put}}$	11.069 (1.8580)	-15.795 (3.0069)	7.9935 (1.6375)	-1.3948 (0.2999)
$\text{AHBS}_{Aq}^{\text{All}}$	3.4757 (0.0514)	-2.9051 (0.0515)	0.6643 (0.0130)	
$\text{AHBS}_{Ac}^{\text{All}}$	-4.3061 (0.5973)	9.4276 (0.8980)	-5.8905 (0.4532)	1.1671 (0.0768)

Panel B: Year = 2008

	β_0 (s.e)	β_1 (s.e)$\times 10^2$	β_2 (s.e)$\times 10^4$	β_3 (s.e)$\times 10^6$
$\text{AHBS}_{Aq}^{\text{Call}}$	5.8005 (0.1039)	-5.0148 (0.0967)	1.1624 (0.0230)	
$\text{AHBS}_{Ac}^{\text{Call}}$	-3.7544 (2.6400)	8.2408 (3.5156)	-5.1616 (1.5836)	1.0423 (0.2422)
$\text{AHBS}_{Aq}^{\text{Put}}$	1.2128 (0.1306)	-0.5121 (0.1466)	0.0302 (0.0428)	
$\text{AHBS}_{Ac}^{\text{Put}}$	5.9470 (4.6378)	-7.2119 (7.7345)	3.1490 (4.4358)	-0.4712 (0.8787)
$\text{AHBS}_{Aq}^{\text{All}}$	3.3414 (0.0450)	-2.7556 (0.0447)	0.6354 (0.0113)	
$\text{AHBS}_{Ac}^{\text{All}}$	-5.6736 (0.3885)	10.403 (0.5577)	-5.8333 (0.2706)	1.0736 (0.0445)

Panel C: Year = 2009

	β_0 (s.e)	β_1 (s.e)$\times 10^2$	β_2 (s.e)$\times 10^4$	β_3 (s.e)$\times 10^6$
$\text{AHBS}_{Aq}^{\text{Call}}$	4.8070 (0.1436)	-4.4547 (0.1447)	1.1063 (0.0369)	
$\text{AHBS}_{Ac}^{\text{Call}}$	-7.8923 (5.6084)	14.4263 (8.3434)	-8.3740 (4.1868)	1.6096 (0.7092)
$\text{AHBS}_{Aq}^{\text{Put}}$	2.4816 (0.0463)	-1.9783 (0.0547)	0.4325 (0.0165)	
$\text{AHBS}_{Ac}^{\text{Put}}$	2.7542 (0.8411)	-2.6693 (1.4376)	0.9771 (0.8376)	-0.1372 (0.1669)
$\text{AHBS}_{Aq}^{\text{All}}$	3.0916 (0.0254)	-2.7022 (0.0284)	0.6529 (0.0081)	
$\text{AHBS}_{Ac}^{\text{All}}$	-1.0154 (0.2467)	3.8604 (0.4025)	-2.8845 (0.2218)	0.6444 (0.0413)

This table presents the mean and standard error of the estimated parameters for each model. For each trading day, there are 33 times for which the AHBS model parameters are estimated. Our first estimate is at 9:10am and then every 10 minutes thereafter until 2:40pm. We estimate the standard error for each day in our sample period as: s.e. $= \hat{\sigma}/\sqrt{33}$. The parameter values and standard errors reported in this table are the mean daily value over all trading days. Dividends were calculated with the implied-forward-dividend AHBS strategy developed in Carr and Wu (2003). For both the quadratic and cubic AHBS models, each parameter is estimated by minimizing the trade equally-weighted mean squared error for each trading day. The subscript letter "A3" means that implied volatility is modeled as a polynomial in the strike price K. A quadratic implied volatility model is denoted by "q" and a cubic by "c". The subset of OTM options utilized is given by the superscript, where "Call" implies only OTM call options were used, "Put" means only OTM put options were used, and "All" indicates that both OTM call and put options were used. Panels A, B, and C provide the parameter estimates for the implied-forward-dividend AHBS strategy for the years 2007, 2008, and 2009, respectively.

Table 2: INS Errors under Ad Hoc AHBS Models - Total

Panel A: Quadratic Polynomial, RMSVE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0303	0.0091	0.0303	0.0091	0.0301	0.0090
0.94 - 0.97	0.0534	0.0183	0.0533	0.0180	0.0532	0.0175
0.97 - 1.00	0.0722	0.0305	0.072	0.0303	0.0713	0.0301
1.00 - 1.03	0.0883	0.0385	0.0878	0.0380	0.0865	0.0369
1.03 - 1.06	0.0703	0.0227	0.0700	0.0222	0.0700	0.0229
1.06 < S/K	0.0381	0.0101	0.0379	0.0100	0.0368	0.0100
Total	0.0589	0.0216	0.0587	0.0213	0.0582	0.0212

Panel B: Quadratic Polynomial, MAE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0245	0.0065	0.0245	0.0066	0.0243	0.0065
0.94 - 0.97	0.0491	0.0155	0.0492	0.0154	0.0494	0.0152
0.97 - 1.00	0.0635	0.0248	0.0636	0.0249	0.0635	0.0250
1.00 - 1.03	0.0802	0.0307	0.0806	0.0307	0.0805	0.0304
1.03 - 1.06	0.0639	0.0183	0.0639	0.0183	0.0643	0.0189
1.06 < S/K	0.0316	0.0072	0.0314	0.0073	0.0305	0.0073
Total	0.0523	0.0172	0.0523	0.0172	0.0523	0.0173

Panel C: Cubic, RMSVE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0156	0.0061	0.0156	0.0061	0.0152	0.0060
0.94 - 0.97	0.0288	0.0129	0.0287	0.0127	0.0286	0.0123
0.97 - 1.00	0.0415	0.0191	0.0413	0.0191	0.0407	0.0189
1.00 - 1.03	0.0500	0.0245	0.0493	0.0240	0.0486	0.0233
1.03 - 1.06	0.0363	0.0185	0.0358	0.0182	0.0364	0.0187
1.06 < S/K	0.0161	0.0074	0.0159	0.0074	0.0158	0.0074
Total	0.0315	0.0148	0.0312	0.0146	0.0310	0.0145

Panel D: Cubic, MAE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0122	0.0043	0.0122	0.0044	0.0119	0.0044
0.94 - 0.97	0.0249	0.0104	0.0249	0.0104	0.0251	0.0103
0.97 - 1.00	0.0343	0.0152	0.0344	0.0154	0.0342	0.0155
1.00 - 1.03	0.0423	0.0187	0.0426	0.0187	0.0428	0.0186
1.03 - 1.06	0.0308	0.0146	0.0308	0.0146	0.0315	0.0153
1.06 < S/K	0.0125	0.0053	0.0124	0.0053	0.0124	0.0054
Total	0.0262	0.0114	0.0263	0.0115	0.0264	0.0116

This table presents INS implied volatility forecast errors using all data from 2007, 2008, and 2009. Errors are given for several moneyness categories and for three horizons 10 minutes (10M), 30 minutes (30M), and 60 minutes (60M). Panels A and B give the quadratic AHBS results for RMSVE and MAE, respectively. Panels C and D give the cubic AHBS results for RMSVE and MAE, respectively.

