Stock Market Momentum, Business Conditions, and GARCH Option Pricing Models

Min-Hsien Chiang
Institute of International Business
National Cheng Kung University
Tainan, TAIWAN

Hsin-Yi Huang
Institute of International Business
National Cheng Kung University
Tainan, TAIWAN

Correspondence:

Min-Hsien Chiang
Institute of International Business
National Cheng Kung University
1 University Rd.
Tainan, TAIWAN
Email: **mchiang@mail.ncku.edu.tw**

Stock Market Momentum, Business Conditions, and GARCH Option Pricing Models

Abstract

This study investigates forecast performance of GARCH option pricing models under the market momentum perspective. Additionally, the possible impacts of financial crises and business conditions on forecast performance of GARCH option pricing models are examined as well. The empirical results demonstrate that market momentum has impacts on forecast performance of GARCH option pricing models. In particular, the EGARCH model performs better in downward market momentum while the standard GARCH performs better in upward market momentum. Further, parsimonious models generally perform much better than richly parameterized models. The findings above are robust to financial crises. Finally, the business conditions are shown to have influences on forecast performance of GARCH option pricing models.

JEL: C52; C53; G13

Keywords: GARCH, Option, Market Momentum, Business Condition, Financial Crisis

1. Introduction

The dynamics of volatility play a very important role in option pricing models. Overwhelming empirical evidence shows that volatility is time varying, which leads to evaluation biases in the Black-Scholes formula with a constant volatility for option pricing. Several option pricing models incorporating non-constant volatility within discrete time and continuous time frameworks have been put forth. Under the discrete time framework, the family of GARCH has been extensively applied to return series in order to capture volatility characteristics, such as persistence, leptokurtosis and asymmetry, while the bivariate diffusion models for volatility were proposed under the continuous time framework. In practice, GARCH models can be easily constructed using historical data of underlying assets of traded options while diffusion models are hard to be implemented using discrete time observations. Additionally, the volatility models between discrete time and continuous time frameworks are not quite distinct from each other. [1] Consequently, option pricing models considering time-varying volatility in the discrete time framework are frequently constructed using the GARCH-family models.

From the option pricing perspective, the GARCH option pricing models contain a risk premium and are not preference-free valuation formula (e.g., Amin and Ng (1993), and Duan (1995)). Extending the risk-neutralization in Rubinstein (1976) and Brennan (1979), Duan (1995) derived a locally risk-neutral valuation relationship for option pricing with the GARCH process in which the expected return of underlying assets equals the risk-free rate and the conditional volatility remains the same as in the preference setting. Empirical evidence regarding performance of GARCH pricing models showed that GARCH option pricing models have smaller valuation errors than the Black-Scholes model (e.g, Amin and Ng (1993), Heston and Nandi (2000), Duan and Zhang (2001), and Bauwens and Lubrano (2002)). Notably, Christoffersen and Jacobs (2004) examined GARCH option pricing models with different GARCH processes and concluded that the GARCH model simply containing the leverage effect perform not worse than more sophisticated GARCH models under

---

[1] For example, Nelson (1991) demonstrated that volatility processes generated from some classes of GARCH models after appropriate reparameterization converged in distribution to bivariate diffusion processes. Duan (1997) analyzed the augmented GARCH processes in which multiplicative and additive shocks are taken into consideration and concluded that most of extant bivariate diffusion models can be represented as the limits of GARCH-family models. Duan, Ritchken, and Sun (2006) derived bivariate jump-diffusion limits of GARCH-Jump models.

out-of-sample forecasts even in-sample fitness weakly favors richly parameterized models. They also found out that densities implied by richly parameterized GARCH processes are not superior to that implied in the leveraged GARCH process, which leads them to suggest that the model adequacy for a GARCH option pricing model with a leverage effect deserves further investigation. Therefore, it is crucial to search for other perspectives to evaluate the performance of GARCH option pricing models.

This paper aims to supplement the GARCH option pricing literature by empirically examining forecast performance of numerous GARCH option pricing models under the market momentum perspective. Past studies on GARCH option pricing models seldom consider the market momentum as the important factor affecting evaluation performance. However, it has long been recognized that there exist asymmetric responses in capital markets for upward and downward market trends. In general, negative returns generate higher volatility than positive returns (French, Schwert and Stambaugh (1987), Schwert (1989a, 1989b), and Engle and Ng (1993)). Meanwhile, Koutmos (1998) found that information efficiency is much better during the downward market than the upward market. Generally, volatility predicted by GARCH-family models can be related to investors' psychological behavior. McQueen and Vorkink (2004) proposed that investors become more sensitive to news when negative shocks arrive and subsequently increase their risk aversion which leads to higher expected volatility. The impacts of negative shocks stay longer since increased sensitivity to news decays slowly. Consequently, volatility clustering and the asymmetric effect (leverage effect) predicted by the GARCH-family models result due to increases in sensitivity to bad news. Notably, Amin, Coval and Seyhun (2004) studied the relationship between option prices and past stock market movements and concluded that past stock market movements significantly raise the probability of violations of option price boundary conditions and implied volatility estimates increase when the stock market experiences downward movements. Consequently, it is worth studying the forecast performance of GARCH option pricing models under market momentum.

Additionally, the evaluation of forecast performance of GARCH option pricing models is examined for financial turmoil events in this paper. It is noticed that the unusual financial event often causes stock price volatility to increase considerably. Schwert (1990) found that the monthly stock price volatility rose dramatically following October 1987 crash in U.S. stock markets. Bates (1991) found that increasing option prices for out-of-the-money options drove implied volatility to increase before October 1987 crash. In addition, Bates (2000) investigated the evaluation performance of option pricing models with stochastic volatility and jump-diffusion processes for October 1987 crash in US. He found that the option pricing model with a jump-diffusion process matched observed option prices better than the option pricing model with a stochastic volatility process only. Studying Korean KOSPI 200 index option prices during 1997 Asian financial crisis, Bhabra, Gonzalez, Kim and Powell (2001) found that implied volatility of out-of-the-money options increased following the financial crisis. Duan and Zhang (2001) examined evaluation performance of NGARCH (nonlinear GARCH) option pricing model using Hang Seng Index Option traded in Hong Kong around the 1997 Asian financial crisis. They concluded that the NGARCH option pricing model outperforms the Black-Scholes option pricing model even after allowing a smile/smirk adjustment. Hence, it provides an opportunity of verifying consistent forecast performance of GARCH option pricing models by inspecting GARCH option pricing models in a turbulent financial environment. The relationship between forecast performance of GARCH option pricing models and macroeconomic factors is examined as well.

Numerous financial studies have indicated that momentum trading strategies are able to generate profits. Jegadeesh and Titman (1993) first documented the profitability of momentum trading strategies. Jegadeesh and Titman (2001) reported that momentum trading profits continue to exist by examining nine more year data than Jegadeesh and Titman (1993). They also found long-term reversals in cumulative returns of momentum portfolios and suggested that investors' delayed overreaction biases (Daniel, Hirshleifer and Subrahmanyam (1998), Barberis, Shleifer and Vishny (1998) and Hong and Stein (1999)) may explain the momentum trading profits instead of cross sectional dispersion in mean returns by Conrad and Kaul (1998). However, the momentum profits may not be an irrational anomaly. Johnson (2002) proposed a model which shows that past returns acting as an instrument for expected future major changes in business conditions could account for underreaction biases in momentum trading strategies. Chordia and Shivakumar (2002) showed empirical evidence of systematic relationship between momentum trading profits and business cycle variables. Although Cooper, Gutierrez Jr. and Hameed (2004) showed that it is market state instead of business cycle variables influencing momentum profits, Avramov and

Chordia (2006) further provided empirical evidence showing that momentum profits are related to asset pricing misspecification which strongly correlates with the business cycle. Consequently, business conditions may affect forecast performance of GARCH option pricing models due to momentum trading strategies.

Empirical results show that market momentum has impacts on the forecast performance of GARCH option pricing models. When the market momentum goes downwards, the EGARCH model performs much better than the rest of models. The GARCH model outperforms other models when market momentum goes upwards. Therefore, the volatility model considering asymmetric effects is essential in option pricing model especially when the market goes downwards but becomes less important when the market goes upwards. Volatility models considering jumps do not consistently outperform other models without jumps. Therefore, results show that forecast performance of parsimoniously parameterized option pricing models performs much better than the richly parameterized GARCH option pricing model. This is consistent with findings in Christoffersen and Jacobs (2004). These findings are still robust when alternative bull/bear classification is adopted.

A further investigation regarding forecast performance of GARCH option pricing models in financial crises shows that the forecast performance of GARCH option pricing models are inferior during the crash period to pre-crash and post crash periods. Additionally, the relationship between market momentum and forecast performance of GARCH option pricing models still shows that the EGARCH model performs better in the downward momentum and the GARCH model performs better in the upward momentum. Therefore, the relationship between market momentum and forecast performance of GARCH option pricing models is robust to financial crashes.

In addition to impacts of market momentum and calibration factors within the Black-Sholes option pricing model, business conditions are shown to have effects on forecast errors of GARCH option pricing models as well. The GARCH, EGARCH, NGARCH, and TGARCH models perform better in recession while GJR-GARCH, NGARCH-Jump and TGARCH-Jump models perform better in expansion.

The remainder of this paper is organized as follows. Section 2 presents GARCH options pricing models, estimation, and performance evaluation methods. The bull and bear market classification method by Lunde and Timmermann (2004) is introduced as well. Section 3 then describes the study data and associated data characteristics. Subsequently, Section 4 outlines and discusses the empirical results of this study. Finally, Section 5 presents the conclusions.

