Journal of CENTRUM Cathedra • Volume 5, Issue 1, 2012 • 91-101

JCC
Journal of
CENTRUM
Cathedra

CENTRUM
CENTRO DE NEGOCIOS

An Application of GARCH Models in Detecting Systematic Bias in Options Pricing and Determining Arbitrage in Options

Mihir Dash *
Alliance University, Bangalore, India

Jaykumar H. Dagha
The Walt Disney Company India Private Limited, Mumbai, India

Pooja Sharma
AMBA Research Private Limited, Bangalore, India

Rashmi Singhal
Thomson Reuters, Bangalore, India

Abstract

Derivatives have become widely accepted as tools for hedging and risk-management, as well as speculation to some extent. A more recent trend has been gaining ground, namely, arbitrage in derivatives.

The critical parameter in derivatives pricing is the volatility of the underlying asset. Exchanges often overestimate volatility in order to cover any sudden changes in market behavior, leading to systematic overpricing of derivatives. Accurate forecasting of volatility would expose systematic overpricing. Unfortunately, volatility is not an easy phenomenon to predict or forecast. One class of models that have proved successful in forecasting volatility in many situations is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family of models.

The objective of the present study is to analyze systematic bias in the pricing of options derivatives. In order to perform the analysis, data were collected for a sample of stock options traded on the National Stock Exchange (NSE) of India and their underlying stocks. In the study, GARCH models are used to forecast underlying stock volatility, and the forecasted volatility is used in the Black-Scholes model in order to determine whether the corresponding options were fairly priced. Any systematic bias in options pricing would provide evidence for arbitrage opportunities.

Keywords: Derivatives, hedging, speculation, arbitrage, volatility, overpricing, GARCH, Black-Scholes model

JEL Classification code: G13

The volatility of financial markets has been the object of numerous developments and applications over the past two decades, both theoretically and empirically. Financial economists are increasingly concerned with modeling volatility in asset returns. Volatility modeling is important because volatility is considered a measure of risk, and investors want a premium for investing in risky assets. Banks and other financial institutions apply value-at-risk models to assess the risks. Modeling and forecasting volatility, or the covariance structure of asset returns, is therefore important.

Unfortunately, volatility is not an easy phenomenon to predict or forecast. One class of models that have proved successful in forecasting volatility in many situations is the GARCH family of models, introduced by Engle (1982) and Bollerslev (1986). GARCH models are discrete time models that have been used to estimate a variety of financial time series such as stock returns, interest rates, and foreign exchange rates. The distinctive feature of GARCH models is their recognition that volatilities and correlations are not constant. During some periods, a particular volatility or correlation may be relatively low, whereas during other periods, it may be relatively high. The models attempt to keep track of the variations in the volatility or correlations through time. GARCH models build on advances in the understanding and modeling of volatility. The models take into account excess kurtosis, or fat-tail behavior, and volatility clustering, two important characteristics of financial time series. The models provide accurate forecasts of variances and covariances of asset returns through the ability to model time-varying conditional variances. GARCH models have been applied in diverse fields such as risk management, portfolio management and asset allocation, option pricing, and foreign exchange.

The GARCH (p, q) model is formulated as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{1}$$

where p is the order of the GARCH (lagged volatility) terms, and q is the order of the ARCH (lagged squared-error) terms. In particular, the GARCH (1, 1) model is given by:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2}$$

In the academic literature, the GARCH (1, 1) process is perceived as a realistic model for volatility. The forecast variance from the GARCH (1, 1) model can be interpreted as a weighted average of three different variance forecasts. The first is a constant variance that corresponds to the long-run average. The second is the forecast made in the previous period. The third is the new information not available when the previous forecast was made. This could be viewed as a variance forecast based on one period of information. The weights on the three forecasts determine how fast the variance changes with new information and reverts to its long-run mean.

Literature Review

The phenomenon of volatility clustering and its adverse implications on options pricing have been a source of concern in the options pricing literature. The Black-Scholes model (Black & Scholes, 1973; Merton, 1973) assumes constant volatility of the underlying process and leads to bias in options pricing, including underpricing for out-of-the-money options (Black, 1975; Gultekin, Rogalski, & Tinic, 1982), low-volatility securities (Black & Scholes, 1972; Gultekin et al., 1982; Whaley, 1982), and short-maturity options (Black, 1975; Whaley, 1982), as well as U-shaped implied volatility curves in relation to exercise price (Rubinstein, 1985; Sheikh, 1991). A sizeable literature exists that addresses the use of GARCH models in options pricing in order to overcome the limitations. The following is a partial overview of the literature.

