Proceedings of the 2007 American Control Conference
Marriott Marquis Hotel at Times Square
New York City, USA, July 11-13, 2007

Forecasting Stock Market Volatility Using Implied Volatility

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Abstract—**We explored the firm-level forecasting power of implied volatility on realized volatility over various horizons. All existing literatures focused on examining forecasting power over the remaining life of options. We built a linear regression model using implied volatility series to forecast future volatility of various horizons. We compared the result with some historical methods and found that the linear regression implied volatility model compares favorably with the moving average method and with GARCH (1,1) for forecasting future volatility over various forecast horizons both in-the-sample and out-of-sample. In addition, we examined whether implied volatility of equity index options is useful in providing volatility information of a firm. This is necessary since not all companies have options listed and traded in an Exchange. Finally, we documented that the forecasting power of implied volatility is related to volume ratio-option trading volume versus stock trading volume. Our evidence indicates that a highly liquid option market is necessary for implied volatility to incorporate all relevant information about future volatility.**

I. INTRODUCTION

DUE to the central role the expected volatility of future returns plays in asset and derivative pricing, risk management, financial market regulation, and even monetary policy, forecasting financial market volatility has received extensive attention by academicians and practitioners. In general, there are two ways to forecast volatility. The first way uses the historical return information while the second way makes use of volatility implied from option markets.

The volatility implied in an option's price is widely regarded as a consensus forecast of future volatility over the remaining life of an option. The existing empirical evidence is somehow conflicting. Day and Lewis (1992) found that implied volatility has information content for actual volatility. But the results of Canina and Figlewski (1993) suggested that implied volatility has almost no predictive power in forecasting future volatility. However, Christensen and Prabhala (1998) used non-overlapping data and found significant power in S&P 100 index options over a longer time span from 1983-1995, and information contained in implied volatility subsumes the information of historical volatility. Christen and Hansen extended this analysis to Danish market time series and found similar results. Fleming (1998) also supported Christensen and Prabhala's result regarding S&P 100 index options. Jorion (1995) examined options on currency futures and Xu and Taylor (1995) achieved similar result for options on spot currencies. Most recently, a study by Poteshman (2000) tried to explain the forecasting bias of S&P 500(SPX) implied volatility in forecasting future volatility.

This paper complements the literature in four ways. First we explore the forecasting power of implied volatility on realized volatility over various horizons. All existing literature focuses on examining forecasting power over the remaining life of an option. Even though some literature runs information content regressions of one-day-ahead realized volatility on implied volatility, like Jorion (1995), Lamoureux and Lastrapes (1993), their focus was still on studying predicating power of implied volatility over the remaining life of options. This paper systematically studies forecasting power over various horizons. We built up a linear regression model of using implied volatility series to forecast future volatility over various horizons and compare the result with some historical methods, like moving average method and the GARCH (1,1) model. We found that a linear regression implied volatility model is a good model for forecasting future volatility over various forecast horizons both in-the-sample and out-of-sample. This evidence suggests not only that implied volatility contains information about future volatility over various

Manuscript received September 22, 2006. This work is sponsored by SPOOZ, INC.

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horizons, but also that we can take advantage of this in forecasting volatility for various horizons. Second, we provided firm-level forecasting power of implied volatility on realized volatility. To our knowledge, there is only one paper on this subject, namely that of by Lamoureux and Lastrapes (1993). Their study is based on ten stocks from April 1982 to March 1984. Compared to their study, this paper employs a more recent and longer period of time. This is necessary since Christensen and Prabhala (1998) claimed that there is an obvious difference in the relationship between implied volatility and realized volatility before and after market crash in 1987. Third, we examined whether implied volatility in market index options (we use implied volatility of the SPX 500 index option here) is useful for providing volatility information for a firm. This is necessary since not all companies have options listed and traded in an Exchange. Fourth, we documented for the first time that forecasting power of implied volatility is related to volume ratio-option trading volume versus stock trading volume. Our evidence indicates that a highly liquid option market is necessary for implied volatility to incorporate all relevant information about future volatility.

The paper is organized as follows: Section 2 describes data and methodology. Section 3 reports in-sample results. Section 4 discusses out-of-sample results.