2. The Option Pricing Models with GARCH Processes

2.1 The GARCH Models

In general, there is no consensus about forecast performances of GARCH-family models. Studies by Engle and Ng (1993), Brailsford and Faff (1996), and Taylor (2004) favored GJR-GARCH to capture the asymmetric effect while studies by Heynen and Kat (1994), Awartani and Corradi (2005), and Stentoft (2005) support the asymmetric effect captured by the EGARCH. Christoffersen and Jacobs (2004) suggested that the option-based objective function is more likely to favor those models allowing for volatility clustering and the leverage effect. Consequently, the conditional variance models considered in this paper are those parsimonious GARCH models considering asymmetric and the leverage effect, namely EGARCH (Nelson (1991)), GJR-GARCH (Glosten, Jagannathan and Runkle (1993)), NGARCH (Engle and Ng (1993)), and TGARCH (Zakoian (1994)). The standard GARCH model is also considered here for the comparison purpose. Those models are listed as follows:

GARCH $$h_t = \alpha_0 + \alpha_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 , \tag{1}$$

EGARCH $$\ln h_t = \alpha_0\left(1-\alpha_1\right) + \alpha_1 \ln h_{t-1} + \beta_1 v_{t-1} + \beta_2\left[\left|v_{t-1}\right| - \sqrt{2/\pi}\right], \tag{2}$$

GJR-GARCH $$h_t = \alpha_0 + \alpha_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 I_{[\varepsilon_{t-1}<0]}, \tag{3}$$

NGARCH $$h_t = \alpha_0 + \alpha_1 h_{t-1} + \beta_1 h_{t-1}\left(v_{t-1} - \theta\right)^2 , \tag{4}$$

TGARCH $$\phi_t = \alpha_0 + \alpha_1 \phi_{t-1} + \beta_1\left|\varepsilon_{t-1}\right| + \beta_2 \max(-\varepsilon_{t-1}, 0) , \quad h_t = \phi_t^2 , \tag{5}$$

where h_t is the conditional variance at time t, α_1 is the GARCH coefficient, β_1 is the ARCH coefficient, and β_2 and θ represent asymmetric and leverage coefficients, respectively. Moreover, $\varepsilon_t = v_t\sqrt{h_t}$, where $v_t \overset{d}{\sim} N(0,1)$. $I_{[\varepsilon_{t-1}<0]}$ is an indicator variable with the value of one when $\varepsilon_{t-1} < 0$ and the value of zero, otherwise.

Fundamentally, compared with the ARCH model, the GARCH model is a more parsimonious model which can accommodate features of the fat tail and volatility clustering commonly found in stock market returns. The EGARCH model proposed by Nelson (1991) exempts from the parameter positive constraint in the GARCH model by modeling logarithm of conditional volatility and can capture the leverage effect in stock market returns. That is, the EGARCH model allows negative return shocks to generate an exponential increase on volatility than positive return shocks. In the vein of modeling the leverage effect, the GJR-GARCH and NGARCH models take the leverage effect in a quadratic form on innovations. That is, the leverage effect magnitude in the GJR-GARCH model depends on the sign of the past innovation while the NGARCH uses a shift parameter to quantify the leverage effect magnitude. Finally, the TGARCH model, similar to the GJR-GARCH model, specifies the conditional volatility process instead of the conditional variance process in the GJR-GARCH model.

Broadie, Chernov and Johannes (2007) studied risk premia associated with jumps in price and volatility of S&P futures options using diffusion models and found that jump risk premia in price and volatility can explain a considerable proportion of option pricing anomalies. Consequently, it is important to study the GARCH option pricing with jumps model in order to capture risk premia associated with jumps in price and volatility. Duan *et al.* (2006) have provided limiting jump-diffusion processes in both price and volatility for the NGARCH-Jump and TGARCH-Jump models. Therefore, the NGARCH-Jump and TGARCH-Jump models proposed by Duan *et al.* (2006) are studied in this paper as well. The dynamics of the NGARCH-Jump and TGARCH-Jump models are expressed as follows:

NGARCH-Jump

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \delta_1 h_{t-1}\left(\frac{\bar{J}_{t-1} - E^P(\bar{J}_{t-1})}{\sqrt{Var^P(\bar{J}_{t-1})}} - \theta\right)^2, \tag{6}$$

TGARCH-Jump

$$\phi_t = \alpha_0 + \alpha_1\phi_{t-1} + \delta_1\phi_{t-1}\left|\frac{\bar{J}_{t-1} - E^P(\bar{J}_t)}{\sqrt{Var^P\left(\bar{J}_t\right)}}\right| + \delta_2\phi_{t-1}\max\left(-\frac{\bar{J}_{t-1} - E^P(\bar{J}_{t-1})}{\sqrt{Var^P(\bar{J}_{t-1})}}, 0\right), \tag{7}$$

and $h_t = \phi_t^2$,

where $\bar{J}_t$ is a standard normal random number plus a Poisson random sum of normal random variables. In particular, $\bar{J}_t = \bar{X}_t^{(0)} + \sum_{j=1}^{N_t}\bar{X}_t^{(j)}$, where $\bar{X}_t^{(0)} \overset{d}{\sim} N\left(0,1\right)$, $\bar{X}_t^{(j)} \overset{d}{\sim} N\left(\bar{\mu}, \bar{\gamma}^2\right)$, and N_t is a Poisson random number with parameter λ at time t.

δ_1 is the jump coefficient, θ is the leverage coefficient, and δ_2 is the threshold coefficient. $E^P(\bar{J}_t) = \lambda\bar{\mu}$ and $Var^P(\bar{J}_t) = 1 + \lambda(\bar{\mu}^2 + \bar{\gamma}^2)$ are the mean and variance, respectively, under physical probability measure *P*. The NGRCH-Jump model nests NGARCH model while the TGARCH-Jump model nests TGARCH.

Under the local risk-neutral valuation relationship (LRNVR) by Duan (1995), the logarithm of stock returns in the mean equation for non-jump models, such as GARCH, EGARCH, GJR-GARCH, NGARCH, and TGARCH, under physical probability measure P is formulated as follows:

$$\ln\frac{S_t}{S_{t-1}} = rf_t - \frac{1}{2}h_t + \psi\sqrt{h_t} + v_t\sqrt{h_t}\ , \tag{8}$$

where S_t is the asset price at time *t*, rf is the risk-free rate, and ψ is the risk premium factor. The asset pricing with jump processes in this paper follows the method by Duan *et al.* (2006). In particular, they assumed a pricing kernel, $m_t/m_{t-1} = \exp(a + bJ_t)$ and an asset price process, $S_t/S_{t-1} = \exp\left(\alpha + \sqrt{h_t}\bar{J}_t\right)$, where *a* and *b* represent parameters related to mean and jump components in pricing kernel, α represents the mean parameter in the asset price, and J_t and $\bar{J}_t$ are the jump processes with a standard normal variable plus a Poisson random sum of normally distributed variables. Therefore, the mean equation for GARCH-Jump models under physical probability measure can be expressed as follows:

$$\ln\frac{S_t}{S_{t-1}} = rf_t - \frac{1}{2}h_t + \left(\psi\sqrt{h_t} + \lambda\kappa(1 - W_t)\right) + \sqrt{h_t}\bar{J}_t\ , \tag{9}$$

where S_t is the asset price at time *t*, rf is the risk-free rate, λ is the Poisson parameter, and the risk premium factors of ψ, κ, and W_t. The asset price process in equation (9) includes factors of the return drift, jump intensity, and jump risk premium.

In this paper, the maximum likelihood estimation is employed to estimate the coefficients of mean and variance equations under the physical probability measure. The residuals are assumed following normality assumptions. Hence, the log likelihood functions (LLF) of GARCH, EARCH, GJR-GARCH, NGARCH, and TGARCH models are formulated as follows:

$$LLF(\boldsymbol{\omega}; \varepsilon_1, \ldots, \varepsilon_T) = \text{-}0.5\sum_{t=2}^{T}\left[\ln(2\pi h_t) + \varepsilon_t^2/h_t\right], \tag{10}$$

where $\boldsymbol{\varpi}$ is the estimated coefficients vector of mean and conditional variance equations using the maximum likelihood function. The ε_t and h_t in equation (10) are derived from mean equation (8) and variance equations from (1) to (5) respectively. The maximum likelihood functions of NGARCH-Jump and TGARCH-Jump models are given as follows:

$$LLF\left(\boldsymbol{\varpi};\varepsilon_1,\ldots,\varepsilon_T\right) = \text{-}0.5\sum_{t=2}^{T}\left[\ln\left(\sum_{i=0}^{\infty}\frac{\lambda^i}{i!}e^{-\lambda}f_i\left(u_i,h_i\right)\right)\right], \tag{11}$$

where $f_i\left(\cdot\right)$ is a normal distribution with a mean of u_i and a variance of h_i which are derived from mean equation (9) and the variance equations from (6) to (7).

Lamoureux and Lastrapes (1993) suggested that parameter estimates in GARCH-family models using the updating estimation approach perform better than those obtained using the rolling estimation approach. Therefore, we estimate parameters from physical probability measure using historical return series and update the coefficients annually by adding additional annual data to the estimation data as the estimation year dues.[2]

2.2 The Asset Pricing and Option Pricing Methods

Following the option pricing estimation approach adopted in Duan (1995) and Duan *et al.* (2006), we estimated coefficients of mean and variance equations using index return series under the physical probability measure to forecast volatilities under the risk-neutral probability measure. The change of the physical probability measure to the risk-neutral probability measure is performed by trimming down the risk premium and parameters of the jump process in GARCH-Jump models in innovations. These modifications make one period ahead conditional variance the same under both probability measures and keep the expected future return equal to the risk-free interest rate. The stock prices are obtained using Monte Carlo simulation with 20,000 sample paths and antithetic variates are employed to compute option prices. The process of asset prices with no jumps under the risk-neutral probability measure Q is presented as follows:

[2] We also used the rolling estimation approach method to estimate parameters in GARCH models and found that the estimation results are similar to those using the updating estimation approach.

$$S_{m,t} = S_{m,t-1} \exp\left[\left(rf_t - \frac{1}{2}h_t\right) + \xi_{m,t}\sqrt{h_t}\right] \ , \ m = 1,\ldots,20{,}000, \text{ and } \ t = 1,\ldots,T \ , \tag{12}$$

where m is sample path, $\zeta_{m,t} \sim N(0,1)$ and v_t in equations from (1) to (5), and in equation (8) is replaced with $\zeta_{m,t} - \psi$ to deriving the forecast variance at time t. The asset price process with jumps can be expressed as follows:

$$S_{m,t} = S_{m,t-1} \exp\left[rf_t - \frac{1}{2}h_t + \lambda\kappa(1 - W_t) + \sqrt{h_t}\tilde{J}_t\right], m = 1,\ldots,20{,}000, \text{ and } \ t = 1,\ldots T \ , \tag{13}$$

where $\tilde{J}_t$ is the jump process under the risk-neutral probability measure Q. $\bar{J}_t$ in equations (6) and (7) are replaced with $\tilde{J}_t - \psi$ to deriving the forecast variance at time *t*. Therefore, the model price of a call option at time t with maturity at time T, $C^{GH}(t,T)$, is obtained using the expected value of the discounted payoff under the risk-neutral probability measure *Q* and given as follows:

$$C^{GH}(t,T) = \exp\left(-rf(T-t)\right)E^{Q}\left[\max\left(S_{m,T} - K, 0\right)\right], \tag{14}$$

where K is the exercise price. The performance measure employed in this paper is the mean absolute dollar forecast error (MAE) which is calculated by averaging the absolute difference between observed option market prices and model prices of options and is defined as follows:[3]

$$MAE = \frac{1}{N}\sum_{i}^{N}\left|C_i - C_i^{GH}\right| \tag{15}$$

where N is the number of contracts, C_i is the market price of a call option i and C_i^{GH} is the associated model price.