Engle and Mustafa (1992) used the GARCH process to study options and their implied conditional volatilities. They estimated the stock price volatility using a GARCH model, and they estimated the GARCH model implied by the option market using a generalized simulation minimization method from option price data. Duan (1995) introduced the GARCH option-pricing model, linking econometric models with the options pricing literature. Heston and Nandi (2000) proposed a closed-form solution for European options pricing in a GARCH model. In Heston and Nandi's model, current volatility is easily estimable from historical asset prices observed at discrete intervals. The model also allowed for correlation between returns of the spot asset and variance and admitted multiple lags in the dynamics of the GARCH process.

Much of the subsequent GARCH option model literature carried the Duan (1995) and Heston and Nandi (2000) frameworks. Duan, Ritchken, and Sun (2007) extended the standard GARCH option-valuation model to include jumps. Christoffersen and Jacobs (2004) compared a range of GARCH models using option prices and returns under the risk-neutral as well as the physical probability measure. They found that, in contrast with returns-based objective functions, options-based objective functions favor models that incorporate volatility clustering and leverage effect. Stentoft (2005) proposed some new simulation techniques using simple least squares regressions, using the LSM method of Longstaff and Schwartz (2001), to price options that have the possibility of early exercise in a GARCH framework. Using an extensive Monte Carlo study, Stentoft (2005) explained some systematic pricing errors. Christoffersen, Heston, and Jacobs (2006) and Christoffersen, Jacobs, Ornthanalai, and Wang (2008) followed the Heston-Nandi procedure of inverting moment-generating functions.

More recently, Barone-Adesi, Engle, and Mancini (2008) proposed a method for pricing options based on GARCH models with filtered historical innovations. They used an incomplete market framework, allowing for different distributions of historical and pricing return dynamics, thus enhancing the model's flexibility to fit market option prices. The model was used to analyze S&P 500 index options; it outperformed other competing GARCH pricing models and ad hoc Black-Scholes models. Barone-Adesi, Engle, and Mancini suggested that, in accordance with their model, implied volatility smiles could be explained by asymmetric volatility and negative skewness of filtered historical innovations.

Thus, an extensive literature exists about the application of GARCH models to options pricing. Most of the literature has addressed theoretical issues, such as model development, estimation, and simulation. In the present study, the literature is extended by examining systematic bias in options pricing in emerging markets like India, where the possibility of thin trading exists.

Data and Methodology

The sample consisted of 41 stocks listed on NSE of India that have options actively traded on the NSE. The sample stocks were chosen from 14 sectors: aviation (Air Deccan and Jet Airways), auto and auto components (Amtek Auto, Hero Honda, and Maruti), banking and financial services (Allahabad Bank, Canara Bank, Corporation Bank, and Reliance Capital), capital goods (ABB, Aditya Birla Nuvo, and AIA Engineering), cement (ACC, Ambuja, and Shree Cement), chemicals (Chambal Fertilizers and Orchid Chemicals), FMCG (Colgate, Dabur, and Hindustan Unilever), IT (3i Infotech, CMC, Infosys Technologies, and Wipro), media (Adlabs, Zee Ltd., and Sun TV), oil and gas (Aban Lloyd, GAIL, and HPCL), pharmaceuticals (Cipla and Dr. Reddy's Ltd.), power (CESC, Reliance Energy, Suzlon, and Tata Power), textiles (Century Textiles, S Kumars, and Welspun Gujarat), and real estate (DLF and Unitech). The associated stock options traded on the NSE were all European-style options.

The data collected for the study consisted of the closing prices of the stocks in the period from January to December 2007 and the closing prices of the corresponding stock options in the period January to March 2008. The data were collected directly from the NSE website.

The objective of the present study is to analyze systematic bias in the pricing of options derivatives. In order to perform the analysis, a GARCH (1, 1) model was used to forecast underlying stock volatility based on historical closing stock price data for the period January to December 2007, and this forecasted volatility is used in the Black-Scholes model in order to determine whether the corresponding options are fairly priced.

The GARCH (1, 1) model is widely used in the financial econometrics literature to capture the characteristics of volatility (Bollerslev, 1986). The GARCH (1, 1) model is expressed as follows:

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t / \Omega_{t-1} \sim (0, h_t)$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (3)$$

where r_t represents daily return, and ε_t represents the residual; the residuals follow a normal distribution with a mean of 0 and variance h_t, conditional on the information set Ω_{t-1} available up to day *t-1*. The GARCH equation has three terms, ω, the long-run average volatility; ε_{t-1}^2, the squared residual from the mean equation (the ARCH term), which provides information about volatility clustering; and h_{t-1}, the last period's forecast variance (the GARCH term). To validate the GARCH (1, 1) model, the LM test was performed.