II. Data and Methodology

The forecasting models using historical return information are based on the equal weighted moving average (MA(q), where q is a look back period), the exponentially weighted moving average (EWMA), and the GARCH models. There is no criterion to decide which q should be chosen for the MA (q) model. In this paper, we choose q same as the forecast horizon, which is commonly used in practice. In particular, n-day future volatility is forecasted as the standard deviation of returns of n-1 prior days (the only exception is for the 1 day ahead forecast, where we use MA (10) because MA (1) is obviously bad from the In-Sample result). Return is as usual defined as $r_t = \ln(P_t / P_{t-1})$, where P_t is the closing price on day t. Daily closing prices of the 50 largest firms of S&P 500, and the S&P 500 index itself from 3/1/1996 to 4/8/2002, are collected in the Bloomberg Database.

For the EWMA model in this paper, we use λ = 0.94, which is used by JP Morgan for the daily volatility updating in their RiskMetrics database. So the next-day forecast volatility is:

$$\sigma_t^2 = 0.06 * {r_{t-1}}^2 + 0.94 * \sigma_{t-1}^2 \qquad (1)$$

We use in this paper the GARCH (1,1) model, introduced by Engle (1982) and Bellerose (1986), given what is said to be the best model in the GARCH (p,q) class for p $\in$ [1,5] and q $\in$ [1,2] (Engle and Patton (2001)). This model is defined by:

$$r_t = \sigma_t \varepsilon_t \qquad (2)$$

$$\sigma_t^2 = w + \alpha (r_{t-1})^2 + \beta \sigma_{t-1}^2 \qquad (3)$$

Where w, α, β are parameters, which are estimated using the maximum likelihood method, assuming the distribution for the innovations, ε_t is Gaussian. The h-step-ahead forecast from the GARCH (1,1) model is given by:

$$E_t(r_{t+h}^2) = w \sum_{i=0}^{h-2} (\alpha + \beta)^i + (\alpha + \beta)^{h-1} \sigma_{t+1}^2$$

(h >2) (4)
(Hwang, S and Satchell, S. (1998)).

Volatility forecasting from the equity option market is implied volatility. The most common implied volatility is derived from the Black-Scholes Model. Daily implied volatility is an average of at-the-money call implied volatility and at-the-money put implied volatility. At-the-money call/put implied volatilities are derived from a weighted average of the implied volatilities of three call/put options closest to the at-the-money strikes with a minimum of 20 business days to expiration. We obtained the implied volatility data series of the same 50 firms as above, the 50 largest firms of S&P 500 from the Bloomberg Database; a few missing values are complemented by previous-day values.

Previous literature has focused on exploring the forecasting power of implied volatility over the remaining life of an option. In this paper, we explore the forecasting power of implied volatility on 1 day-, 10 day-, 20 day-, 30 day-, 45 day-, and 60 day-ahead actual volatility both in-sample and out-of-sample. We build a linear regression model for this implied volatility forecast, namely

$$\sigma_t = a + b \sigma_{t-1}^{IV} + \varepsilon_t \qquad (5)$$

Where σ_t is actual volatility over a period (1 day, 10 day, 20 day, 30 day, 45 day, 60 day) from day t, σ_{t-1}^{IV} is the implied volatility of day t-1. We first did a regression using in-the-sample data to obtain the coefficient for intercept a and the coefficient for implied volatility b . Then we calculated the implied volatility forecast for future 1 day, 10 day, 20 day, 30 day, 45 day, 60 day volatility given the two coefficients a , b and the above equation for the out-of-sample period. We called this the "IV model (method)" or the "linear regression implied volatility model (method)."

We investigated whether the implied volatility of index options is useful in prediction of the volatility of individual stocks. In the same way as in the IV model, we can run regression of actual volatility of individual stocks on implied volatility of S&P 500 index options using in-sample data.

$$\sigma_t = a + b\sigma_{t-1}^{MIV} + \varepsilon_t \tag{6}$$

Where σ_{t-1}^{MIV} is implied volatility of S&P 500 index options of day t-1. Then we calculated implied volatility forecast for future 10 day, 20 day, 30 day, 45 day, 60 day volatility given the two coefficient s a , b and the above equation the out-of-sample period. We call this model the "MIV model (method)". This investigation is helpful to determine whether it is possible to use market implied volatility to forecast actual volatility for those stocks, which do not have traded equity options.