Table 3: 10M, 30M, 60M OOS Performance errors under Absolute AHBS Models - 2007

Panel A: Quadratic Polynomial, RMSVE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0403	0.0194	0.0447	0.0276	0.0492	0.0332
0.94 - 0.97	0.0703	0.0375	0.0815	0.0533	0.0878	0.0609
0.97 - 1.00	0.0912	0.0581	0.1064	0.0808	0.1168	0.0924
1.00 - 1.03	0.1072	0.0820	0.1183	0.1005	0.1259	0.1104
1.03 - 1.06	0.0821	0.0514	0.0912	0.0660	0.1015	0.0797
1.06 < S/K	0.0299	0.0215	0.0353	0.0284	0.0389	0.0328
Total	0.0704	0.0452	0.0799	0.0597	0.0872	0.0687

Panel B: Quadratic Polynomial, MAE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0332	0.0139	0.0361	0.0207	0.0402	0.0260
0.94 - 0.97	0.0622	0.0287	0.0707	0.0422	0.0772	0.0507
0.97 - 1.00	0.0770	0.0441	0.0894	0.0634	0.1002	0.0749
1.00 - 1.03	0.0922	0.0642	0.1011	0.0797	0.1100	0.0921
1.03 - 1.06	0.0705	0.0400	0.0774	0.0531	0.0873	0.0656
1.06 < S/K	0.0220	0.0148	0.0260	0.0201	0.0288	0.0238
Total	0.0598	0.0345	0.0671	0.0468	0.0743	0.0559

Panel C: Cubic, RMSVE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0281	0.0187	0.0342	0.0267	0.0393	0.0327
0.94 - 0.97	0.0492	0.0351	0.0627	0.0516	0.0698	0.0597
0.97 - 1.00	0.0696	0.0540	0.0876	0.0782	0.0988	0.0911
1.00 - 1.03	0.0842	0.0684	0.0986	0.0912	0.1080	0.1002
1.03 - 1.06	0.0613	0.0470	0.0739	0.0626	0.0861	0.0767
1.06 < S/K	0.0242	0.0188	0.0307	0.0260	0.0351	0.0309
Total	0.0530	0.0405	0.0649	0.0563	0.0732	0.656

Panel D: Cubic, MAE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0218	0.0133	0.0264	0.0199	0.0315	0.0256
0.94 - 0.97	0.0409	0.0263	0.0518	0.0409	0.0599	0.0496
0.97 - 1.00	0.0568	0.0401	0.0712	0.0610	0.0839	0.0739
1.00 - 1.03	0.0694	0.0520	0.0814	0.0705	0.0929	0.0837
1.03 - 1.06	0.0501	0.0360	0.0604	0.0498	0.0725	0.0628
1.06 < S/K	0.0173	0.0129	0.0222	0.0185	0.0259	0.0225
Total	0.0429	0.0303	0.0525	0.0437	0.0615	0.0533

This table presents OOS implied volatility forecast errors for 2007. Errors are given for several moneyness categories and for three horizons 10 minutes (10M), 30 minutes (30M), and 60 minutes (60M). Panels A and B give the quadratic AHBS results for RMSVE and MAE, respectively. Panels C and D give the cubic AHBS results for RMSVE and MAE, respectively.

Table 4: 10M, 30M, 60M OOS Performance errors under Absolute AHBS Models - 2008

Panel A: Quadratic Polynomial, RMSVE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0430	0.0270	0.0512	0.0375	0.0595	0.0467
0.94 - 0.97	0.0859	0.0572	0.1053	0.0797	0.1238	0.0975
0.97 - 1.00	0.1058	0.0782	0.1252	0.1015	0.1455	0.1207
1.00 - 1.03	0.1309	0.0686	0.1458	0.0941	0.1596	0.1146
1.03 - 1.06	0.1065	0.0546	0.1206	0.0775	0.1321	0.0974
1.06 < S/K	0.0805	0.0374	0.0861	0.0527	0.0937	0.0670
Total	0.0922	0.0539	0.1059	0.0740	0.1194	0.0909

Panel B: Quadratic Polynomial, MAE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0299	0.0172	0.0349	0.0242	0.0407	0.0311
0.94 - 0.97	0.0736	0.0447	0.0882	0.0637	0.1062	0.0810
0.97 - 1.00	0.0899	0.0612	0.1040	0.0797	0.1218	0.0989
1.00 - 1.03	0.1163	0.0511	0.1258	0.0728	0.1381	0.0941
1.03 - 1.06	0.0931	0.0417	0.1026	0.0605	0.1126	0.0793
1.06 < S/K	0.0676	0.0279	0.0710	0.0399	0.0769	0.0534
Total	0.0785	0.0407	0.0879	0.0569	0.0997	0.0732

Panel C: Cubic, RMSVE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0288	0.0241	0.0390	0.0353	0.0480	0.0447
0.94 - 0.97	0.0605	0.0529	0.0825	0.0765	0.1027	0.0951
0.97 - 1.00	0.0700	0.0676	0.0947	0.0935	0.1180	0.1151
1.00 - 1.03	0.0771	0.0645	0.0999	0.0889	0.1189	0.1107
1.03 - 1.06	0.0637	0.0525	0.0858	0.0754	0.1029	0.0975
1.06 < S/K	0.0452	0.0364	0.0578	0.0519	0.0701	0.0669
Total	0.0576	0.0497	0.0768	0.0704	0.0937	0.0886

Panel D: Cubic, MAE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0188	0.0152	0.0255	0.0226	0.0321	0.0300
0.94 - 0.97	0.0483	0.0404	0.0666	0.0604	0.0864	0.0790
0.97 - 1.00	0.0548	0.0514	0.0753	0.0729	0.0973	0.0949
1.00 - 1.03	0.0617	0.0479	0.0796	0.0693	0.0990	0.0904
1.03 - 1.06	0.0506	0.0395	0.0679	0.0588	0.0846	0.0792
1.06 < S/K	0.0350	0.0270	0.0445	0.0390	0.0560	0.0532
Total	0.0449	0.0370	0.0600	0.0540	0.0762	0.0713

This table presents OOS implied volatility forecast errors for 2008. Errors are given for several moneyness categories and for three horizons 10 minutes (10M), 30 minutes (30M), and 60 minutes (60M). Panels A and B give the quadratic AHBS results for RMSVE and MAE, respectively. Panels C and D give the cubic AHBS results for RMSVE and MAE, respectively.