The Black-Scholes model is a model for pricing European call and put options, as follows:

$$C = S_0 N(d_1) - Xe^{-rt} N(d_2) \tag{4}$$

and

$$P = -S_0 N(-d_1) + Xe^{-rt} N(-d_2) \tag{5}$$

where S_0 is the initial stock price, X is the strike/exercise price, r is the risk-free rate, σ is the volatility, and τ is the time to expiration, with

$$d_1 = \left[\log_e (S_0 / X) + (r + \frac{1}{2}\sigma^2)\tau \right] \Big/ \sigma\sqrt{\tau} \tag{6}$$

and

$$d_2 = \left[\log_e (S_0 / X) + (r - \frac{1}{2}\sigma^2)\tau \right] \Big/ \sigma\sqrt{\tau} \tag{7}$$

For the analysis, the Black-Scholes model was used to price each stock option, with the initial price S_0 as the closing price of the stock on 31 December, 2007, and with the strike price X closest to this price, with an expiration period of three months (i.e., $\tau = 0.25$). For each stock, the volatility forecast using the GARCH (1, 1) model was used as the Black-Scholes parameter σ. The risk-free rate was taken as 4.5% p.a. The Black-Scholes model was used to compute implied volatilities, equating the call and put prices with the quoted call and put prices and solving for σ.

The analysis focused on two aspects: comparing projected volatility from the GARCH model with implied volatility from the Black-Scholes model, and comparing projected call and put prices as described above with quoted call and put prices. The differences were investigated against differences in capitalization and trading volume by categorizing the sample stocks in terms of capitalization as follows: low (less than Rs 25 billion), mid (between Rs 25 billion and Rs 100 billion), and high (greater than Rs 100 billion); and in terms of trading volume: low (less than 100 million traded units per year), moderate (between 100 million and 250 million units traded per year), and high (greater than 250 million units traded per year).

Analysis and Interpretation

The parameter estimates of the GARCH (1, 1) model for all the sample stocks are shown in Table 1. The GARCH (1, 1) model was found to be significant for all the sample stocks. In addition, considerable evidence exists of persistence of volatility, ranging between 75% and 99%, and of long-run volatility, ranging between 1.9% and 5.9%.

The results of the volatility and pricing analysis of the sample stock options are shown in Table 2 and Table 3, respectively. The implied volatility based on call prices is overestimated as compared to the projected volatility from the GARCH model for 73.2% of the sample stock options. Moreover, the implied volatility based on put prices is overestimated as compared to the projected volatility from the GARCH model for 87.8% of the sample stock options. In contrast, the call price is overvalued as compared to the projected call price based on the projected volatility from the GARCH model applied in the Black-Scholes model for 63.4% of the sample stock options. Finally, the put price is overvalued as compared to the projected put price based on the projected volatility from the GARCH model applied in the Black-Scholes model for 85.4% of the sample stock options.

The results of the paired-samples t-test for the implied volatilities (for both calls and puts) and the projected volatility (from the GARCH model) are shown in Table 4. The mean implied volatilities (for both calls and puts) are significantly lower than the mean projected volatility. In addition, the implied volatility based on call prices is significantly lower than the implied volatility based on put prices.

The results of the paired-samples *t*-test for the quoted option prices and the projected option prices (based on the Black-Scholes model using GARCH volatilities) are shown in Table 5. The mean call price is significantly higher than the mean projected call price, and the mean put price is significantly higher than the mean projected put price.

The results of the paired-samples *t*-test for the overpricing of call and put option prices (as compared to forecasts based on the Black-Scholes model using GARCH volatilities) are shown in Table 6. The mean overpricing of call options is significantly lower than the mean overpricing of put options.

The results of the analysis of overestimation of volatility against market capitalization and trading volume are shown in Tables 7, 9, and 10. There is generally a higher overestimation of volatility with higher market capitalization, and a higher overestimation of volatility for moderate trading volume. The differences between low, mid, and high capitalization and between low, moderate, and high trading volume are not statistically significant because of the small sample sizes.

The results of the analysis of overvaluation of option prices against market capitalization and trading volume are shown in Tables 8, 11, and 12. There is generally a higher overvaluation of option prices with higher market capitalization and higher overvaluation of options prices with higher trading volume. In addition, overvaluation of put prices is much higher than the overvaluation of call prices, with higher capitalization and higher trading volumes. Again, the differences between low, mid, and high capitalization and between low, moderate, and high trading volume are not statistically significant because of the small sample sizes.