To evaluate the performance of various methods, we need to compare forecasted volatilities with actual volatilities. Unfortunately, the actual volatility is not directly observed and hence it has to be estimated from stock price movement. A common approach in the literature is to use the absolute or squared daily return to estimate the daily volatility. In more recent literature, daily volatility has been estimated from high frequency data. Since we only have a data set at the daily frequency, we calculate the volatility as:

$$\sigma_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r}\,)^2} \tag{7}$$

Where r_i is the daily return on day i, n is the number of trading days in a period and $\bar{r}_i$ is the average daily return during the period. For one day, n =1, $\sigma_t = \sqrt{r_i^2}$

To figure out a reason why the volatility information in implied volatility varies across firms, we introduce an indicator to explain the difference. Volume ratio, which is defined as total option trading volume (including call and put volume) divided by stock trading volume, may be a good indicator of forecasting power of implied volatility on realized stock volatility since it indicates the efficiency and liquidity of an option relative to its underlying.

Before we start to forecast volatility, there remains the question of how we divide our sample. The 1273 observations from March 1, 1996 to March 1,2001 are used to fit the models and the out-of-sample period covers the remaining 273 observations from March 2, 2001 to April 8, 2002. The division is arbitrary, but the out-of-sample period contains the down market after the September 11 terrorist attack, making volatility forecast more difficult.

III. In-Sample Comparisons of Forecasting Ability

After preparing the time series of realized volatility, implied volatility, and GARCH volatility, we ran the following regressions separately:

$$\sigma_t = a + b\sigma_{t-1}^{IV,G} + \varepsilon_t \tag{8}$$

Where σ_t is actual volatility over a period from day t, σ_{t-1}^{IV} is the implied volatility of day t-1, σ_{t-1}^{G} is the GARCH volatility of day t-1. If volatility forecasts contain some information about the future actual volatility, then the slope coefficient b should be significantly different from zero.

Whether implied volatility encompasses the information about future volatility that could be obtained from other forecasts is a question being examined by regressing the actual volatility on the implied volatility and the other forecasts as follows:

$$\sigma_t = a + b\sigma_{t-1}^{IV} + c\sigma_{t-1}^{G} + d\sigma_{t-1}^{MA} + \varepsilon_t \tag{9}$$

Because of limited space, we will not show detail results of those regressions mention above. The result of regression equation (9) shows that the daily-implied volatility contains a substantial amount of information for volatility over the next day for both SPX and individual firms. The regression for the long horizon in terms of equation (5) shows that the implied volatility contains information for actual volatility for all firms over all horizons. The result of regression (6) shows that the market implied volatility contains information for actual volatility for almost all firms for all horizons.

IV. OUT-OF_SAMPLE FORECASTS

A. Error Measurements

In literature, a variety of statistics have been used to compare forecast errors. These include mean square forecast error (MSFE), mean absolute error (MAFE), mean percentage forecast error (MPFE), LINEX loss function etc. In this paper, we use error measurements by taking the requirement of volatility in derivative trading and VaR in risk management.

Since relative relationship between implied volatility and realized volatility is at heart of option trading, we decided to use MPFE as a criterion to decide which one is the winner in terms of usage by option traders. By definition,

$$\text{MPFE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{\sigma}_{i+h} - \sigma_{i+h}|}{\sigma_{i+h}}$$

Where n is the number of out-of-sample observations minus the number of days of the forecast horizon; σ_t is the actual volatility at the period t; $\hat{\sigma}$ is the forecasted volatility at the period t.