2.3 Bull and Bear Markets by Lunde and Timmermann (2004)

In order to examine whether the findings are robust to classification of market trends using market momentum, we adopt an alternative approach proposed by Lunde and Timmermann (2004) to classify bull and bear markets.[4] Lunde and

[3] The root mean squared errors are also performed and the same conclusions are reached.

[4] The approach proposed by Pagan and Sossounov (2003) was performed to identify the bull and bear market states as well. The identification results are similar to those using Lunde and Timmerman's (2004) approach.

Timmermann's (2004) approach is able to identify the bull and bear markets as systematic up and down movements rather than merely looking at short-term price movements. Assume that BB_t is a bull market indicator with the value of one if the stock market is in a bull state and of zero if the stock market in a bear state. The current price at time t is P_t, λ_1 is the price movement threshold triggering a switch from a bear market to a bull market, and λ_2 is the price movement threshold triggering a switch from a bull market to a bear market. Furthermore, suppose that the stock market at current is at a local maximum, where $BB_t = 1$, and set the current maximum price $P_t^{\max} = P_t$. The durations for a market price to exceed a local maximum price and for a market price passing through the lower barrier price are denoted as $\tau_{\max}$ and $\tau_{\min}$, respectively, which are defined as follows:

$$\tau_{\max}\left(P_t^{\max}, t \mid BB_t = 1\right) = \inf\left\{t + \tau : P_{t+\tau} \geq P_t^{\max}\right\}. \tag{16}$$

$$\tau_{\min}\left(P_t^{\max}, t, \lambda_2 \mid BB_t = 1\right) = \inf\left\{t + \tau : P_{t+\tau} < \left(1 - \lambda_2\right)P_t^{\max}\right\}. \tag{17}$$

If $\tau_{\max} < \tau_{\min}$, then current bull market states remains unchanged and local maximum price is reset to be $P_{t+\tau_{\max}}^{\max} = P_{t+\tau_{\max}}$. On the other hand, if $\tau_{\min} < \tau_{\max}$, the trend of the bull market ends and the stock price falls and crosses through the threshold barrier, $\left(1 - \lambda_2\right)P_t^{\max}$ at time $t + \tau_{\min}$. Hence, the market state turns into a bear market in which a local minimum price is reached as $P_{t+\tau_{\min}}^{\min} = P_{t+\tau_{\min}}$.

When the market currently is at the bear state with $BB_t = 0$, the duration variables of $\tau_{\max}$ and $\tau_{\min}$ are redefined as follows:

$$\tau_{\min}\left(P_t^{\min}, t \mid BB_t = 0\right) = \inf\left\{ t + \tau : P_{t+\tau} \leq P_t^{\min}\right\}. \tag{18}$$

$$\tau_{\max}\left(P_t^{\min}, t, \lambda_1 \mid BB_t = 0\right) = \inf\left\{ t + \tau : P_{t+\tau} > \left(1 + \lambda_1\right)P_t^{\min}\right\}. \tag{19}$$

Similarly, if $\tau_{\min} < \tau_{\max}$, the trend of the bear market continues and the local minimum price is reset to be $P_{t+\tau_{\min}}^{\min} = P_{t+\tau_{\min}}$. If $\tau_{\max} < \tau_{\min}$, the market state switches to a bull market at time $t + \tau_{\max}$ and the local maximum price is set to be $P_{t+\tau_{\max}}^{\max} = P_{t+\tau_{\max}}$. This identification process continues until all data points are used up.

Figures 1 shows the identification of bull and bear markets for the daily S&P 500 index data of 1996 to 2005 using the threshold values of λ_1 and λ_2 equal to 20 and 15, respectively.[5] It is obvious that the identified states using Lunde and Timmerman's approach match the observed pattern of S&P 500 index data very well. In general, the stock market experienced an upward trend pre-2000 and post-2002 while it went through a two year downward trend during the periods of March 2000 to July 2002 even though a short market reversal was found after an U.S. 911 shock in 2001.

3. Sample Description

The daily bid and ask prices of S&P 500 call options[6] of all moneyness and with maturities between 10 and 180 days are retrieved through the database provided by the Chicago Board Options Exchange (CBOE). Options with maturity less than 10 days are discarded for the possible liquidity-related bias problem. Basically, the S&P 500 index options are European-style options. The midquotes of option prices are used as option prices in order to avoid upward biases in the day-end option prices owing to the bid-ask bounced influences. The midquotes of three-month Treasury bill rates as the surrogate for risk-free rates are obtained from the DataStream. The daily data of S&P 500 indices and associated dividends are obtained from the CRSP. The sample period extends from January 1990 to December 2005. Following Bakshi, Cao and Chen (1997), we obtain daily dividend-exclusive S&P 500 index series for later use in option price computation as follows:

$$\overline{D}(t,\tau)=\sum_{s=1}^{\tau-t} e^{-R(t,s)s} D(t+s). \tag{20}$$

where $\overline{D}$ is the present value of future cash dividends, $R(t,s)$ is s-period yield to maturity from date t, s is the period between option trading date to ex-dividend date, and τ is the maturity date. Regarding the moneyness dimension, sample data according to the current stock price, *S*, and exercise price, *K*, are classified into in-the-money (ITM, if $(S-K)/K \geq 3\%$), near-the-money (NTM, if $-3\% \leq (S-K)/K < 3\%$), or out-of-the-money (OTM, if $(S-K)/K < -3\%$). Table 1

[5] We also tried other pair values of λ_1 and λ_2 employed in Lunde and Timmerman (2004) and obtained the similar conclusions as presented here.

[6] We also performed analyses on put options and obtain similar results reported here.

presents summary statistics for number of contracts, average trading volume, average midquotes, average spreads, and average percentage spreads, and average implied volatilities for all categories of moneyness and maturities of S&P 500 index calls. As in Amin *et al.* (2004), the market momentum of a certain transaction day is calculated using cumulative returns of past sixty transaction days and five categories of cumulative past market returns are constructed.

As shown in Table 1, the trading is much more intense in NTM options with nearby and medium maturities. Following next in trading volume is the OTM options since OTM options are cheaper in terms of hedging purpose.[7] Options with nearby and medium maturities trade more frequently in comparison with long maturity options. ITM options have highest averages of midquotes and spreads but lowest average percentage spreads. Similar to ITM options, long maturity options have higher averages of midquotes and spreads and lower percentage spreads. Generally, short maturity options tend to have higher implied volatilities. Further, the implied volatilities are higher in ITM options and lower in OTM options. This negative slope pattern between moneyness and implied volatilities was also found in Bakshi, Kapadia and Madan (2003) and Bollen and Whaley (2004) when examining index options.[8]

In terms of market momentum, trading is much more intensive for OTM options when past returns are less than -10% while trading activity becomes more intensive for NTM options when past returns are above -10%. This may indicate that investors tend to use OTM options as portfolio insurance when the market is deeply downward. Given a moneyness, the trading volume falls with increasing past returns for OTM options while the trading volume increases with increasing past returns for ITM options with nearby and long maturities. For NTM options, the trading volume has a hump when past returns are from -5% to 5%. Therefore, investors are likely to trade more in ITM options when past returns are high. Given a moneyness, the average midquote and average implied volatility show a mild U-shaped pattern as shown in Figure 2, which decreases first with increasing past returns but increases when past returns are larger than 10%. The patterns of average spreads and average percentage

[7] Bollen and Whaley (2004) found large net buying pressure in out-of-money calls and puts and suggested that portfolio insurer may prefer these options.
[8] The reason for this negative relationship between moneyness and implied volatilities could be due to higher negative skewness of index options (Bakshi et al. (2003)) or net buying pressure (Bollen and Whaley (2004)).

spreads, given a moneyness, are declining with increasing past returns. Furthermore, the slope between moneyness and implied volatilities becomes more negative when past returns increases, which can be seen in Figure 3. In sum, the market momentum influences trading patterns and price characteristics of options. This reveals the important role of market momentum in option pricing.

4. Empirical Analysis

4.1 Forecast Performance under Market Momentum

Table 2 shows estimated coefficients of mean and conditional variance equations and the values of the log likelihood function for each set of sequential years from 1990 using the updating method under physical probability measure. It is found that persistence behavior, asymmetric effects, leverage effects, and jump effects are prevalent in all conditional variance models for all estimation periods. The in-sample fitness is better for those models considering asymmetric, leverage and jump effects since log-likelihood values of those GARCH models are much larger.

Table 3 presents forecast performance results through MAEs for all models. Generally, the EGARCH model has much smaller forecast errors and performs much better than other models. Following next to the EGARCH model in forecast performance are the GARCH, the TGARCH, the NGARCH, and the GJR-GARCH models. Surprisingly, the NGARCH-Jump and the TGARCH-Jump models do not perform much better than other models. In comparison with other models, the GARCH model performs much better for ITM and NTM options while the EGARCH performs very well for OTM options. For OTM options with shorter maturity, the GJR-GARCH model performs relatively well. However, the forecast errors of the GJR-GARCH model dramatically become larger when time to maturity goes larger. Consequently, the findings here are consistent with findings in Christoffersen and Jacobs (2004) that the forecast performance of richly parameterized option pricing models does not perform much better than the option pricing model with simple GARCH process.

The results also show that option pricing models with EGARCH, GJR-GARCH, TGARCH-Jump, and NGARCH-Jump processes have smaller forecast errors for the OTM options while option pricing models with NGARH and TGARCH processes have smaller forecast errors for the ITM options. This pattern seems to be independent of maturities. This evidence is similar to findings in Bauwens and Lubrano (2002). They found that option pricing models considering asymmetric conditional volatility have a significant influence for ITM options. Consequently, richly parameterized option pricing models may provide gains on predicted option prices for ITM and OTM options.