Discussion

Volatility permeates modern financial theories and decision-making processes. The GARCH family of models provides accurate measures and good forecasts of future volatility, which is critical for evaluation of option pricing. The results of the study indicate that the implied volatilities for both calls and puts are predominantly overestimated, as compared to the projected volatility, based on the GARCH model; and call and put option prices are predominantly overvalued as compared to the projected call and put options prices based on the Black-Scholes model with GARCH volatilities. Further, put options are overpriced in relation to call options, as compared to the forecasts based on the GARCH and Black-Scholes models. Overestimation of volatility and overvaluation of options prices increases with higher market capitalization and moderate/higher trading volume for the underlying stocks. The systematic bias could also be associated with thin trading, a characteristic of trading in options and more particularly stock options, in emerging markets like India. The possible connections require further investigation.

The observed discrepancies in the market make it necessary for investors to forecast volatility. Options are priced based on volatility, but a difference exists between the theoretical pricing of options and their actual pricing. To take advantage of such mispricing in the market, arbitrage can be implemented. If the projected call price were higher than the quoted call price, buying a call option would yield arbitrage, whereas if the projected call price were lower than the quoted call price, selling a call option would yield arbitrage. Likewise, for put options, if the projected put price were higher than the quoted put price, selling a put option would yield arbitrage, whereas if the projected put price were lower than the quoted put price, buying a put option would yield arbitrage.

Unfortunately, the results of the study are indicative rather than conclusive. The major limitations of the study are the relatively small sample size and the limited research period considered for the study. The research period has a particular drawback because of the global crisis towards the tail end of the period studied. In order to generalize the results of the study, similar analyses would need to be conducted for different periods and take into account the macroeconomic factors that might affect the pricing of options.

Through the study, understanding of option prices and systematic mispricing by exchanges is provided. Further research could assess the arbitrage profits for each of the stock-option strategies. Further investigation might also consider the estimation of the prices for index and currency options using the GARCH model as applied in the present study.