Table 5: 10M, 30M, 60M OOS Performance errors under Absolute AHBS Models - 2009

Panel A: Quadratic Polynomial, RMSVE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0271	0.0161	0.0316	0.0221	0.0342	0.0263
0.94 - 0.97	0.0416	0.0267	0.0508	0.0375	0.0568	0.0439
0.97 - 1.00	0.0577	0.0377	0.0690	0.0506	0.0774	0.0591
1.00 - 1.03	0.0600	0.0496	0.0700	0.0613	0.0778	0.0681
1.03 - 1.06	0.0514	0.0315	0.0594	0.0422	0.0649	0.0500
1.06 < S/K	0.0244	0.0151	0.0278	0.0199	0.0304	0.0237
Total	0.0437	0.0295	0.0515	0.0390	0.0570	0.0453

Panel B: Quadratic Polynomial, MAE

Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0215	0.0118	0.0248	0.0167	0.0274	0.0208
0.94 - 0.97	0.0352	0.0207	0.0423	0.0294	0.0484	0.0365
0.97 - 1.00	0.0485	0.0288	0.0571	0.0392	0.0656	0.0480
1.00 - 1.03	0.0511	0.0389	0.0585	0.0486	0.0669	0.0563
1.03 - 1.06	0.0442	0.0244	0.0500	0.0331	0.0553	0.0409
1.06 < S/K	0.0183	0.0104	0.0205	0.0139	0.0226	0.0170
Total	0.0365	0.0225	0.0422	0.0302	0.0478	0.0367

Panel C: Cubic, RMSVE

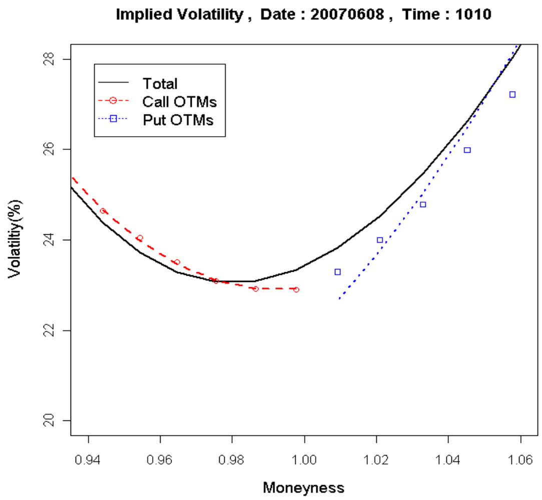
Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0192	0.0160	0.0246	0.0223	0.0282	0.0272
0.94 - 0.97	0.0300	0.0261	0.0406	0.0370	0.0473	0.0435
0.97 - 1.00	0.0403	0.0372	0.0503	0.0508	0.0616	0.0596
1.00 - 1.03	0.0401	0.0399	0.0524	0.0522	0.0606	0.0604
1.03 - 1.06	0.0324	0.0301	0.0425	0.0410	0.0496	0.0491
1.06 < S/K	0.0152	0.0137	0.0199	0.0188	0.0236	0.0228
Total	0.0296	0.0272	0.0389	0.0371	0.0452	0.0438

Panel D: Cubic, MAE

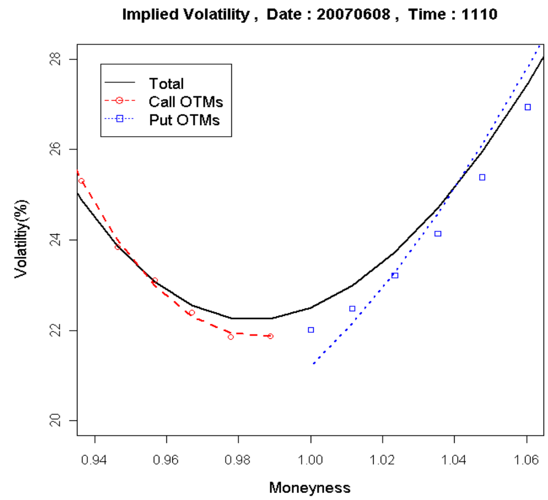
Time	10M		30M		60M	
S/K	CON	SEP	CON	SEP	CON	SEP
S/K < 0.94	0.0145	0.0117	0.0187	0.0167	0.0223	0.0212
0.94 - 0.97	0.0238	0.0200	0.0327	0.0291	0.0395	0.0362
0.97 - 1.00	0.0317	0.0281	0.0402	0.0394	0.0510	0.0485
1.00 - 1.03	0.0313	0.0302	0.0411	0.0401	0.0499	0.0495
1.03 - 1.06	0.0253	0.0229	0.0333	0.0318	0.0404	0.0400
1.06 < S/K	0.0106	0.0094	0.0140	0.0132	0.0171	0.0164
Total	0.0229	0.0204	0.0303	0.0284	0.0368	0.0354

This table presents OOS implied volatility forecast errors for 2009. Errors are given for several moneyness categories and for three horizons 10 minutes (10M), 30 minutes (30M), and 60 minutes (60M). Panels A and B give the quadratic AHBS results for RMSVE and MAE, respectively. Panels C and D give the cubic AHBS results for RMSVE and MAE, respectively.