Table 4 reports empirical results for forecasting performance of distinct GARCH models under five categories of cumulative market returns. As in Amin *et al.* (2004), the market momentum of a certain transaction day is calculated using cumulative returns of past sixty transaction days. Panel A shows that the EGARCH model has the smallest overall MAE and perform much better than other models when past cumulative returns are less than -10%. Additionally, the TGARCH and NGARCH-Jump models perform next to the EGARCH model. The TGARCH model performs very well for ITM options while the NGARCH-Jump model performs well for OTM options with medium and long maturities. The GARCH model performs not very well when past returns are deeply negative.

When past returns are from -10% to -5%, Panel B demonstrates that, as in Panel A, the EGARCH model still has the smallest MAE and the TGARCH model performs very well for ITM options. However, the NGARCH-Jump model performs not very well in comparison with its performance in Panel A. The forecast performance of the GARCH model improves in comparison with its performance in Panel A.

When past returns are from -5% to 5% in Panel C of Table 4, the GARCH model starts to take its forecast performance dominance in NTM options, although the average performance of the EGARCH model is still better. As shown in Panels D and E of Table 4, the performance of the GARCH model dominates other models when past returns become larger. Therefore, empirical evidence indicates that the option pricing model with the EGARCH process perform much better under the downward market momentum while option pricing with the GARCH process is better for predicting option prices under the upward market momentum.

4.2 Forecast Performance in Bull and Bear Markets by Lunde and Timmermann (2004)

Table 5 presents MAEs for estimation models under bull and bear markets using Lunde and Timmermann (2004) method. It is found that the option pricing using the EGARCH model performs much better than other models in bear markets while the GARCH model performs much better in bull markets. The TGARCH model performs well for the ITM options with medium to longer maturities in bull and bear markets. In contrast to the EGARCH model, the GJR-GARCH model has better forecast performance in bull markets than in bear markets. Similar to the GARCH performance in bull markets, the NGARCH and TGARCH models perform much better in bull markets than in bear markets.

Consequently, findings here indicate a similar pattern in forecast performance as shown in Table 4. That is, the EGARCH model captures option prices much better in lower past returns while the GARCH model takes the lead in forecast performance in higher past returns. Furthermore, forecast performance of the GARCH option pricing models in bull markets is better than in bear markets.

4.3 Forecast Performance in Financial Crises

The impacts of financial turmoil events, namely Russian financial crisis, 9/11 attacks, and the WorldCom scandal,[9] on forecast errors are examined in this section. Table 6 reports the forecast performance of each model around financial turmoil events. For the pre-crash period, the EGARCH model has the much smaller MAE in comparison with other models while the GARCH model has forecast performance next to the EGARCH model. The TGARCH model performs very well for the ITM options. Furthermore, the GJR-GARCH model has smaller forecast errors for options with the short maturity. The NGARCH-Jump model performs very well for OTM options of medium and long maturities. Generally, these empirical findings are similar to those found in Section 4.1.

During the crash period, the overall forecast performance of all models is inferior to the pre-crash period. On average, the EGARCH model still has well above forecast performance than the rest of models. On the other hand, following next in forecast

[9] On July 21, 2002, the telecommunications giant, WorldCom, filed for the bankruptcy protection, which is the largest corporate insolvency ever in United States history. The pre-bankruptcy total asset of WorldCom is one and half larger than the Enron’s and the disclosed accounting fraud severely shocked business market.

performance is the TGARCH model instead of the GARCH model found in the pre-crash period. Additionally, the NGARGH-Jump model performs much better during the crash period. Therefore, the gains in forecast performance of option prices using richly parameterized option pricing models lie in the financial turmoil period.

The results for the post-crash period show a similar pattern as in the pre-crash period. That is, the EGARCH still has it dominance over other models while the GARCH model performs very well next to the EGARCH model. Further, the TGARCH model still has a better forecast performance in ITM options. Consequently, the forecast performances of option pricing models with GARCH-family processes perform differently between pre-crash, during the crash, and post-crash periods.

Since financial turmoil periods have impacts on model performances, it is crucial to understand if what we found regarding forecasting performance under market momentum post different patterns around the financial turmoil periods. Table 7 reports empirical results for forecasting performances in the pre-crash period. The patterns of forecasting performances for all models are similar to what we found in Table 4. The EGARCH model performs much better under the downward market momentum while the GARCH model is better for predicting option prices under the upward market momentum. Shown in Tables 8 and 9, the forecast performances among models show the same pattern as in the pre-crash period whether during the crash or post-crash periods, except that forecast errors are generally much larger during the crash period in comparison with forecast errors in the other two periods. Therefore, forecast performances of option pricing models with GARCH-family processes under market momentum stay intact to financial turmoil periods.

4.4 Forecast Performance and Business Conditions

In this section, we examine whether macroeconomic factors influencing business conditions and momentum trading payoffs may explain portions of forecast errors generated by option pricing models with GARCH-family processes. Empirical results from previous sections reveal that market momentum has impacts on forecast errors of options pricing models with GARCH-family processes. Amin *et al*. (2004) showed that violations of the American put-call boundary conditions hinge on past stock market momentum and strongly positive past market returns raise up call option prices. Chordia and Shivakumar (2002) showed that momentum trading payoffs according to market momentum are able to be predicted by adopted macroeconomic variables and the stock-specific factor is insignificant to momentum trading payoffs. Consequently, there may exist a relationship between business conditions and forecast errors. In order to search for the relationship between business conditions and forecasting performance, we first obtain adjusted absolute dollar forecast errors without any calibration effects within the option pricing model and then use adjusted absolute dollar forecast errors for further investigation. This approach enables us to construct a more precise relationship between business conditions and forecast performance.

First, the absolute dollar forecast errors for each model are regressed on the market state and those calibration factors within the Black-Sholes option pricing model, namely implied volatility, time to maturity, moneyness, and interest rates using the follow regression:

$$AE_{i,t}^{GH} = w_0 + w_1 RM_{t-60,t-1} + w_2 IMPLYvol_{i,t} + w_3 TM_{i,t} + w_4 \frac{S_t - K_i}{K_i} + w_5 rf_t + e_{i,t}^{GH} , \qquad (17)$$

where $AE_{i,t}^{GH}$ is the i-th option's absolute dollar forecast error at time *t*, $RM_{t-60,t-1}$ is the cumulative past sixty-day index return, $IMPLYvol_{i,t}$ is the i-th option's implied volatility at time *t*, which is obtained using the Black-Scholes model, $TM_{i,t}$ is the time to maturity of option i at time *t*, S_t is S&P 500 index at time *t*, K_i is the i-th option's exercise price, $(S_t - K_i)/K_i$ is the i-th option's moneyness at time *t*, and rf_t is the midquote of three-month U.S. T-Bill rates at time *t*. The reason why we include the market state here is due to findings in Cooper *et al*. (2004) who showed that the market state is a major factor influencing momentum trading profits instead of macroeconomic variables related to business conditions. Therefore, it is better to take the market state effect into consideration before we take a further step.

Table 10 reports the estimation results of equation (17). The market state does have significant impacts on forecasting performances of GARCH-family models. Same as found in previous sections, past returns have significant impacts on forecast errors. The EGARCH, GJR-GARCH, NGARCH-Jump and TGARCH-Jump models demonstrate a decrease in forecast errors when the market momentum goes downward. In contrast, the GARCH, NGARCH, and TGARCH models show a decrease in forecast errors when the market momentum goes upward. The forecast errors are significantly and positively correlated with implied volatilities, time to maturity, and risk-free rates for all models while the relationships between moneyness and forecast errors are significant but alternates in signs among models. The GARCH, NGARCH and TGARCH perform well for ITM options while the EGARCH, GJR-GARCH, NGARG-Jump, and TGARCH-Jump models perform well for OTM options.

After controlling effects of calibration factors in option pricing models on forecast errors, adjusted dollar forecast errors retrieved from residuals of equation (17) for each model are regressed against macroeconomic factors adopted in Fama and French (1989) and Chordia and Shivakumar (2002). The regression is formulated as the following equation:

$$ADJ\_AE_{i,t}^{GH} = c_0 + c_1 DIV_{t-1} + c_2 DEF_{t-1} + c_3 TERM_{t-1} + \eta_{i,t}, \tag{18}$$

where $ADJ\_AE_{i,t}^{GH}$ is i-th option's adjusted dollar forecast error at time *t*, which is the residual from equation (17), DIV_{t-1} is the lagged dividend yield of S&P 500 index, DEF_{t-1} is the lagged default spread which is defined as yield spread between Moody's Baa-rated bonds and Moody's Aaa-rated bonds, and $TERM_{t-1}$ is the lagged yield spread between ten-year Treasury bonds and six-month Treasury bills. The dividend yield reflects the mean reversion in stock returns across several economic cycles and a proxy for the time-varying risk premium. The default spread aims to capture the default risk premium resulting from the credit risk. The yield spread between long-term and short-term yields reflects the short-term business cycles. Generally, values of dividend yield, default spread, and term spread are higher during recessions.

Table 11 reports estimation results of relationships between adjusted dollar forecast errors, market trends, and macroeconomic factors. There is a significantly negative relationship between dividend yields (*DIV*) and adjusted forecast errors for all models. This shows that option pricing models considering time-varying volatility have better prediction capability as time-varying risk premiums are present. Once the credit risk (*DEF*) is present and significant, all models have inferior forecast performance since the relationship between *DEF* and forecast errors are significantly positive in all models. This means that all models cannot track option prices very well once the default risk premium is higher. As for the term structure effect (*TERM*), all models, except GJR-GARCH, NGARH-Jump, and TGARCH-Jump models, have a negative relationship between term spreads and adjusted dollar forecast errors. This shows that higher term spreads reduce forecast errors in those models. This shows a decreasing pattern in forecast errors once the future short-term business condition is expected to be lower.

Generally, empirical results shown on Table 11 suggest that the GARCH, EGARCH, NGARCH, and TGARCH models perform much better in option price forecasting in higher dividend yields, and higher term spreads. This means that these models provide better option price forecasts when business conditions are in recession. On the other hand, the GJR-GARCH, NGARCH-Jump and TGARCH-Jump models perform much better when business conditions are in expansion since option pricing models with jumps have better forecast power in lower values of default risk premium and term spreads.

5. Conclusion

Previous studies have shown the market momentum has impacts on violations of option boundary conditions. However, the issue regarding relationship between extant option pricing models and market momentum has not been extensively explored. Therefore, this paper is to examine the relationship between forecast performance of option pricing models with GARCH-family processes and market momentum. This relationship was examined under financial crisis periods as well. Further, the relationship between forecast performance of GARCH option pricing models and business cycle variables was examined in order to understand whether forecast performance of GARCH option pricing models would be affected by momentum trading behavior which varies with the business cycle.