Table 1
GARCH Parameter Estimates Test for Significance

Stock	α	β	α+β	ω	v_L	$\sqrt{v_L}$	LM test	*p*-value
Air Deccan	0.1540	0.7435	0.8974	0.0002	0.0017	4.08%	8.3011	0.0040
Jet Airways	0.1117	0.6256	0.7373	0.0002	0.0007	2.68%	4.0694	0.0437
Amtek Auto	0.0772	0.8761	0.9532	0.0000	0.0005	2.20%	5.0080	0.0252
Hero Honda	0.0351	0.9080	0.9431	0.0000	0.0004	1.90%	4.1045	0.0428
Maruti	0.1066	0.7685	0.8750	0.0001	0.0006	2.39%	3.9393	0.0472
Allahabad Bank	0.0052	0.9848	0.9900	0.0000	0.0009	3.04%	4.5035	0.0338
Canara Bank	0.0041	0.8011	0.8052	0.0002	0.0008	2.88%	4.0284	0.0447
Corporation Bank	0.0320	0.8834	0.9154	0.0001	0.0009	2.94%	4.0198	0.0450
Reliance Cap	0.1544	0.8045	0.9589	0.0001	0.0016	4.02%	3.8739	0.0490
ABB	0.0823	0.8399	0.9222	0.0000	0.0004	2.09%	3.8175	0.0507
Abirlanuvo	0.0102	0.8704	0.8806	0.0001	0.0007	2.61%	4.2740	0.0387
Aia Eng	0.0568	0.8104	0.8671	0.0001	0.0007	2.70%	4.0111	0.0452
ACC	0.2996	0.4573	0.7569	0.0002	0.0008	2.74%	4.0138	0.0451
Ambuja	0.2064	0.7429	0.9493	0.0000	0.0007	2.56%	11.2423	0.0008
Shree Cement	0.0127	0.8436	0.8563	0.0001	0.0007	2.62%	3.8846	0.0487
Chambal Fert	0.2495	0.7405	0.9900	0.0001	0.0054	7.33%	6.7833	0.0092
Orchid Chem	0.0529	0.8402	0.8931	0.0001	0.0009	2.96%	4.5528	0.0329
Colgate	0.0215	0.7550	0.7765	0.0001	0.0004	2.09%	4.9061	0.0268
Dabur	0.0166	0.8939	0.9106	0.0000	0.0005	2.14%	5.4446	0.0196
HUL	0.1003	0.8085	0.9088	0.0000	0.0004	2.02%	4.6554	0.0310
3i Infotech	0.0898	0.8661	0.9559	0.0000	0.0008	2.77%	4.2376	0.0395
CMC	0.5013	0.2487	0.7500	0.0003	0.0013	3.58%	38.1188	0.0000
Infosys	0.1120	0.8154	0.9274	0.0000	0.0004	2.05%	4.3189	0.0377
Wipro	0.1120	0.8708	0.9828	0.0000	0.0008	2.87%	6.9097	0.0086
Adlabs	0.1031	0.8636	0.9667	0.0000	0.0015	3.83%	6.9745	0.0083
SUN TV	0.1005	0.8895	0.9900	0.0000	0.0035	5.93%	4.1666	0.0412
ZEE	0.0518	0.7674	0.8191	0.0001	0.0008	2.75%	4.7608	0.0291
Aban	0.0552	0.9113	0.9665	0.0000	0.0008	2.74%	4.2260	0.0398
GAIL	0.0650	0.9127	0.9777	0.0000	0.0010	3.10%	4.4750	0.0344
HPCL	0.8816	0.1084	0.9900	0.0000	0.0011	3.32%	7.5916	0.0059
CIPLA	0.2666	0.5272	0.7939	0.0001	0.0006	2.43%	3.8541	0.0496
DRL	0.1087	0.6883	0.7970	0.0000	0.0002	1.56%	4.4185	0.0356
Matrix Labs	0.0307	0.7193	0.7500	0.0002	0.0007	2.64%	4.2514	0.0392
CESC	0.1118	0.7885	0.9004	0.0001	0.0008	2.86%	9.9668	0.0016
Reliance Energy	0.1388	0.7961	0.9350	0.0001	0.0010	3.17%	19.5933	0.0000
Suzlon	0.0017	0.7483	0.7500	0.0003	0.0011	3.36%	4.5128	0.0336
S Kumars	0.0242	0.8002	0.8244	0.0001	0.0008	2.82%	4.8514	0.0276
DLF	0.0535	0.7805	0.8339	0.0001	0.0008	2.83%	4.3670	0.0366
Unitech	0.0234	0.7972	0.8206	0.0003	0.0015	3.87%	4.0851	0.0433
Century	0.1081	0.7849	0.8930	0.0001	0.0010	3.14%	3.8878	0.0486
Welspun Guj	0.0891	0.9009	0.9900	0.0000	0.0018	4.23%	4.6248	0.0315

Table 2
Underestimation/Overestimation of Volatility of the Sample Stocks

Stock	Implied Volatility (C)	Implied Volatility (P)	Projected Volatility	% diff calls	% diff puts
Air Deccan	0.3283	0.4150	0.3851	-14.74	7.77
Jet Airways	0.3722	0.3594	0.3204	16.18	12.17
Amtek Auto	0.3029	0.4520	0.4210	-28.03	7.38
Hero Honda	0.3738	0.3306	0.1721	117.23	92.09
Maruti	0.2901	0.4695	0.2345	23.72	100.18
Allahabad Bank	0.4537	0.5863	0.3472	30.67	68.86
Canara Bank	0.5184	0.5834	0.4066	27.50	43.50
Corporation Bank	0.6797	0.7192	0.4883	39.19	47.27
Reliance Cap	0.5361	0.7554	0.3499	53.23	115.89
ABB	0.6711	0.4371	0.3597	86.58	21.52
Abirlanuvo	0.4577	0.6294	0.4361	4.97	44.3
Aia Eng	0.3980	0.5514	0.3756	5.97	46.81
ACC	0.5344	0.5091	0.2248	137.67	126.43
Ambuja	0.3410	0.3381	0.3150	8.23	7.31
Shree Cement	0.5511	0.5509	0.2246	145.33	145.25
Chambal Fert	0.3335	0.4486	0.3824	-12.79	17.33
Orchid Chem	0.5645	0.6488	0.2637	114.12	146.09
Colgate	0.3716	0.5361	0.1488	149.73	260.26
Dabur	0.3664	0.2909	3.0014	-87.79	-90.31
HUL	0.3400	0.4403	0.1149	196.03	283.31
3i Infotech	0.4092	0.3774	0.5909	-30.75	-36.14
CMC	0.3716	0.5361	0.4607	-19.34	16.36
Infosys	0.3810	0.3467	0.3823	-0.34	-9.30
Wipro	0.3353	0.3801	0.2940	14.03	29.29
Adlabs	0.4696	0.6194	0.3658	28.38	69.35
SUN TV	0.6477	0.7026	0.6745	-3.98	4.17
ZEE	0.4265	0.6280	0.3058	39.45	105.33
Aban	0.5571	0.5602	0.3843	44.97	45.78
GAIL	0.5861	0.5008	0.3522	66.41	42.19
HPCL	0.3335	0.3641	0.2012	65.80	80.98
CIPLA	0.3903	0.4311	0.3923	-0.51	9.91
DRL	0.3738	0.3306	0.1517	146.51	117.98
Matrix Labs	0.2767	0.4889	0.3892	-28.92	25.60
CESC	0.4514	0.6153	0.4323	4.41	42.32
Reliance Energy	0.5441	0.6180	0.1725	215.48	258.37
Suzlon	0.7025	0.7509	0.3545	98.16	111.81
S Kumars	0.5331	0.5811	0.7672	-30.51	-24.25
DLF	0.3597	0.4461	0.1027	250.19	334.27
Unitech	0.7584	0.6465	0.7718	-1.73	-16.24
Century	0.5915	0.6540	0.4534	30.46	44.26
Welspun Guj	0.6072	0.6102	0.4228	43.64	44.33