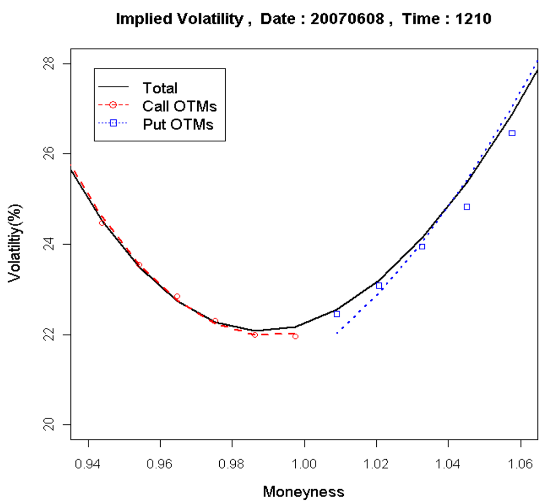
Figure 1: Volatility smile, Call sneer, and Put sneer



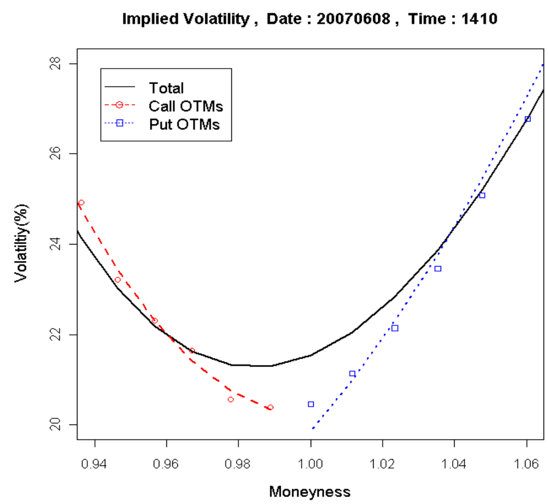
(a) IVs and their curve: 10:10



(b) IVs and their curve: 11:10



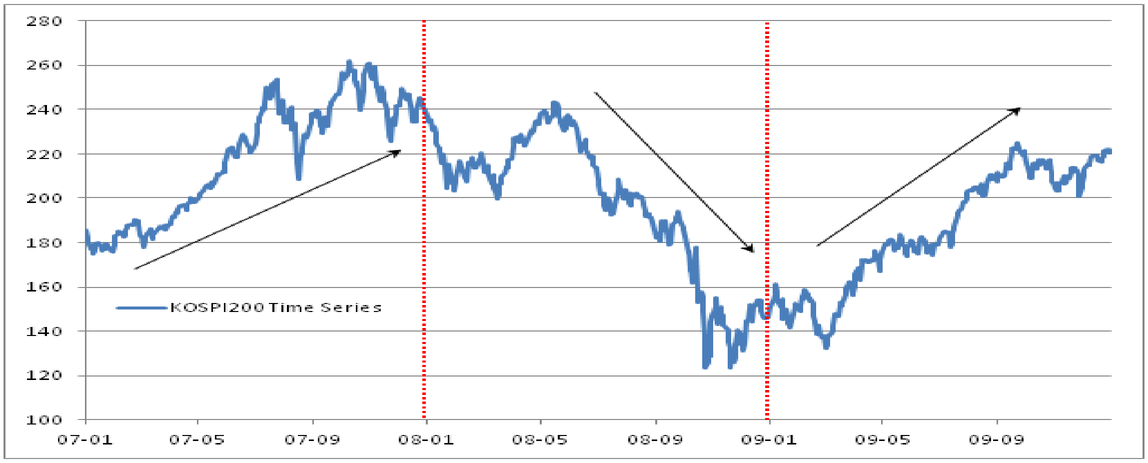
(c) IVs and their curve: 12:10



(d) IVs and their curve: 14:10

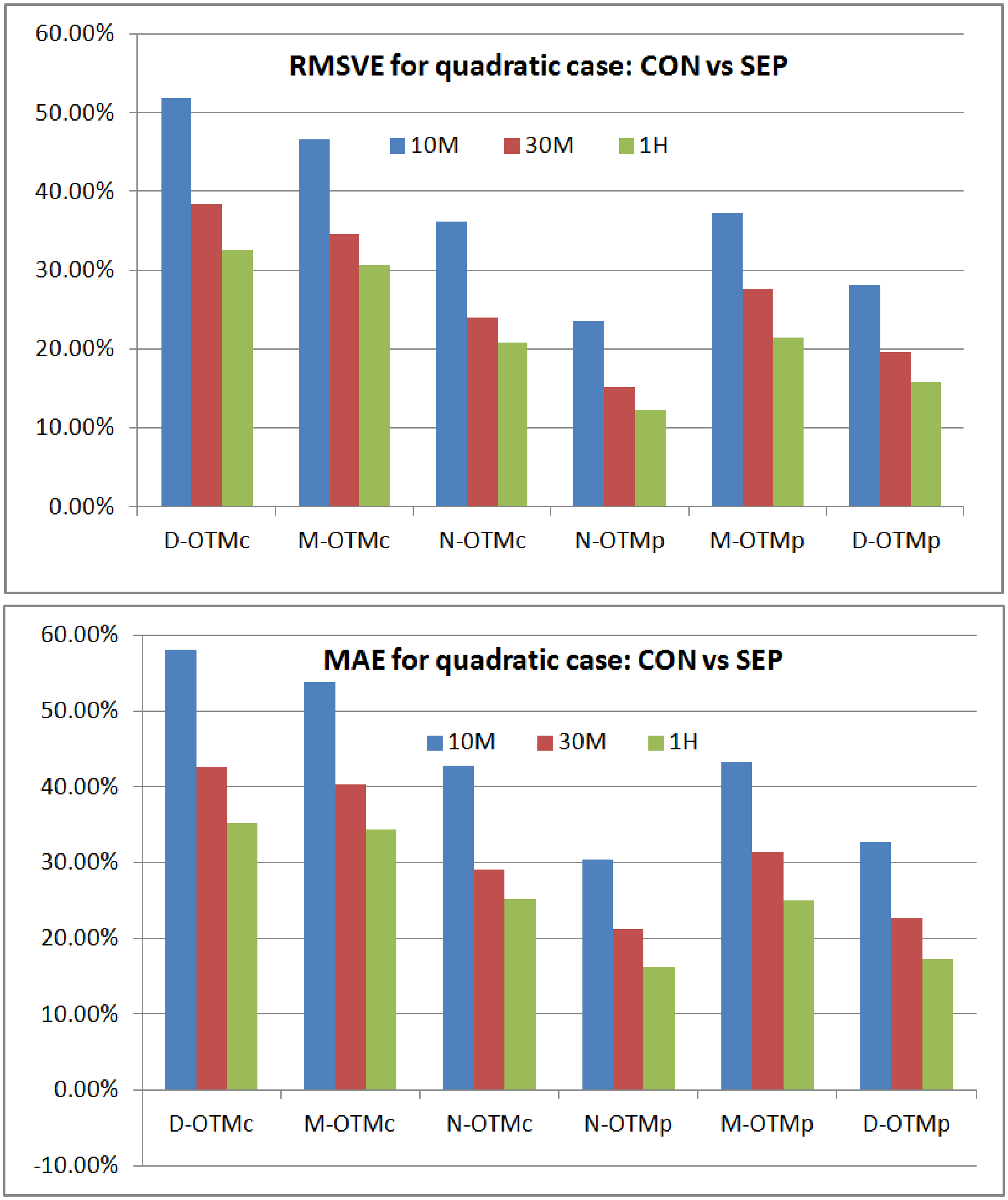
This figure shows the volatility smile, the call sneer, and the put sneer. Two empirical facts are illustrated. First, the volatility smile, which is estimated using puts and calls, is continuous and smooth at $S/K = 1$ and is symmetric about this point. Second, an asymmetry usually exists between the slope of the call and put sneers. There is a gap or discontinuity in both slope and value at $S/K = 1$ between the call and put sneers. The curves represent the AHBS_{Aq} model implied volatility smile estimated by using both OTM calls and OTM puts (solid black line), the AHBS_{Aq} model implied volatility call sneer estimated by only using OTM calls (red dashed line), and the AHBS_{Aq} model implied volatility put sneer estimated by only using OTM puts (blue dotted line). Also shown are the market estimates of implied volatility derived from item 3. The market estimates are given when only OTM calls are used as input (red circles) and only OTM puts are used as input (blue squares). As can be seen from these graphs, the slopes of the implied volatility differ when using the AHBS_{Aq} model whether the put and calls are used simultaneously or separately. Also, the gap, and the fact that its magnitude time varies, is apparent in the separately estimated sneers.