The empirical evidence shows that the market momentum has significant impacts on the forecast performance of different GARCH option pricing models. Generally, the EGARCH model performs much better when market momentum is downward while the standard GARCH model performs much better when market momentum is upward. Meanwhile, the forecast performance of richly parameterized option pricing models does not perform much better than the simple GARCH option pricing model, which is consistent with findings in Christoffersen and Jacobs (2004). The findings above are robust to the alternative bull/bear classification by Lunde and Timmermann (2004) method. Meanwhile, the relationship between market momentum and forecast performance of GARCH option pricing models also survives in financial crash periods. The relationship between forecast performance of GARCH option pricing models and business cycle variables is shown to be significant as well.

References

Amin, Kaushik I., and Victor K. Ng, 1993, Option Valuation with Systematic Stochastic Volatility, *The Journal of Finance* 48, 881-910.

Amin, Kaushik KA, Joshua D. JC Coval, and H. Nejat HS Seyhun, 2004, Index Option Prices and Stock Market Momentum, *The Journal of Business* 77, 835 – 874.

Avramov, Doron, and Tarun Chordia, 2006, Asset Pricing Models and Financial Market Anomalies, *The Review of Financial Studies.* 19, 1001-1040.

Awartani, Basel M. A., and Valentina Corradi, 2005, Predicting the Volatility of the S&P-500 Stock Index via GARCH Models: the role of asymmetries, *International Journal of Forecasting* 21, 167-183.

Bakshi, Gurdip, Charles Cao, and Zhiwu Chen, 1997, Empirical Performance of Alternative Option Pricing Models, *The Journal of Finance* 52, 2003-2049.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options, *The Review of Financial Studies* 16, 101-143.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Bates, David S., 1991, The Crash of '87: Was It Expected? The Evidence from Options Markets, *The Journal of Finance* 46, 1009-1044.

Bates, David S., 2000, Post-'87 Crash Fears in the S&P 500 Futures Option Market, *Journal of Econometrics* 94, 181-238.

Bauwens, Luc, and Michel Lubrano, 2002, Bayesian Option Pricing using Asymmetric GARCH Models, *Journal of Empirical Finance* 9, 321-342.

Bhabra, Gurmeet S., Liliana Gonzalez, Myeong Sup Kim, and John G. Powell, 2001, Volatility Prediction during Prolonged Crises: Evidence from Korean Index Options, *Pacific-Basin Finance Journal* 9, 147-164.

Bollen, Nicolas P. B., and Robert E. Whaley, 2004, Does Net Buying Pressure Affect the Shape of Implied Volatility Functions? , *The Journal of Finance* 59, 711-753.

Brailsford, Timothy J., and Robert W. Faff, 1996, An Evaluation of Volatility Forecasting Techniques, *Journal of Banking & Finance* 20, 419-438.

Brennan, M. J., 1979, The Pricing of Contingent Claims in Discrete Time Models, *The Journal of Finance* 34, 53-68.

Broadie, Mark, Mikhail Chernov, and Michael Johannes, 2007, Model Specification and Risk Premia: Evidence from Futures Options, *The Journal of Finance* 62, 1453-1490.

Chordia, Tarun, and Lakshmanan Shivakumar, 2002, Momentum, Business Cycle, and Time-Varying Expected Returns, *The Journal of Finance* 57, 985-1019.

Christoffersen, Peter, and Kris Jacobs, 2004, Which GARCH Model for Option

Valuation?, *Management Science* 50, 1204-1221.
Conrad, Jennifer, and Gautam Kaul, 1998, An Anatomy of Trading Strategies, *The Review of Financial Studies* 11, 489-519.
Cooper, Michael J., Roberto C. Gutierrez Jr., and Allaudeen Hameed, 2004, Market States and Momentum, *Journal of Finance* 59, 1345-1365.
Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *The Journal of Finance* 53, 1839-1885.
Duan, Jin-Chuan, 1995, THe GARCH Option Pricing Model, *Mathematical Finance* 5, 13-32.
Duan, Jin-Chuan, 1997, Augmented GARCH (p,q) Process and Its Diffusion Limit, *Journal of Econometrics* 79, 97-127.
Duan, Jin-Chuan, and Hua Zhang, 2001, Pricing Hang Seng Index Options around the Asian Financial Crisis - A GARCH approach, *Journal of Banking & Finance* 25, 1989-2014.
Duan, Jin-Chuan, Peter Ritchken, and Zhiqiang Sun, 2006, Approximating GARCH-Jump Models, Jump-Diffusion and Option Pricing, *Mathematical Finance* 16, 21-52.
Engle, Robert F., and Victor K. Ng, 1993, Measuring and Testing the Impact of News on Volatility, *The Journal of Finance* 48, 1749-1778.
Fama, Eugene F., and Kenneth R. French, 1989, Business Conditions and Expected Returns on Stocks and Bonds, *Journal of Financial Economics* 25, 23-49.
French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, Expected Stock Returns and Volatility, *Journal of Financial Economics* 19, 3-29.
Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle, 1993, On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, *The Journal of Finance* 48, 1779-1801.
Heston, Steven L., and Saikat Nandi, 2000, A Closed-Form GARCH Option Valuation Model, *The Review of Financial Studies* 13, 585-625.
Heynen, Ronald C., and Harry M. Kat, 1994, Volatility Prediction: a Comparison of the Stochastic Volatility, GARCH(1,1) and EGARCH(1,1) Models, *The Journal of Derivatives* 50-65.
Hong, Harrison, and Jeremy C. Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, *The Journal of Finance* 54, 2143-2184.
Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *The Journal of Finance* 48, 65-91.
Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *The Journal of Finance* 56, 699-720.

Johnson, Timothy C., 2002, Rational Momentum Effects, *The Journal of Finance* 57, 585-608.

Koutmos, Gregory, 1998, Asymmetries in the Conditional Mean and the Conditional Variance: Evidence from Nine Stock Markets, *Journal of Economics and Business* 50, 277-290.

Lamoureux, Christopher G., and William D. Lastrapes, 1993, Forecasting Stock-Return Variance: Toward an Understanding of Stochastic Implied Volatilities, *The Review of Financial Studies* 6, 293-326.

Lunde, Asger, and Allan Timmermann, 2004, Duration Dependence in Stock Prices: An Analysis of Bull and Bear Markets, *Journal of Business & Economic Statistics* 22, 253-273.

McQueen, Grant, and Keith Vorkink, 2004, Whence GARCH? A Preference-Based Explanation for Conditional Volatility, *The Review of Financial Studies* 17, 915-949.

Nelson, Daniel B., 1991, Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica* 59, 347-370.

Pagan, Adrian R., and Kirill A. Sossounov, 2003, A Simple Framwork for Analyzing Bull and Bear Markets, *Journal of Applied Econometrics* 18, 23-46.

Rubinstein, Mark, 1976, The Valuation of Uncertain Income Streams and the Pricing of Options, *The Bell Journal of Economics* 7, 407-425.

Schwert, G. William, 1989a, Why Does Stock Market Volatility Change Over Time?, *The Journal of Finance* 44, 1115-1153.

Schwert, G. Willian, 1989b, Business cycles, financial crises and stock volatility, *Carnegie-Rochester Conference Series on Public Policy* 3, 83-126.

Schwert, G. William, 1990, Stock Volatility and the Crash of '87, *The Review of Financial Studies* 3, 77-102.

Stentoft, Lars, 2005, Pricing American Options When the Underlying Asset Follows GARCH Processes, *Journal of Empirical Finance* 12, 576-611.

Taylor, James W., 2004, Volatility Forecasting with Smooth Transition Exponential Smoothing, *International Journal of Forecasting* 20, 273-286.

White, Halbert, 1980, A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica* 48, 817-838.

Zakoian, Jean-Michel, 1994, Threshold Heteroskedastic Models, *Journal of Economic Dynamics and Control* 18, 931-955.

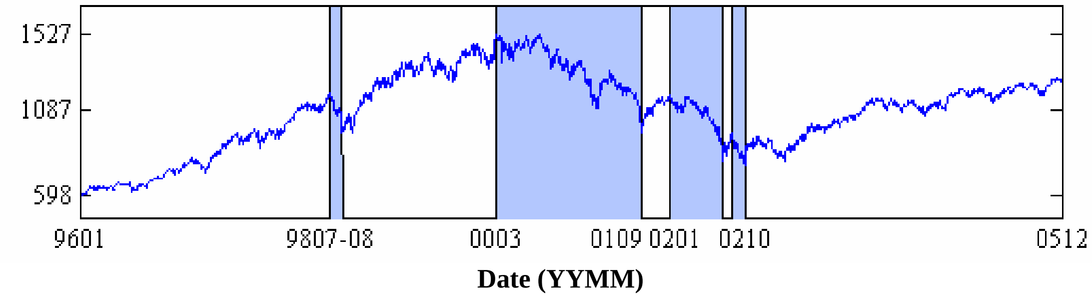

Figure 1. S&P 500 index levels and bull/bear periods. This figure displays the daily S&P 500 index levels from January1, 1996 – December 30, 2005. In addition, the bull and bear periods identified using the framework of Lunde and Timmermann (2004) with the price movement threshold of (20, 15). The shaded areas are bear markets while other periods are bull markets.

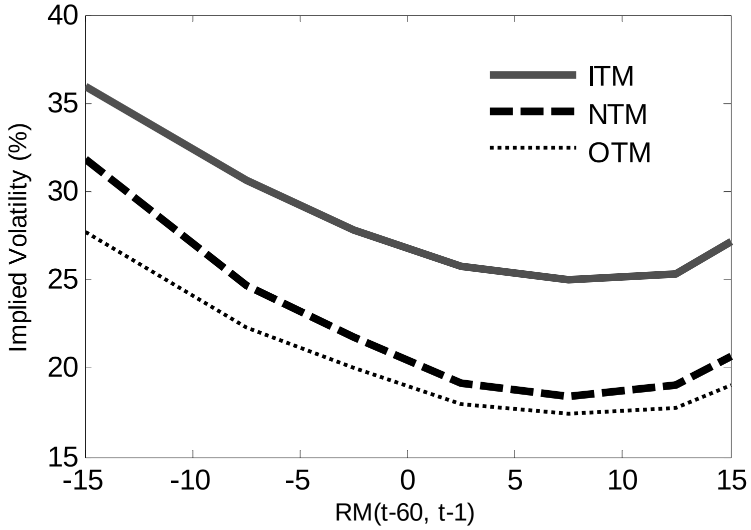

Figure 2. Estimated Implied Volatilities of S&P 500 index call options from January 1, 1996 to December 30, 2005. This figure presents the relationship between the average implied volatilities of call options for three moneyness categories and the cumulative returns of past 60-day S&P 500 indices, RM(t-60, t-1). Call options are classified into three moneyness categories of (1) out-of-the-money (OTM, if $(S-K)/K <$ -0.03), (2) near-the-money (NTM, if $-0.03 \leq (S-K)/K < 0.03$), and (3) in-the-money (ITM, if $(S-K)/K \geq 0.03$). The implied volatilities are derived using the Black–Scholes formula and are averaged based on RM with five categories of (1) RM<-10%, (2) -10%$\leq$RM<-5%, (3) -5%$\leq$RM<5%, (4) 5%$\leq$RM<10%, and (5) 10%$\leq$RM.