Table 3
Undervaluation/Overvaluation of the Price of the Sample Options

Stock	Quoted call price	Projected call price	% diff calls	Quoted put price	Projected put price	% diff puts
Air Deccan	10.5500	12.1027	-12.83	10.1000	9.2805	8.83
Jet Airways	52.3000	63.8106	-18.04	62.3000	39.6696	57.05
Amtek Auto	10.5000	13.9597	-24.78	11.9500	11.0395	8.25
Hero Honda	58.6500	65.2187	-10.07	35.4000	44.3458	-20.17
Maruti	62.8000	53.5622	17.25	68.1500	28.8330	136.36
Allahabad Bank	9.3500	7.4778	25.04	9.2500	5.0457	83.33
Canara Bank	25.0500	21.6982	15.45	26.1500	17.6468	48.19
Corporation Bank	49.7000	37.3626	33.02	41.9000	27.0282	55.02
Reliance Cap	138.4500	94.7738	46.08	166.6500	71.8123	132.06
ABB	158.9000	93.2039	70.49	78.9500	62.6185	26.08
Abirlanuvo	132.2500	124.4401	6.28	170.3500	116.3203	46.45
Aia Eng	120.2000	136.5927	-12.00	150.8000	124.9288	20.71
ACC	117.4500	52.1989	125.00	103.3000	43.3635	138.22
Ambuja	9.6000	1.5141	534.05	8.4000	3.9090	114.89
Shree Cement	145.8500	67.4554	116.22	121.6500	43.2997	180.95
Chambal Fert	20.8000	23.2817	-10.66	19.8000	16.4333	20.49
Orchid Chem	24.2000	12.1541	99.11	24.6500	9.2448	166.64
Colgate	31.1500	14.1940	119.46	38.5000	9.0215	326.76
Dabur	8.8500	55.9261	-84.18	4.4000	52.9459	-91.69
HUL	15.0500	5.5536	171.00	17.5000	3.9953	338.01
3i Infotech	12.1000	17.3915	-30.43	10.9500	17.1713	-36.23
CMC	31.1500	37.9377	-17.90	38.5000	32.7652	17.50
Infosys	155.8000	156.2677	-0.30	111.9500	124.8872	-10.36
Wipro	38.1000	34.2405	11.27	30.4500	22.3859	36.02
Adlabs	49.7000	40.1636	23.74	51.7500	28.4570	81.85
SUN TV	47.8500	49.5762	-3.48	40.7000	38.8917	4.65
ZEE	29.1000	21.7890	33.55	35.4000	15.9006	122.63
Aban	361.4500	263.5073	37.17	282.2000	182.4835	54.64
GAIL	38.8500	24.6854	57.38	27.6500	18.6470	48.28
HPCL	17.9000	11.8435	51.14	14.6500	7.1901	103.75
CIPLA	15.4000	15.4648	-0.42	11.7500	10.4976	11.93
DRL	30.5500	26.5671	14.99	19.7500	13.2443	49.12
Matrix Labs	15.5000	20.7781	-25.40	20.9000	16.2258	28.80
CESC	44.8500	43.0987	4.06	53.6500	36.8921	45.42
Reliance Energy	91.1500	34.6269	163.23	87.5500	19.7818	342.58
Suzlon	190.1500	104.5588	81.86	171.2000	73.7591	132.11
S Kumars	12.1500	17.1435	-29.13	11.9000	15.8654	-24.99
DLF	47.6500	17.7570	168.34	47.8500	7.8262	511.41
Unitech	36.8000	237.6931	-84.52	29.1500	235.2408	-87.61
Century	97.9500	76.9307	27.32	93.3000	62.7856	48.60
Welspun Guj	31.2000	21.8863	42.56	30.5500	21.0879	44.87