Figure 2: Time Series of KOSPI 200



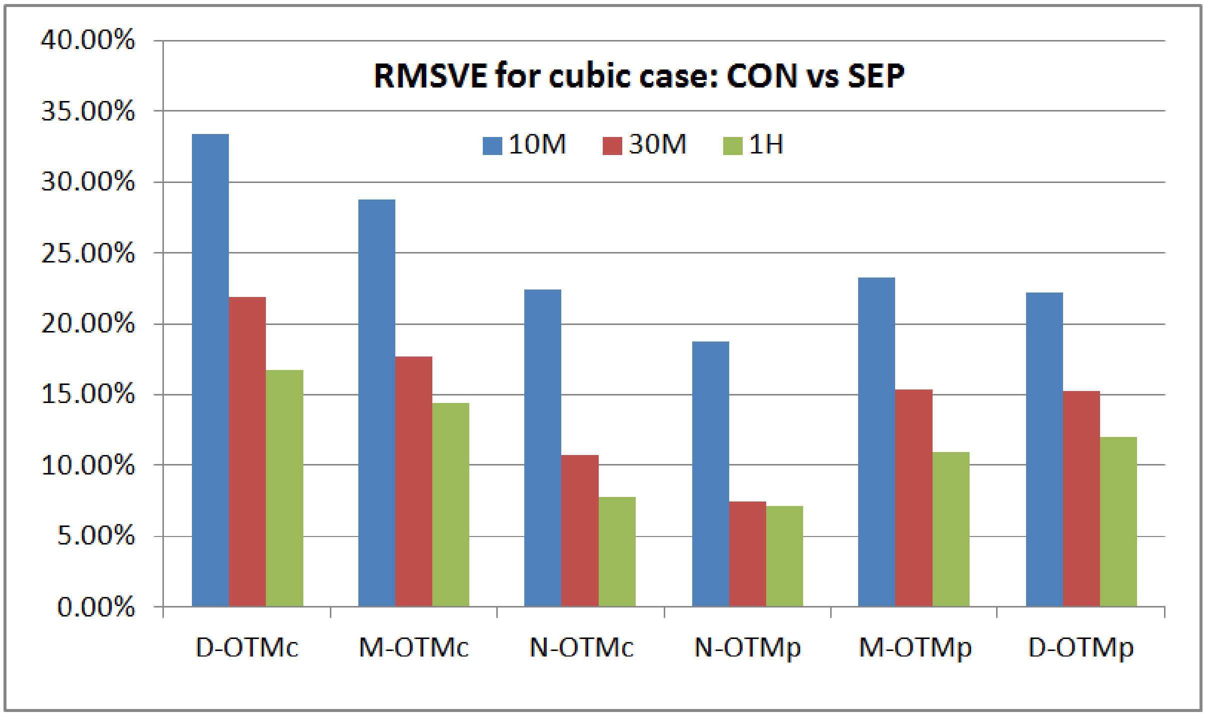
This figure shows the KOSPI 200 Index and a trend line for the three years 2007, 2008, and 2009. The plot indicates that during the 2008 liquidity crises the market experienced an overall down trend and exhibited high volatility. Prior to the crisis, the time series for 2007 experienced an up trend with considerable volatility in the later half of the year. In the post-crisis year, there was again an up trend, but with much less volatility.