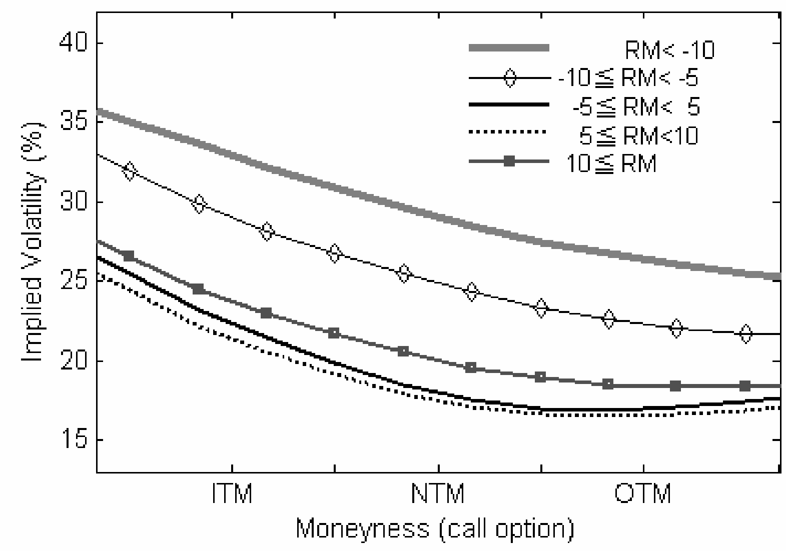

Figure 3. Estimated Implied Volatilities of S&P 500 index call options from January 1, 1996 to December 30, 2005. This figure presents the relationship between the average implied volatilities of call options for five market momentum categories and three moneyness categories. Call options are classified into five market momentum categories based on the cumulative returns of past 60-day S&P 500 indices, RM(t-60, t-1). The five categories are (1) RM<-10%, (2) -10%≤RM<-5%, (3) -5%≤RM<5%, (4) 5%≤RM<10%, and (5) 10%≤RM. The implied volatilities are derived using the Black–Scholes formula and are averaged based on three moneyness categories: (1) out-of-the-money (OTM, if $(S-K)/K <$ -0.03), (2) near-the-money (NTM, if -0.03 $\leq (S-K)/K <$ 0.03), and (3) in-the-money (ITM, if $(S-K)/K \geq 0.03$).

Table 1
Sample Statistics of S&P 500 Index Call Options

The sample contains S&P 500 index call options traded on the CBOE from January 1996 to December 2005. Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. The number of call contracts is 114,214 in the period of 2,519 trading days. Call options are classified into three days-to-maturity categories of 10-29, 30-89, and 90-180 days, and three moneyness categories of out-of-the-money (OTM, if $(S-K)/K <$ -0.03), near-the-money (NTM, if -0.03 $\le (S-K)/K <$ 0.03), and in-the-money (ITM, if $(S-K)/K \ge$ 0.03). We also classify the sample period into the five categories of market momentum using cumulative returns of past 60-day S&P 500 indices, *RM(t-60, t-1)*. This table shows the number of contracts, average trading volume per day, average midquotes, average spreads, average percentage spreads, and average implied volatilities. The midquote is the midpoint of daily last bid/ask quotes in a trading day. The spread indicates the differences between bid and ask prices. The percentage spread is the spread divided by the associated midquote. The implied volatility is derived using the Black–Scholes formula.

Days to Maturity	10 - 29			30 - 89			90-180			
Moneyness	OTM	NTM	ITM	OTM	NTM	ITM	OTM	NTM	ITM	ALL
No. of contracts	6,355	14,919	9,905	22,104	24,402	14,221	10,864	6,415	5,029	114,214
Average Trading volume per day										
RM <-10%	6,103	5,965	873	8,610	7,348	1,088	3,381	1,562	272	35,202
-10%≤ RM <-5%	4,095	5,775	801	8,179	8,249	1,220	1,732	1,371	296	31,719
-5%≤ RM < 5%	2,437	8,948	889	5,388	9,476	976	1,623	1,657	318	31,710
5%≤ RM <10%	2,055	8,282	1,177	3,859	8,792	1,185	1,453	1,347	624	28,772
10%≤ RM	1,660	5,939	1,102	3,957	7,209	1,354	1,758	1,274	559	24,812
Average Midquotes										
RM <-10%	$5.67	$26.53	$104.84	$11.65	$44.98	$120.77	$18.56	$65.89	$157.18	$42.95
-10%≤ RM <-5%	4.97	25.04	115.50	11.13	43.72	138.88	21.50	69.04	166.19	48.98
-5%≤ RM < 5%	3.83	18.52	102.14	8.29	29.85	122.23	17.29	51.77	162.54	44.81
5%≤ RM <10%	3.51	17.49	97.97	7.66	27.67	108.14	16.13	47.25	141.96	45.56
10%≤ RM	3.73	20.19	104.70	9.58	34.26	130.07	20.45	56.86	160.91	59.01
Average Spreads										
RM <-10%	$0.82	$1.80	$2.10	$1.30	$2.26	$2.29	$1.61	$2.36	$2.57	$1.71
-10%≤ RM <-5%	0.71	1.63	2.04	1.14	2.06	2.18	1.55	2.12	2.21	1.62
-5%≤ RM < 5%	0.59	1.23	1.88	0.88	1.58	1.90	1.26	1.81	1.96	1.41
5%≤ RM <10%	0.48	1.10	1.70	0.76	1.42	1.75	1.13	1.60	1.75	1.31
10%≤ RM	0.51	1.16	1.65	0.87	1.48	1.70	1.19	1.61	1.69	1.36
Average Spreads (%)										
RM <-10%	19.03	7.43	2.61	17.31	5.44	2.39	14.92	3.77	2.03	11.05
-10%≤ RM <-5%	19.25	7.48	2.39	15.30	5.25	2.11	12.09	3.32	1.69	9.37
-5%≤ RM < 5%	19.34	8.41	2.53	15.43	6.33	2.14	11.86	4.01	1.65	8.45
5%≤ RM <10%	16.97	7.84	2.46	13.90	6.04	2.13	10.88	3.77	1.61	7.16
10%≤ RM	17.21	6.80	2.19	13.08	4.85	1.82	9.06	3.19	1.37	6.10
Average Implied Volatilities										
RM <-10%	0.274	0.296	0.365	0.258	0.288	0.341	0.237	0.271	0.320	0.281
-10%≤ RM <-5%	0.228	0.245	0.324	0.218	0.247	0.315	0.215	0.246	0.289	0.246
-5%≤ RM < 5%	0.181	0.169	0.250	0.165	0.174	0.238	0.172	0.190	0.245	0.188
5%≤ RM <10%	0.170	0.167	0.247	0.162	0.171	0.227	0.168	0.185	0.230	0.186
10%≤ RM	0.174	0.189	0.264	0.183	0.201	0.262	0.187	0.208	0.259	0.214

Table 2 Parameter Estimation of GARCH models

The parameter estimates for each model are obtained using the maximum likelihood estimation method on an annual updating base. Daily closing S&P 500 indices from January 1996 to December 2005 are used as input data. LLF represents the log likelihood values. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Mean equation $\ln S_t/S_{t-1} = rf - 1/2\,h_t + \psi\sqrt{h_t} + \varepsilon_t$.

GARCH $h_t = \alpha_0 + \alpha_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2$.

EARCH $\ln h_t = \alpha_0(1-\alpha_1) + \alpha_1 \ln h_{t-1} + \beta_1 \nu_{t-1} + \beta_2\left[|\nu_{t-1}| - \sqrt{2/\pi}\right]$.

GJR-GARCH $h_t = \alpha_0 + \alpha_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 I[\varepsilon_{t-1} < 0]$.

NGARCH $h_t = \alpha_0 + \alpha_1 h_{t-1} + \beta_1 h_{t-1}(\nu_{t-1} - \theta)^2$.

TGARCH $\phi_t = \alpha_0 + \alpha_1 \phi_{t-1} + \beta_1|\varepsilon_{t-1}| + \beta_2 \max(-\varepsilon_{t-1}, 0)$, $h_t = \phi_t^2$.