With the growing usage of VaR as a risk management tool, the need for prediction of short-term variance and covariance becomes greater. The Basle Committee's Market Risk Amendment to the Capital Accord in 1998 (Basle Committee On Banking Supervision (1999)) specifies that banks have to calculate the price risk of their financial activities and set aside sufficient capital to cover the market risk. The regulation requires the need of accurate volatility prediction. Over-prediction of future volatility requires more costly capital, while under-prediction leads to boundary violations. Under-prediction matters more than over-prediction in accordance with the Basle Capital Accord. The under prediction situation is certainly worse than providing some more capital when volatility is overestimated. Considering the asymmetry, we use a LINEX loss function defined by:

$$L(\alpha) = \frac{1}{n}\sum_{i=1}^{n} |\hat{\sigma}_i - \sigma_i| + |\exp(\alpha(\hat{\sigma}_i - \sigma_i)) - 1|$$

Where α is a given parameter, which captures the degree of asymmetry. There are two reasons why we choose this Linex Loss function. First, if we choose α =0, the asymmetry disappears and the LINEX loss function is the same as the mean absolute forecast error (MAFE), which is an important error measurement in a lot of literatures. Second, if we restraint our choice of α to be a negative number, then larger loss will be generated for under-predications than over-predictions. However there are no criteria to choose the exact value of α . It depends on how much under-predication should be penalized relative to over-predication. In this study, we arbitrarily choose α = -1, which implies, for example, that a forecast of error of –1 generates a loss that is about 1.67 times as large as an error of +1, a reasonable figure.

TABLE 5 OUT –OF-SAMPLE ONE DAY AHEAD FORECAST

(a) Full Sample (all 50 firms)

Error\Method	IV	MA(10)	EWMA	GARCH
MPFE	5.25	5.71	5.51	6.94
LINEX	0.34	0.37	0.42	0.39
MAFE	0.16	0.18	0.20	0.19

(b) Top Ten Volume Ratio Firms

Error\Method	IV	MA(10)	EWMA	GARCH
MPFE	4.43	5.39	5.01	6.81
LINEX	0.28	0.30	0.34	0.31
MAFE	0.14	0.15	0.17	0.16

(c) Bottom Ten Volume Ratio Firms

Error\Method	IV	MA(10)	EWMA	GARCH
MPFE	6.18	7.32	7.34	7.71
LINEX	0.34	0.37	0.45	0.40
MAFE	0.16	0.19	0.22	0.21

MPFE is mean percentage forecast error and MAFE is mean absolute forecast error. LINEX is the Loss function defined in the paper with α = -1. All the entries are the mean values of the sample.

B. Results

Since one day head forecasting uses different methods, we reported one day ahead forecast error in table 5 and other horizon forecasts in table 6. Table 7 and Table 8 report the comparison of the IV method against two other methods; they show how many companies in the fifty firms have bigger errors for the IV method than for other methods.

Table 6 OUT-OF-SAMPLE RESULTS FOR 10, 20, 30, 45, 60 DAY HORIZON

(a) Full Sample (all 50 firms)

Method\horizon	10 day	20 day	30 day	45 day	60 day
IV (MPFE)	0.44	0.37	0.34	0.33	0.32
(LINEX)	0.22	0.20	0.19	0.19	0.22
(MAFE)	0.11	0.10	0.098	0.095	0.094
MA (MPFE)	0.40	0.34	0.32	0.30	0.33
(LINEX)	0.24	0.22	0.21	0.20	0.26
(MAFE)	0.12	0.11	0.11	0.10	0.11
MIV (MPFE)	0.55	0.44	0.41	0.38	0.38
(LINEX)	0.27	0.24	0.23	0.21	0.30
(MAFE)	0.14	0.12	0.11	0.11	0.11
GARCH(MPFE)	0.58	0.56	0.56	0.57	0.58
(LINEX)	0.25	0.25	0.25	0.26	0.26
(MAFE)	0.14	0.15	0.15	0.16	0.17

(b) Top ten Volume Ratio Firms

Method\horizon	10 day	20 day	30 day	45 day	60 day
IV (MPFE)	0.35	0.29	0.28	0.27	0.27
(LINEX)	0.21	0.20	0.19	0.19	0.23
(MAFE)	0.11	0.10	0.098	0.095	0.094
MA (MPFE)	0.38	0.32	0.31	0.29	0.29
(LINEX)	0.26	0.24	0.23	0.22	0.30
(MAFE)	0.13	0.12	0.12	0.11	0.11
MIV (MPFE)	0.42	0.34	0.32	0.30	0.29
(LINEX)	0.29	0.23	0.22	0.20	0.30
(MAFE)	0.14	0.11	0.11	0.10	0.10
GARCH(MPFE)	0.49	0.49	0.52	0.55	0.56
(LINEX)	0.28	0.30	0.31	0.32	0.33
(MAFE)	0.14	0.15	0.16	0.17	0.17