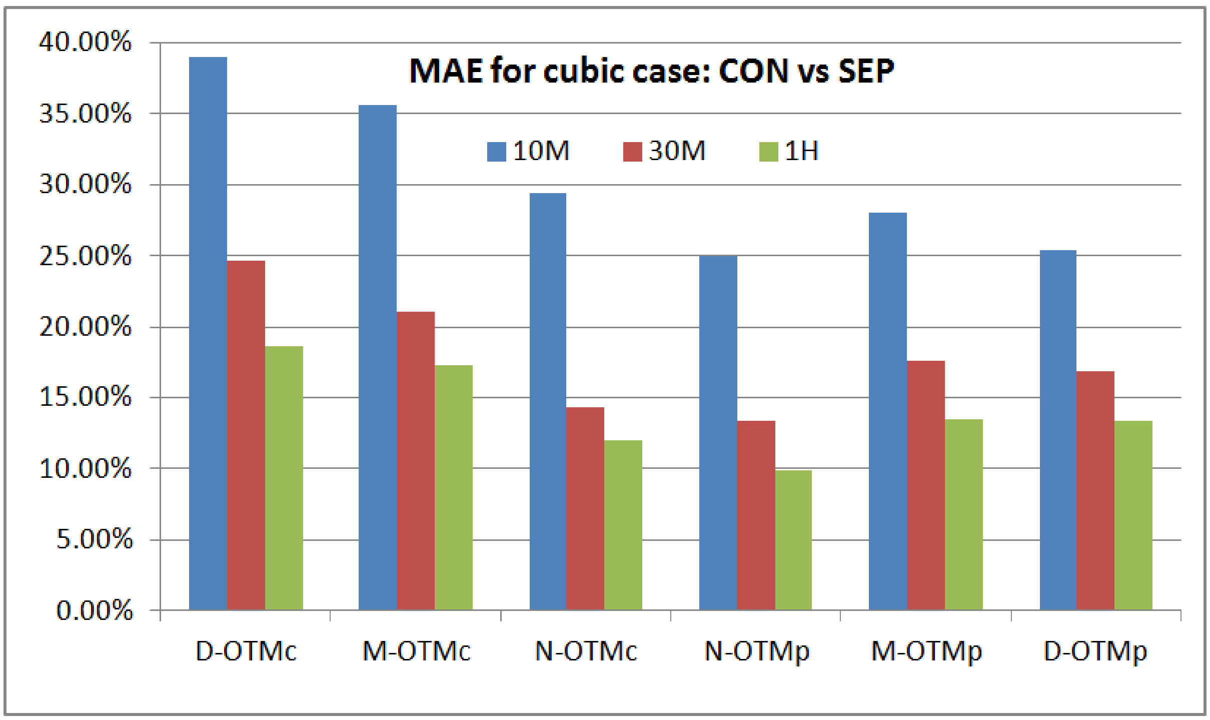
Figure 3: 2007 Conventional vs. Separation Method - Quadratic AHBS



This table shows the benefit (in terms of reduced OOS forecast error) of implementing the SEP methodology over the CON methodology. Results are shown for the quadratic AHBS model ($AHBS_{Aq}$) using minute-by-minute data from the year 2007. The height of the bars visually compares the forecast error between the CON and SEP methodology for each forecast period for several subsets of option contracts. That is, each bar represents the improvement (positive) or loss (negative) in forecast performance realized by using the SEP in place of the CON methodology. The forecast gain is shown across six different moneyness classes. For calls and puts separately, results are shown for deep-out-of-the-money (D-OTM), medium-out-of-the-money (M-OTM), and near-out-of-the-money (N-OTM). Panel A gives the results for the RMSVE error measure, while Panel B gives the results for the MAE error measure. Three different forecast horizons are provided: 10 minutes (10M), 30 minutes (30M), and one hour (1H).

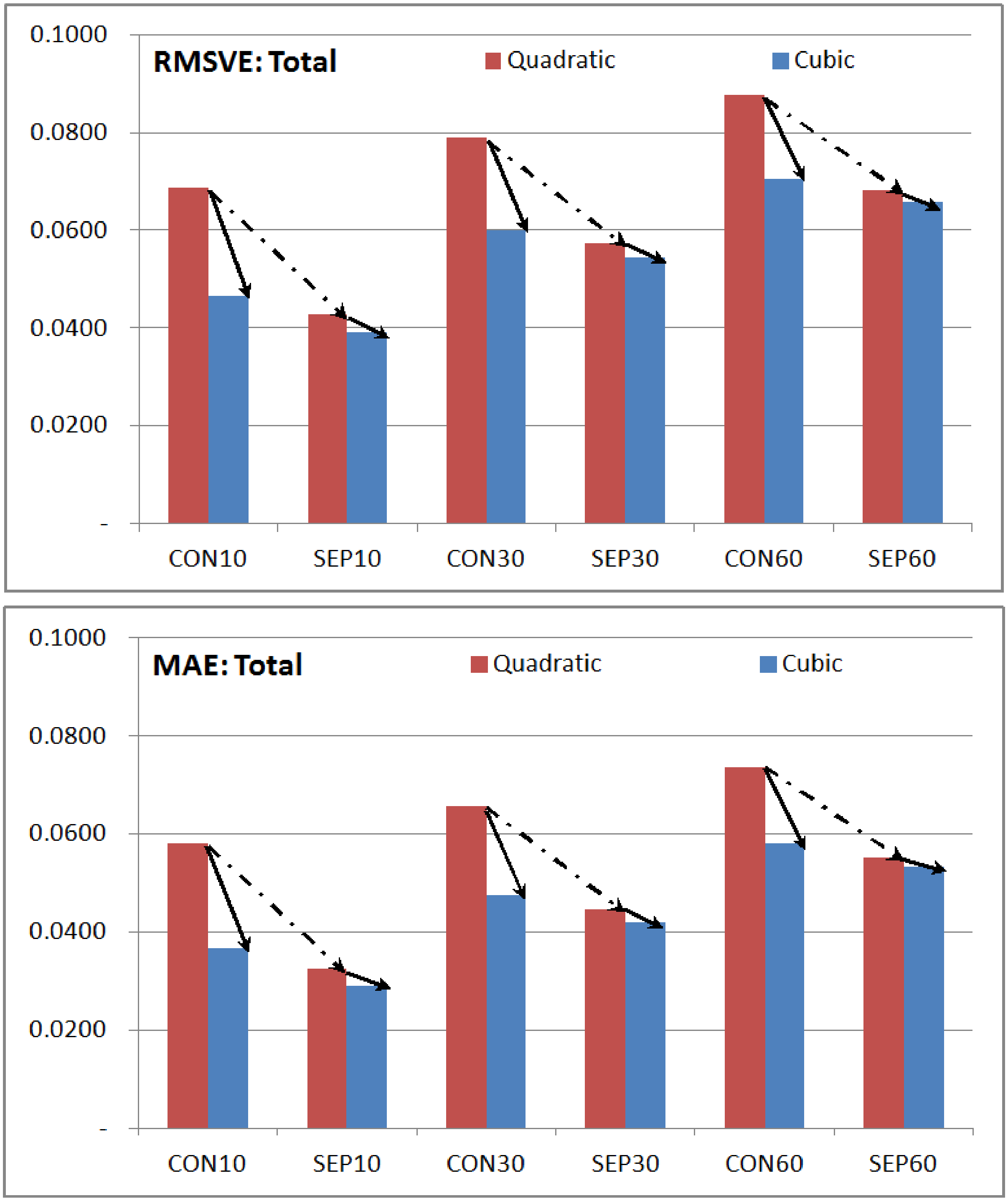
Figure 4: 2007 Conventional vs. Separation Methodology - Cubic AHBS