Estimation Period		**1990-1995**	**1990-1996**	**1990-1997**	**1990-1998**	**1990-1999**	**1990-2000**	**1990-2001**	**1990-2002**	**1990-2003**	**1990-2004**
	LLF	5,420	6,305	7,070	7,833	8,603	9,322	10,040	10,730	11,530	12,425
	ψ	0.049*	0.056**	0.064***	0.074***	0.072***	0.064***	0.060***	0.053***	0.058***	0.058***
GARCH	α_0	1.7E-07***	3.6E-07***	2.7E-07***	5.9E-07***	5.3E-07***	4.4E-07***	5.6E-07***	6.1E-07***	5.5E-07***	5.2E-07***
	α_1	0.973***	0.963***	0.962***	0.937***	0.942***	0.944***	0.936***	0.932***	0.936***	0.939***
	β_1	0.022***	0.029***	0.033***	0.055***	0.051***	0.052***	0.058***	0.063***	0.059***	0.057***
	LLF	5,426	6,317	7,088	7,860	8,633	9,356	10,086	10,786	11,586	12,482
	ψ	0.032	0.039*	0.042*	0.045**	0.046**	0.034*	0.027	0.018	0.024	0.025
EGARCH	α_0	-9.694***	-9.734***	-9.539***	-9.428***	-9.394***	-9.273***	-9.258***	-9.193***	-9.207***	-9.247***
	α_1	0.986***	0.978***	0.978***	0.979***	0.981***	0.981***	0.979***	0.980***	0.982***	0.982***
	β_1	-0.039***	-0.053***	-0.063***	-0.074***	-0.074***	-0.083***	-0.090***	-0.094***	-0.089***	-0.086***
	β_2	0.074***	0.095***	0.118***	0.127***	0.123***	0.125***	0.125***	0.122***	0.116***	0.112***
	LLF	5,427	6,313	7,078	7,851	8,623	9,346	10,074	10,773	11,572	12,469
	ψ	0.043*	0.047*	0.053**	0.055**	0.055***	0.044**	0.033*	0.023	0.030*	0.030*
GJR-GARCH	α_0	1.4E-07***	6.2E-07***	8.1E-07***	1.1E-06***	1.0E-06***	1.0E-06***	1.1E-06***	1.2E-06***	1.0E-06***	1.0E-06***
	α_1	0.984***	0.955***	0.938***	0.922***	0.929***	0.929***	0.924***	0.923***	0.929***	0.932***
	β_1	0.000	0.012*	0.019**	0.017**	0.015**	0.013*	0.010	0.008	0.007	0.006
	β_2	0.022***	0.038***	0.057***	0.084***	0.083***	0.092***	0.105***	0.114***	0.105***	0.100***
	LLF	5,427	6,315	7,082	7,854	8,627	9,352	10,081	10,782	11,583	12,480
	ψ	0.041	0.042*	0.046**	0.048**	0.048**	0.035*	0.026	0.016	0.022	0.022
NGARCH	α_0	4.0E-07***	9.4E-07***	9.8E-07***	1.0E-06***	9.3E-07***	9.7E-07***	1.1E-06***	1.2E-06***	1.1E-06***	1.1E-06***
	α_1	0.953***	0.918***	0.907***	0.896***	0.902***	0.897***	0.885***	0.879***	0.886***	0.888***
	β_1	0.025***	0.039***	0.053***	0.059***	0.056***	0.058***	0.061***	0.06***	0.057***	0.055***
	θ	0.703***	0.784***	0.680***	0.718***	0.738***	0.788***	0.851***	0.918***	0.916***	0.934***
	LLF	5,427	6,317	7,088	7,860	8,634	9,357	10,086	10,786	11,587	12,483
	ψ	0.035	0.041*	0.043**	0.045**	0.046**	0.032*	0.025	0.016	0.022	0.024
TGARCH	α_0	9.5E-05***	1.5E-04***	1.4E-04***	1.5E-04***	1.4E-04***	1.5E-04***	1.6E-04***	1.7E-04***	1.5E-04***	1.5E-04***
	α_1	0.958***	0.941***	0.934***	0.930***	0.933***	0.932***	0.930***	0.931***	0.935***	0.937***
	β_1	0.014*	0.018**	0.026***	0.025***	0.023***	0.020***	0.017**	0.014**	0.013**	0.012**
	β_2	0.044***	0.059***	0.070***	0.083***	0.083***	0.091***	0.099***	0.104***	0.099***	0.095***

Table 2 (continued)

GARCH-Jump — Mean equation:
$$\ln\frac{S_t}{S_{t-1}} = r_f - \frac{1}{2}h_t + \psi\sqrt{h_t} + \lambda\kappa\left(1-W_t\right) + \sqrt{h_t}\bar{J}_t$$

NGARCH-Jump:
$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \beta_1 h_{t-1}\left(\frac{\bar{J}_{t-1}-\lambda\bar{\mu}}{\sqrt{1+\lambda\hat{\gamma}^2}} - \theta\right)^2$$

TGARCH-Jump:
$$\phi_t = \alpha_0 + \alpha_1\phi_{t-1} + \beta_1\phi_{t-1}\left|\frac{\bar{J}_{t-1}-\lambda\bar{\mu}}{\sqrt{1+\lambda\hat{\gamma}^2}}\right| + \beta_2\phi_{t-1}\max\left(-\frac{\bar{J}_{t-1}-\lambda\bar{\mu}}{\sqrt{1+\lambda\hat{\gamma}^2}},0\right),\quad h_t = \phi_t^2.$$

Estimation Period		1990-1995	1990-1996	1990-1997	1990-1998	1990-1999	1990-2000	1990-2001	1990-2002	1990-2003	1990-2004
	LLF	5,470	6,363	7,140	7,916	8,685	9,416	10,145	10,840	11,640	12,537
	ψ	0.045*	0.042**	0.034**	0.068***	0.061***	0.062***	0.032**	0.045**	0.031***	0.030***
	α_0	8.2E-08**	1.2E-07***	1.0E-07***	1.7E-07**	1.9E-07**	2.8E-07***	2.5E-07**	4.9E-07***	1.7E-07***	2.2E-07***
	α_1	0.936***	0.932***	0.932***	0.911***	0.915***	0.908***	0.900***	0.888***	0.893***	0.893***
NGARCH-	β_1	0.033***	0.040***	0.044***	0.054***	0.051***	0.054***	0.056***	0.057***	0.055***	0.053***
Jump	θ	0.784***	0.590**	0.569***	0.696***	0.691***	0.775***	0.821***	0.914***	0.912***	0.935***
	$\bar{\mu}$	-0.028	-0.040	-0.056	-0.080	-0.083	-0.144**	-0.124**	-0.175**	-0.097**	-0.115**
	$\bar{\gamma}$	1.754***	1.705***	1.714***	1.516***	1.370***	1.283***	1.292***	1.185***	1.369***	1.227***
	λ	1.594***	1.504***	1.637***	1.374***	1.291***	0.842**	1.260**	0.590**	2.141***	1.749***
	κ	0.535***	0.736***	0.844***	0.559***	0.630***	0.582***	0.786***	0.593***	0.740***	0.795***
	LLF	5,465	6,360	7,136	7,906	8,672	9,393	10,117	10,803	11,599	12,496
	ψ	0.034**	0.059**	0.027*	0.039***	0.009	0.070***	0.057***	0.075***	0.026***	0.041***
	α_0	5.5E-05**	9.4E-05**	9.9E-05***	1.2E-04***	1.0E-04***	1.2E-04***	1.4E-04***	1.4E-04**	8.0E-05**	1.0E-04***
TGARCH-	α_1	0.942***	0.922***	0.920***	0.911***	0.923***	0.918***	0.91***	0.906***	0.912***	0.915***
Jump	β_1	0.028*	0.028*	0.042***	0.048***	0.050***	0.053***	0.054***	0.057***	0.055***	0.053***
	β_2	0.028*	0.049***	0.037**	0.039***	0.026*	0.027*	0.034**	0.035***	0.031***	0.031***
	$\bar{\mu}$	-0.028	-0.033	-0.048	-0.074	-0.065	-0.085	-0.103**	-0.094*	-0.098	-0.093*
	$\bar{\gamma}$	2.040***	1.865***	1.680***	1.529***	1.484***	1.375***	1.364***	1.410***	1.940***	1.538***
	λ	1.860***	1.789***	1.669***	1.504***	1.631***	1.376***	1.483***	1.889***	2.892***	2.300***
	κ	0.783***	0.500***	1.173***	0.984***	1.779***	0.595***	0.699***	0.501***	0.971***	0.804***

Table 3
Mean Absolute Dollar Forecast Errors by Maturities and Moneyness

This table reports mean absolute dollar forecast errors of S&P 500 index call options traded on the CBOE from January 1996 to December 2005. Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. Call options are classified into three days-to-maturity categories of 10-29, 30-89, and 90-180 days, and three moneyness categories of out-of-the-money (OTM, if $(S-K)/K <$ -0.03), near-the-money (NTM, if $-0.03 \le (S-K)/K < 0.03$), and in-the-money (ITM, if $(S-K)/K \ge 0.03$).

Days to Maturity	10 - 29			30 - 89			90 - 180			
Moneyness	OTM	NTM	ITM	OTM	NTM	ITM	OTM	NTM	ITM	ALL
GARCH	2.99	2.71	2.29	4.98	4.34	3.98	7.93	7.27	7.48	4.60
EGARCH	2.20	2.51	2.44	3.52	4.59	4.50	5.57	7.98	8.43	4.23
GJR-GARCH	1.48	2.75	2.98	4.41	9.17	7.75	12.05	22.98	17.54	7.69
NGARCH	3.41	2.80	2.34	5.88	5.27	4.19	9.86	9.17	7.45	5.32
TGARCH	2.98	2.73	2.33	4.87	4.86	4.08	7.41	7.80	7.06	4.67
NGARCH-Jump	1.82	3.10	5.01	3.44	6.79	7.17	7.36	16.06	17.24	6.31
TGARCH-Jump	2.49	3.84	4.21	4.92	7.84	7.27	9.32	16.10	17.83	7.11

Table 4
Mean Absolute Dollar Forecast Errors by Maturities and Moneyness under Market Momentum

This table reports mean absolute dollar forecast errors of S&P 500 index call options traded on the CBOE from January 1996 to December 2005 under market momentum. Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. Call options are classified into three days-to-maturity categories of 10-29, 30-89, and 90-180 days, and three moneyness categories of out-of-the-money (OTM, if $(S-K)/K<$ -0.03), near-the-money (NTM, if -0.03 $\leq (S-K)/K<$ 0.03), and in-the-money (ITM, if $(S-K)/K \geq$ 0.03). The market momentum is defined as the cumulative returns of past 60-day S&P 500 indices, RM(t-60, t-1), in which there are five categories: (1) RM<-10%, (2) -10%$\leq$RM<-5%, (3) -5%$\leq$RM<5%, (4) 5%$\leq$RM<10%, and (5) 10%$\leq$RM.