(c) Bottom Ten Volume Ratio Firms

Method\horizon	10 day	20 day	30 day	45 day	60 day
IV (MPFE)	0.56	0.47	0.44	0.42	0.42
(LINEX)	0.22	0.20	0.20	0.20	0.23
(MAFE)	0.11	0.10	0.10	0.10	0.10
MA (MPFE)	0.41	0.37	0.36	0.34	0.34
(LINEX)	0.20	0.19	0.19	0.18	0.23
(MAFE)	0.10	0.096	0.094	0.10	0.090

MIV (MPFE)	0.69	0.58	0.54	0.50	0.49
(LINEX)	0.25	0.24	0.23	0.22	0.29
(MAFE)	0.13	0.12	0.12	0.11	0.11
GARCH(MPFE)	0.56	0.45	0.39	0.36	0.34
(LINEX)	0.22	0.20	0.19	0.18	0.17
(MAFE)	0.11	0.10	0.094	0.089	0.086

Let us look at part (a) of table 5 and table 6. Firstly, the linear regression implied volatility model appears to be a good model of forecasting future volatility. In the one-day ahead forecast, it performs better than MA (10), EWMA, and GARCH in terms of MPFE even though the forecasting horizons do not match. These implied volatility series are derived from options with a minimum of 20 business days to expiration and the difference between the forecast horizon (1 day) and the remaining time of the option is at least 19 days.

Table 7 OUT-OF-SAMPLE ONE DAY AHEAD COMPARSION OF IV WITH OTHER MODELS

(a) Full Sample (all 50 firms)

Error\methods	IV > MA(10)	IV > EWMA	IV > GARCH
MPFE	17	27	1
LINEX	6	2	2
MAFE	5	1	1

(b) Top Ten Volume Ratio firms

Error\Methods	IV > MA(10)	IV > EWMA	IV > GARCH
MPFE	2	2	0
LINEX	0	0	0
MAFE	0	0	0

(c) Bottom Ten Volume Ratio firms

Error\Methods	IV > MA(10)	IV > EWMA	IV > GARCH
MPFE	4	7	0
LINEX	2	1	0
MAFE	2	1	0

Secondly, In terms of MAFE and LINEX, the linear regression implied volatility model is always the winner for all forecast horizons. As we discussed above, the MAFE and LINEX error measurement is important in symmetric and asymmetric VaR calculation, so this linear regression implied volatility model could be especially useful in forecasting volatility for asset management.

Table 8.OUT-OF-SAMPLE COMPARSION OF IV WITH OTHER MODELS

(a) Out-of-Sample other horizons

Comp.\horizon	10 day	20 day	30 day	45 day	60 day
IV>MA(MPFE)	28	28	23	21	23
(LINEX)	17	17	18	19	16
(MAFE)	18	18	19	19	21
IV>MIV(MPFE)	12	11	12	12	12
(LINEX)	8	9	10	12	2
(MAFE)	9	11	11	12	13
IV>GARCH(MPFE)	20	23	26	25	25
(LINEX)	15	19	22	24	32
(MAFE)	14	20	21	24	25

(b) Top Ten Volume Ratio Firms

Comp.\horizon	10 day	20 day	30 day	45 day	60 day
IV>MA(MPFE)	3	3	3	3	4
(LINEX)	2	3	3	3	2
(MAFE)	2	3	3	3	4
IV>SPX(MPFE)	4	4	4	4	4
(LINEX)	1	1	2	4	0
(MAFE)	2	3	3	4	4
IV>GARCH(MPFE)	3	5	5	4	5
(LINEX)	0	2	3	4	5
(MAFE)	0	3	3	4	5