Table 4
Paired-Samples t-*Tests for Volatility*

	mean	std. dev.	correlation	*p*-value	*t*-test	*p*-value
Implied Volatility (call)	0.457	0.129	0.670	0.000	-10.578	0.000
Implied Volatility (put)	0.517	0.121				
Implied Volatility (call)	0.457	0.129	0.363	0.000	-2.549	0.011
Projected Volatility	0.821	2.592				
Implied Volatility (put)	0.517	0.121	0.150	0.007	-2.101	0.036
Projected Volatility	0.821	2.592				

Table 5
Paired-Samples t-*Tests for Prices*

	mean	std. dev.	correlation	*p*-value	*t*-test	*p*-value
Quoted call price	65.456	69.628	0.788	0.000	2.975	0.003
Projected call price	58.193	62.168				
Quoted put price	55.748	58.824	0.665	0.000	5.247	0.000
Projected put price	42.309	51.617				

Table 6
Paired-Samples t-*Tests for Prices of Call and Put Options*

	mean	std. dev.	correlation	*p*-value	*t*-test	*p*-value
Overpricing of calls	7.262	43.527	0.939	0.000	-7.004	0.000
Overpricing of puts	13.438	45.670				

Table 7
Overestimation of Volatility against Capitalization and Volume

		Capitalization			Volume			
		Low	Mid	High	Low	Moderate	High	Overall
% age diff vol. (C)	mean	19.0	49.3	71.4	38.2	64.8	38.7	47.4
	std. dev.	58.1	67.8	89.0	62.2	70.5	89.9	73.9
% age diff vol. (P)	mean	35.6	76.8	87.9	58.0	81.1	65.7	68.3
	std. dev.	57.3	86.3	109.4	69.2	74.0	120.2	88.1

Table 8
Overpricing of Call and Put Options against Capitalization and Volume

		Capitalization			Volume			
		Low	Mid	High	Low	Moderate	High	Overall
% age diff price (C)	mean	12.2	37.9	75.3	19.6	44.7	63.9	42.2
	std. dev.	49.9	55.8	157.2	49.6	55.9	160.8	99.5
% age diff price (P)	mean	46.1	92.1	248.4	60.9	93.2	238.3	128.2
	std. dev.	66.8	109.9	564.6	89.4	93.4	569.3	329.6

Table 9
Overestimation/Underestimation of Volatility against Capitalization

Capitalization		% diff vol. (C)		% age diff vol. (P)	
		Underestimated	Overestimated	Underestimated	Overestimated
Low	mean	-22.7	60.7	-30.2	48.8
	std. dev.	8.1	56.4	8.4	53.3
Mid	mean	-45.9	62.9	-90.3	88.0
	std. dev.	59.3	58.7	–	76.5
High	mean	-10.4	96.0	-12.8	106.2
	std. dev.	16.1	87.1	4.9	109.4
Overall	mean	-23.6	73.5	-35.3	82.7
	std. dev.	24.2	68.6	32.4	83.7

Table 10
Overestimation/Underestimation of Volatility against Volume

Volume		% diff vol. (C)		% age diff vol. (P)	
		Underestimated	Overestimated	Underestimated	Overestimated
Low	mean	-20.1	61.5	–	58.0
	std. dev.	11.6	58.6	–	69.2
Moderate	mean	-30.6	80.7	-30.2	99.6
	std. dev.	0.2	62.8	8.4	61.9
High	mean	-23.5	77.6	-38.6	97.0
	std. dev.	36.5	92.7	44.9	118.8
Overall	mean	-23.6	73.5	-35.3	82.7
	std. dev.	24.2	68.6	32.4	83.7

Table 11
Overpricing/Underpricing of Call and Put Options against Capitalization

Capitalization		% age diff price (C)		% age diff price (P)	
		Undervalued	Overvalued	Undervalued	Overvalued
Low	mean	-20.5	57.9	-30.6	61.5
	std. dev.	7.7	47.6	8.0	62.3
Mid	mean	-33.2	54.3	-91.7	104.3
	std. dev.	44.3	44.8	–	101.9
High	mean	-24.1	137.4	-39.4	334.7
	std. dev.	35.3	173.7	42.1	623.5
Overall	mean	-24.3	80.6	-45.2	157.9
	std. dev.	26.2	106.2	35.5	348.4