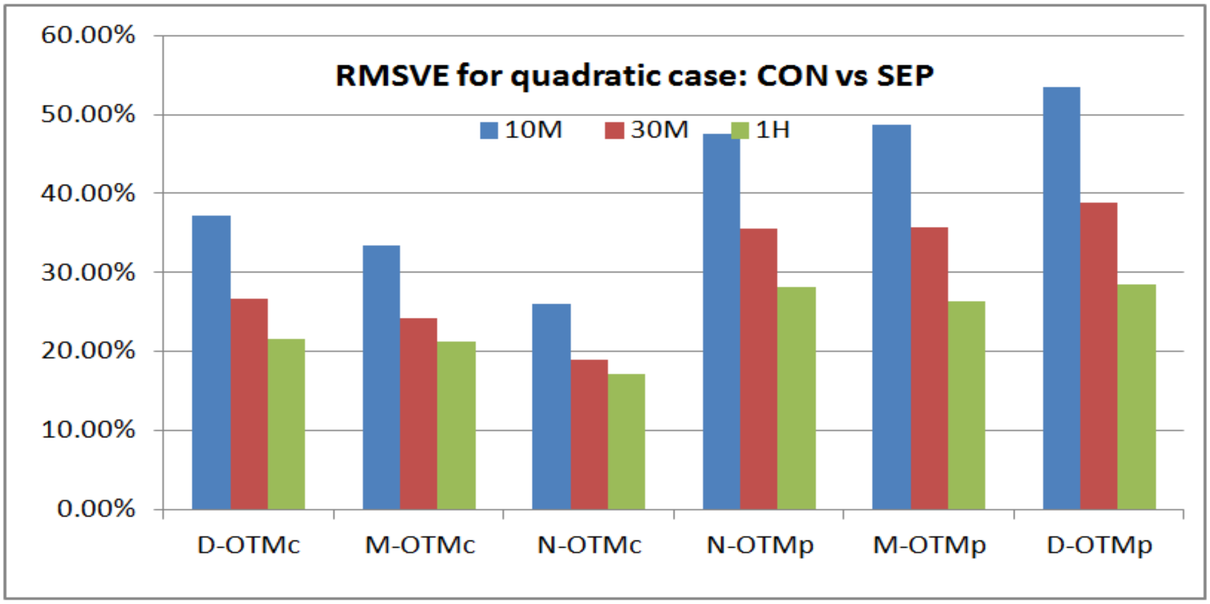
This table shows the benefit (in terms of reduced OOS forecast error) of implementing the SEP methodology over the CON methodology. Results are shown for the cubic AHBS model ($AHBS_{Ac}$) and for the year 2007. The height of the bars visually compares the forecast error between the CON and SEP methodology for each forecast period for several subsets of option contracts. That is, each bar represents the improvement (positive) or loss (negative) in forecast performance realized by using the SEP in place of the CON methodology. The forecast gain is shown across six different moneyness classes. For calls and puts separately, results are shown for deep-out-of-the-money (D-OTM), medium-out-of-the-money (M-OTM), and near-out-of-the-money (N-OTM). Panel A gives the results for the RMSVE error measure, while Panel B gives the results for the MAE error measure. Three different forecast horizons are provided: 10 minutes (10M), 30 minutes (30M), and one hour (1H).

Figure 5: RMSVE and MAE

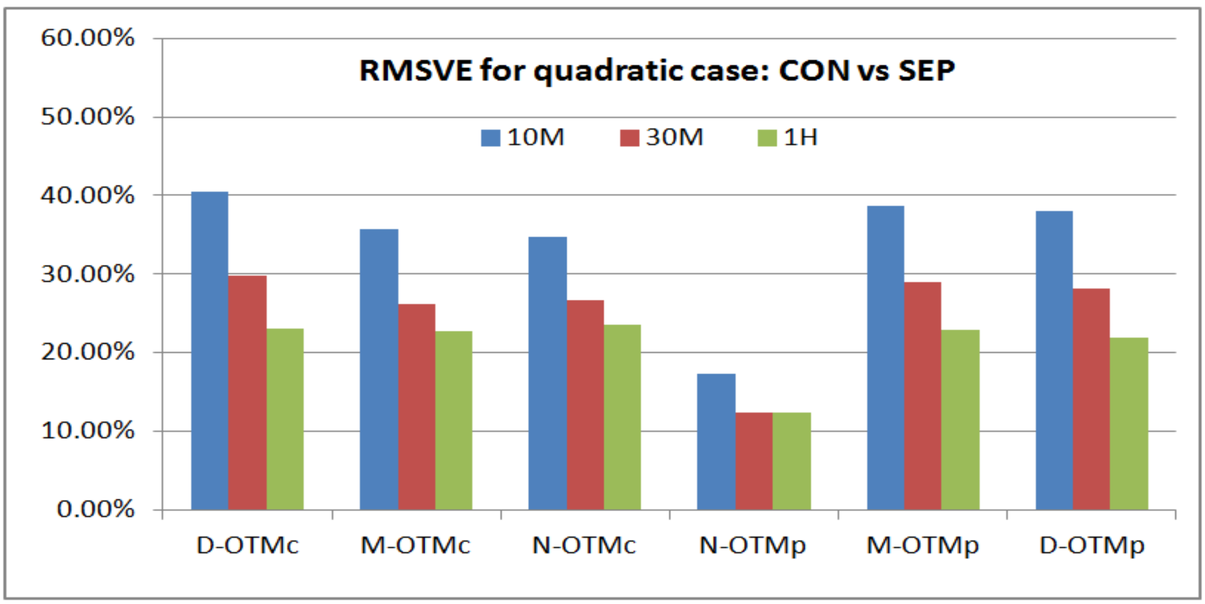


This table shows the benefit (in terms of reduced OOS forecast error) of implementing one strategy over another. All three years 2007, 2008, and 2009 are used in the estimates. The solid black is the gain from implementing a cubic over a quadratic AHBS model. The dashed black is the gain from utilizing the SEP methodology rather than the CON methodology. Three different forecast horizons are provided: 10 minutes (10), 30 minutes (30), and one hour (60). For example, SEP60 indicates that the call and put sneers were estimated separately and the forecast horizon was one hour.