(c) Bottom Ten Volume Ratio Firms

Comp.\horizon	10 day	20 day	30 day	45 day	60 day
IV>MA(MPFE)	9	9	7	6	6
(LINEX)	7	6	6	6	4
(MAFE)	7	6	6	6	6
IV>SPX(MPFE)	2	2	2	3	3
(LINEX)	3	3	3	3	1
(MAFE)	3	3	3	3	3
IV>GARCH(MPFE)	6	7	7	7	7
(LINEX)	6	7	7	7	8
(MAFE)	6	7	7	7	7

Third, the IV method is best for 60-day horizon forecast in terms of every error measurement, and errors of the IV method decrease more rapidly than those of other methods. So this regression implied volatility model is particularly useful in long horizon forecasting.

Table 9 OUT-OF-SAMPLE COMPARSION OF SPX WITH OTHER MODELS

Comp.\horizon	10 day	20 day	30 day	45 day	60 day
SPX<MA(MPFE)	14	18	21	21	22
(LINEX)	21	22	23	24	19
(MAFE)	21	22	23	24	23
SPX<IV(MPFE)	12	11	12	12	12
(LINEX)	8	9	10	12	2
(MAFE)	9	11	11	12	13
SPX<GARCH (MPFE)	21	22	18	19	19
(LINEX)	18	21	19	19	13
(MAFE)	19	21	20	19	20

Fourth, when we look at Table 8, we note that only a few entries are greater than 25 (half of 50). This means that more than half firms had fewer errors for the IV method than for any other methods. Combining Table 8 and Table 6 part (a), we can find some cases where the mean error of the IV method is greater, but there are more companies where the IV method performs better. For example, even though the mean IV's MAPE for 45 day (0.3260) is greater than MA's MPFE (0.2992), but only 21 firms' IV methods have higher MPFE than their MA methods have.

In summary, implied volatility contains information about future volatility over various horizons and we can take advantage of this in forecasting volatility for various horizons through a linear regression model. This linear regression implied volatility model is a good model of forecasting future volatility for various forecast horizons compared with moving average method and GARCH (1,1).

Next, we tried to find the reason why the volatility information in implied volatility varies across firms. In the same way as we analyzed in-the-sample, we used volume ratio as a possible indicator of efficiency and liquidity of stock options. We compared the results in table 5 and table 6, part (b) and (c). These parts report the results for sub samples of ten firms with the top ten and bottom ten volume ratios, respectively.

We found that as volume ratio declines, the forecasting power of implied volatility decreases. The IV method always has less mean error in part b than in part c for any horizon and for any error measurement, which is not the case for other methods. This means the top ten volume ratio firms always give us more accurate prediction than the bottom ten volume ratio firms in terms of any error measurements. These results are consistent with in-the-sample results.

In addition, part (b) and part(c) of table 7 support this argument. The number of top 10 volume ratio firms, whose IV method has larger error than that of other methods, is not more than that of the bottom 10 volume ratio firms. This trend also holds in the comparison of part (b) and part (c) of table 8, where there even are some exceptions in the comparison between the IV method and the MIV method.

Finally, we investigated whether the SPX index implied volatility is useful to forecast future firm volatility by comparing the MIV method with other methods in part (a) of table 6.

Even though the mean errors of the MIV method are always greater than those of the IV method in part (a) of table 6 in any horizon and in any error measurement, the MPFE and the MAFE the MIV method are always less than those of GARCH method. This result is consistent with the in-sample result. The MIV method outperforms the MA method in 30, 45, 60 day's LINEX. In addition, Table 9 gives the number of companies out of 50 firms, whose error for the MIV method is less than those of other methods. The smallest one is 9 and many are close to 25, one half of total. Combining Table 9 and Table 6 part (a), we found some cases in which the mean of the MIV method is greater, but close to 25 companies' MIV method performs better. For example, MIV's 45 day mean LINEX (0.2147) is greater than MA's 20 day mean LINEX (0.1992), but 24 firms' MIV perform better than their MA method. MIV's 30 day mean LINEX (0.2269) is greater than GARCH's 10 day mean LINEX (0.2113), but 23 firms' MIV perform better than their MA. In summary, at the least, the market implied volatility does not perform worse than historical methods like MA or GARCH (1,1).

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