Table 12
Overpricing/Underpricing of Call and Put Options against Volume

Volume		% diff price (C)		% diff price (P)	
		Undervalued	Overvalued	Undervalued	Overvalued
Low	mean	-16.0	55.2	-20.2	67.1
	std. dev.	8.0	48.2	–	89.8
Moderate	mean	-29.8	57.1	-30.6	113.9
	std. dev.	0.9	50.1	8.0	83.9
High	mean	-32.2	146.1	-63.2	328.8
	std. dev.	40.8	182.2	45.8	626.3
Overall	mean	-24.3	80.6	-45.2	157.9
	std. dev.	26.2	106.2	35.5	348.4

References

Barone-Adesi, G., Engle, R. F., & Mancini, L. (2008). A GARCH option pricing model with filtered historical simulation. *Review of Financial Studies*, *21*(3), 1223-1258.

Black, F. (1975). Fact and fantasy in the use of options. *Financial Analysts Journal*, *31*(4), 36-41, 61-72.

Black, F., & Scholes, M. (1972). The valuation of option contracts and a test of market efficiency. *Journal of Finance, 27*(2), 399-417.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637-654.

Bollerslev T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics*, *31*(3), 307-327.

Christoffersen, P., Heston, S. L., & Jacobs, K. (2006). Option valuation with conditional skewness. *Journal of Econometrics*, *131*, 253-284.

Christoffersen, P., & Jacobs, K. (2004). Which GARCH model for option valuation. *Management Science*, *50*(9), 1204-1221.

Christoffersen, P., Jacobs, K., Ornthanalai, C., & Wang, Y. (2008). Option valuation with long-run and short-run volatility components. *Journal of Financial Economics*, *90*(3), 272-297.

Duan, J.-C. (1995). The GARCH option pricing model. *Mathematical Finance*, *5*(1), 13-32.

Duan, J.-C., Ritchken, P., & Sun, Z. (2007). *Jump starting GARCH: pricing and hedging options with jumps in returns and volatilities* (Unpublished Working Paper). Toronto, Canada: University of Toronto.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987-1007.

Engle, R. F., & Mustafa, C. (1992). Implied ARCH models from options prices. *Journal of Econometrics*, *52*(1-2), 289-311.

Gultekin, N. B., Rogalski, R. J., & Tinic, S. M. (1982). Option pricing model estimates: some empirical results. *Financial Management*, *11*(1), 58-69.

Heston, S. L., & Nandi, S. (2000). A closed-form GARCH option valuation model. *The Review of Financial Studies*, *13*, 585-625.

Longstaff, F. A., & Schwartz, E. S. (2001). Valuing American options by simulation: a simple least-squares approach. *The Review of Financial Studies, 14*(1), 113-147.

Merton, R. C. (1973). Theory of rational option pricing. *Bell Journal of Economics and Management Science*, *4*(1), 141-183.

Rubinstein, M. (1985). Nonparametric tests of alternative option pricing models using all reported trades and quotes on the 30 most active CBOE option classes from August 23, 1976 through August 31, 1978. *Journal of Finance, 40*(2), 455-480.

Sheikh, A. (1991). Transactions data tests of S&P 100 call option pricing. *Journal of Financial and Quantitative Analysis*, *26*(4), 459-475.

Stentoft, L. (2005). Pricing American options when the underlying asset follows GARCH processes. *Journal of Empirical Finance*, *12*(4), 576-611.

Whaley, R. E. (1982). Valuation of American call options on dividend-paying stocks: empirical tests. *Journal of Financial Economics*, *10*, 29-58.

Authors Note

Mihir Dash, School of Business, Alliance University, Chikkahagade Cross, Chandapura-Anekal Road, Anekal, Bangalore-562106, India.

Jaykumar H. Dagha, The Walt Disney Company India Private Limited, 4th Floor, Peninsula Tower 1, Ganpatrao Kadam Marg, Lower Parel, Mumbai-400013, India.

Pooja Sharma, AMBA Research Private Limited, 12th Floor, Concorde Block, UB City, Vittal Mallya Road, Bangalore-560001, India.

Rashmi Singhal, Thomson Reuters, Pinnacle, No. 15 Bahai´s Bhavan Road, Opp. Ashok Nagar Police Station, Bangalore-560025, India.

Correspondence concerning this article should be addressed to Mihir Dash, Email: mihirda@rediffmail.com