Figure 6: Robust Test for RMSVE: Conventional vs. Separation Methodology - Quadratic AHBS



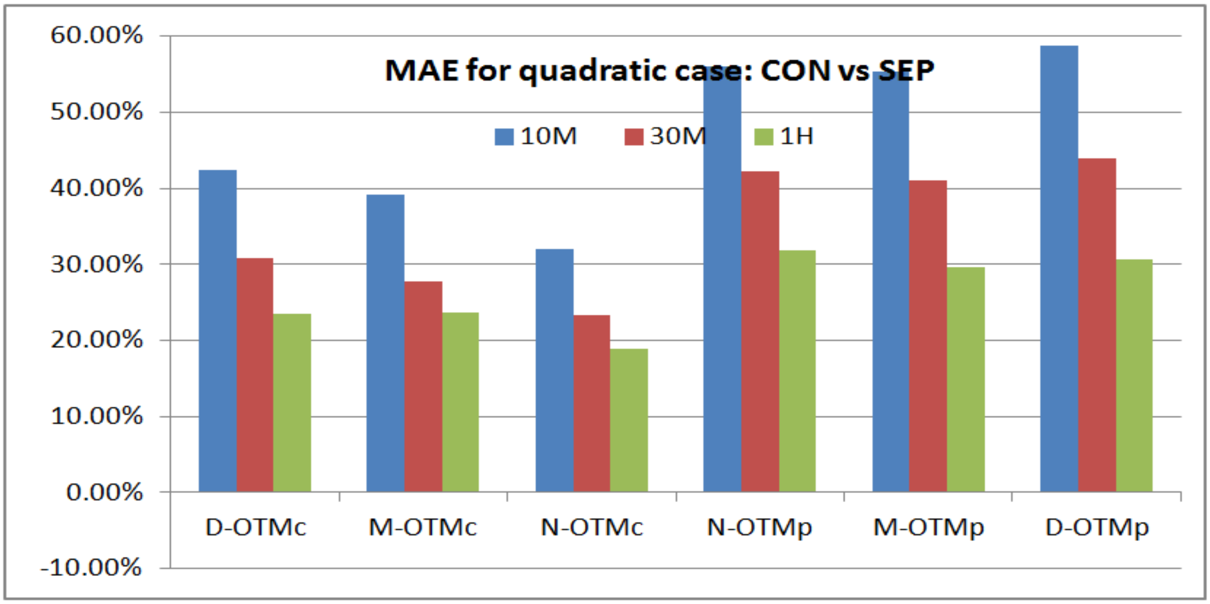
(a) RMSVE - 2008



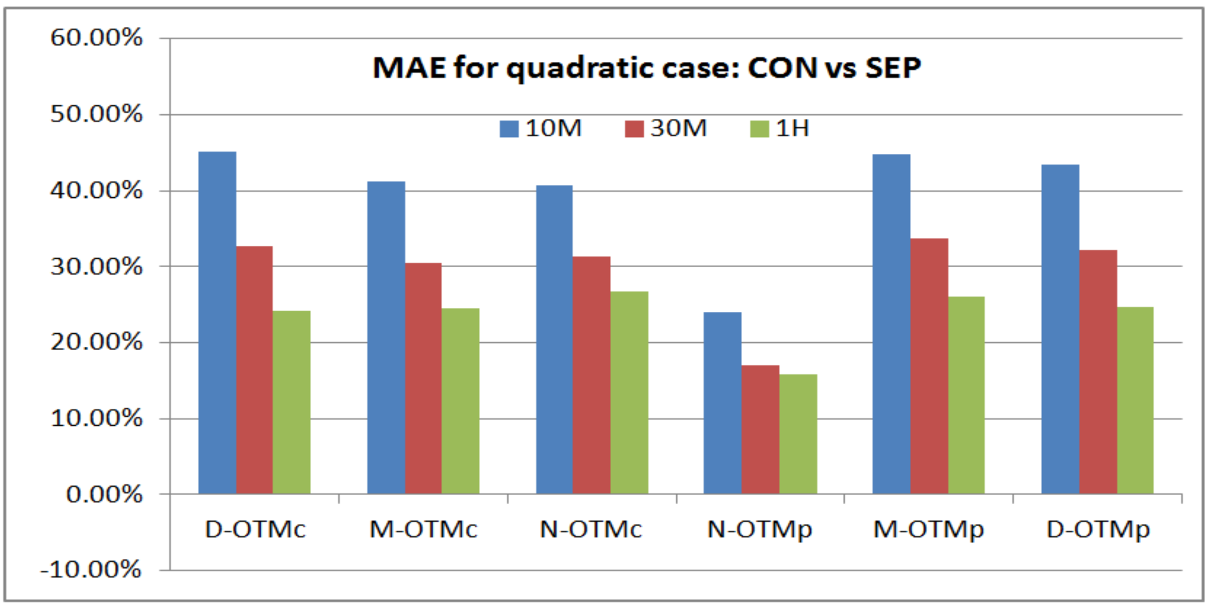
(b) RMSVE - 2009

This table shows the benefit (in terms of reduced OOS forecast error) of implementing the SEP methodology over the CON methodology. Results are shown for the quadratic AHBS model ($AHBS_{Aq}$) for the years 2008 and 2009. The height of the bars visually compares the RMSVE forecast error between the CON and SEP methodology for each forecast period for several subsets of option contracts. That is, each bar represents the improvement (positive) or loss (negative) in forecast performance realized by using the SEP in place of the CON methodology. The forecast gain is shown across six different moneyness classes. For calls and puts separately, results are shown for deep-out-of-the-money (D-OTM), medium-out-of-the-money (M-OTM), and near-out-of-the-money (N-OTM). Panel A gives the 2008 results, while Panel B gives the 2009 results. Three different forecast horizons are provided: 10 minutes (10M), 30 minutes (30M), and one hour (1H).

Figure 7: Robust Test for MAE: Conventional vs. Separation Methodology - Quadratic AHBS



(a) RMSVE - 2008



(b) RMSVE - 2009

This table shows the benefit (in terms of reduced OOS forecast error) of implementing the SEP methodology over the CON methodology. Results are shown for the quadratic AHBS model ($AHBS_{Aq}$) for the years 2008 and 2009. The height of the bars visually compares the MAE forecast error between the CON and SEP methodology for each forecast period for several subsets of option contracts. That is, each bar represents the improvement (positive) or loss (negative) in forecast performance realized by using the SEP in place of the CON methodology. The forecast gain is shown across six different moneyness classes. For calls and puts separately, results are shown for deep-out-of-the-money (D-OTM), medium-out-of-the-money (M-OTM), and near-out-of-the-money (N-OTM). Panel A gives the 2008 results, while Panel B gives the 2009 results. Three different forecast horizons are provided: 10 minutes (10M), 30 minutes (30M), and one hour (1H).