Days to Maturity	10 - 29			30 - 89			90 - 180			
Moneyness	OTM	NTM	ITM	OTM	NTM	ITM	OTM	NTM	ITM	Total
Panel A. RM < -10%										
GARCH	3.33	3.87	3.57	8.70	8.73	6.55	14.31	12.03	10.20	8.12
EGARCH	2.34	2.73	3.40	3.77	5.32	6.12	4.29	7.88	9.98	4.41
GJR-GARCH	1.62	3.30	4.29	5.10	12.63	11.35	12.14	28.07	21.81	8.71
NGARCH	5.36	5.21	3.06	11.69	11.26	6.40	18.81	16.64	10.63	10.43
TGARCH	4.20	4.13	3.05	7.66	7.75	5.37	9.64	8.91	7.03	6.74
NGARCH-Jump	2.80	3.24	6.57	4.78	5.95	6.69	5.29	10.93	15.80	5.64
TGARCH-Jump	2.73	6.59	8.57	6.05	14.82	13.69	11.30	26.86	25.50	10.18
Panel B. -10% ≤RM <-5%										
GARCH	4.07	3.85	3.14	6.22	5.41	4.91	9.64	9.65	8.85	6.04
EGARCH	2.45	2.75	3.17	3.41	5.01	6.58	5.08	9.75	11.23	4.71
GJR-GARCH	1.82	3.44	3.91	5.47	13.40	10.67	14.59	30.68	24.40	9.93
NGARCH	4.48	3.75	2.69	7.48	5.91	4.89	11.24	10.69	7.77	6.68
TGARCH	3.57	3.18	2.83	5.43	5.07	5.41	7.50	8.67	7.87	5.36
NGARCH-Jump	2.27	3.63	6.69	3.26	7.90	9.07	8.06	19.77	21.54	6.98
TGARCH-Jump	2.75	5.94	7.46	6.30	12.22	11.08	11.91	24.74	25.23	9.91
Panel C. -5%≤ RM < 5%										
GARCH	3.14	2.80	2.15	4.86	4.19	3.44	7.32	6.66	6.94	4.35
EGARCH	2.55	2.72	2.23	4.06	4.61	3.74	6.15	7.48	7.78	4.26
GJR-GARCH	1.41	2.35	2.79	3.75	7.97	7.06	11.31	21.76	17.24	6.95
NGARCH	3.41	2.81	2.13	5.68	5.09	3.43	9.29	8.49	6.56	5.00
TGARCH	3.13	2.89	2.15	5.18	4.98	3.37	7.86	7.53	6.45	4.67
NGARCH-Jump	1.65	2.76	5.07	3.02	5.88	6.68	6.86	15.03	17.33	5.76
TGARCH-Jump	2.62	3.44	3.76	4.69	6.65	6.17	8.22	13.19	16.38	6.22
Panel D. 5%≤RM < 10%										
GARCH	2.09	2.02	1.97	2.98	3.38	3.40	5.25	5.98	6.28	3.38
EGARCH	1.47	1.91	2.16	2.48	3.77	3.76	5.29	7.23	6.69	3.51
GJR-GARCH	1.20	2.73	2.63	4.27	8.41	6.46	11.02	20.12	14.51	7.02
NGARCH	1.85	1.98	2.16	3.07	3.99	3.65	6.50	7.73	6.25	3.77
TGARCH	1.86	2.00	2.11	3.01	3.77	3.50	5.98	7.11	5.96	3.60
NGARCH-Jump	1.15	3.08	4.40	3.19	6.80	6.38	7.63	15.54	15.41	6.18
TGARCH-Jump	2.06	3.46	3.39	4.09	6.95	5.80	8.58	14.87	15.04	6.30
Panel E. 10%≤ RM										
GARCH	1.86	2.73	2.40	3.24	4.66	4.94	6.02	8.61	9.32	4.51
EGARCH	1.27	2.74	2.84	2.51	5.77	6.22	5.50	10.69	11.43	5.07
GJR-GARCH	1.68	4.09	3.22	6.13	12.63	8.81	14.86	26.87	18.92	9.85
NGARCH	1.51	2.95	2.83	2.91	5.90	6.02	6.13	10.22	10.45	5.12
TGARCH	1.36	2.72	2.81	2.48	5.33	5.91	5.07	9.30	10.34	4.74
NGARCH-Jump	1.70	4.47	4.54	4.72	10.86	9.16	11.16	22.06	19.07	8.95
TGARCH-Jump	1.90	4.20	3.76	4.75	9.87	8.17	10.73	20.25	20.35	8.41

Table 5
Mean Absolute Dollar Forecast Errors by Maturities and Moneyness under Bull and Bear Markets

This table reports mean absolute dollar forecast errors of S&P 500 index call options traded on the CBOE from January 1996 to December 2005 under bull/bear markets which are identified using Lunde and Timmermann (2004) framework. Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. Call options are classified into three days-to-maturity categories of 10-29, 30-89, and 90-180 days, and three moneyness categories of out-of-the-money (OTM, if $(S-K)/K <$ -0.03), near-the-money (NTM, if -0.03 $\leq (S-K)/K < 0.03$), and in-the-money (ITM, if $(S-K)/K \geq 0.03$).

Days to Maturity	10 - 29			30 - 89			90 - 180			
Moneyness	OTM	NTM	ITM	OTM	NTM	ITM	OTM	NTM	ITM	Total
Panel A. Bull Market										
GARCH	2.50	2.35	2.10	4.16	3.74	3.84	6.75	6.61	7.42	4.03
EGARCH	1.78	2.39	2.34	3.23	4.73	4.55	5.81	8.71	8.49	4.26
GJR-GARCH	1.55	2.64	2.80	4.21	8.57	7.39	11.74	21.67	16.71	7.38
NGARCH	2.55	2.43	2.23	4.44	4.66	4.14	7.79	8.43	7.41	4.55
TGARCH	2.22	2.44	2.24	3.92	4.60	4.13	6.51	7.91	7.37	4.28
NGARCH-Jump	1.65	3.08	4.55	3.52	6.87	6.97	8.03	16.01	16.59	6.39
TGARCH-Jump	2.18	3.52	3.84	4.38	7.27	6.89	8.89	15.67	17.60	6.74
Panel B. Bear Market										
GARCH	3.84	4.26	3.26	7.18	7.08	4.71	11.21	9.84	7.79	6.65
EGARCH	2.94	3.04	2.91	4.32	3.96	4.27	4.89	5.08	8.14	4.12
GJR-GARCH	1.35	3.21	3.83	4.95	11.84	9.57	12.91	28.11	21.32	8.77
NGARCH	4.92	4.44	2.87	9.73	8.01	4.44	15.62	12.07	7.65	8.13
TGARCH	4.32	4.00	2.81	7.39	6.02	3.83	9.93	7.37	5.61	6.05
NGARCH-Jump	2.13	3.18	7.33	3.23	6.43	8.19	5.46	16.27	20.22	6.02
TGARCH-Jump	3.04	5.20	5.99	6.39	10.40	9.17	10.52	17.80	18.93	8.44

Table 6
Mean Absolute Dollar Forecast Errors by Maturities and Moneyness in Financial Crises

This table reports mean absolute forecast errors of S&P 500 index call options traded on the CBOE from January 1996 to December 2005 for three financial crises: Russian debt default (August 17, 1998), 9/11 attack (September 11, 2001), and the WorldCom scandal (July 21, 2002). Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. The pre-crash period is defined as three months prior to the crisis event. The during-crash period is defined as three months after the crisis event occurred. The post-crash period is defined as from the fourth month after the crisis event occurred till three months before the next crisis event. Call options are classified into three days-to-maturity categories of 10-29, 30-89, and 90-180 days, and three moneyness categories of out-of-the-money (OTM, if $(S-K)/K <$ -0.03), near-the-money (NTM, if $-0.03 \leq (S-K)/K < 0.03$), and in-the-money (ITM, if $(S-K)/K \geq 0.03$).

Days to Maturity	10 - 29			30 - 89			90 - 180			
Moneyness	OTM	NTM	ITM	OTM	NTM	ITM	OTM	NTM	ITM	Total
Panel A. Pre-Crash Period										
GARCH	1.77	2.27	2.72	4.17	4.71	4.02	7.15	8.35	7.72	4.51
EGARCH	2.49	2.42	2.49	3.69	3.98	3.74	4.81	6.12	7.63	3.85
GJR-GARCH	0.79	2.60	3.39	4.20	10.30	7.65	11.08	25.21	17.71	7.71
NGARCH	3.37	3.08	2.48	6.98	6.31	4.13	11.69	11.62	7.97	6.51
TGARCH	3.22	2.97	2.45	5.74	5.15	3.67	8.33	8.39	6.49	5.24
NGARCH-Jump	1.59	2.25	4.12	2.81	5.07	4.69	5.17	13.48	15.70	4.65
TGARCH-Jump	1.49	3.19	4.65	3.39	6.68	6.65	6.95	17.41	18.70	5.96
Panel B. During-Crash Period										
GARCH	4.35	4.64	3.60	8.89	7.08	6.38	14.14	10.11	10.84	7.97
EGARCH	1.86	3.09	4.30	3.01	7.79	9.26	4.77	13.76	14.73	5.67
GJR-GARCH	2.02	3.55	4.67	5.42	14.02	12.79	13.17	31.02	25.15	10.01
NGARCH	5.13	4.11	3.51	8.82	7.64	7.21	14.85	12.87	11.36	8.38
TGARCH	3.68	3.38	3.74	5.38	6.62	7.50	7.54	9.43	10.50	6.04
NGARCH-Jump	3.35	3.59	5.57	4.72	7.24	7.69	6.37	14.99	18.57	6.55
TGARCH-Jump	2.41	5.97	8.02	5.53	14.29	13.34	11.10	28.17	27.38	10.35
Panel C. Post-Crash Period										
GARCH	3.29	2.94	2.25	5.36	4.72	3.89	8.18	7.77	7.40	4.80
EGARCH	2.60	2.66	2.26	4.14	4.75	4.09	6.34	8.19	8.13	4.41
GJR-GARCH	1.49	2.79	2.98	4.69	9.75	8.01	12.85	25.48	19.01	8.13
NGARCH	3.61	2.91	2.22	6.42	5.64	3.85	10.46	9.65	6.95	5.49
TGARCH	3.35	2.93	2.18	5.64	5.28	3.71	8.42	8.41	6.73	4.97
NGARCH-Jump	1.63	3.24	5.86	3.44	7.06	8.19	7.71	17.24	19.24	6.76
TGARCH-Jump	2.84	3.75	4.15	5.32	7.54	7.16	9.49	15.18	18.35	7.08

Table 7
Mean Absolute Dollar Forecast Errors by Maturities and Moneyness in the Pre-Crash Period under Market Momentum

This table reports mean absolute forecast errors of S&P 500 index call options traded on the CBOE from January 1996 to December 2005 in the pre-crash period under market momentum for three financial crises: Russian debt default (August 17, 1998), 9/11 attack (September 11, 2001), and the WorldCom scandal (July 21, 2002). Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. The pre-crash period is defined as three months prior to the crisis event. Call options are classified into three days-to-maturity categories of 10-29, 30-89, and 90-180 days, and three moneyness categories of out-of-the-money (OTM, if $(S-K)/K<$ -0.03), near-the-money (NTM, if $-0.03 \leq (S-K)/K < 0.03$), and in-the-money (ITM, if $(S-K)/K \geq 0.03$). The market momentum is defined as the cumulative returns of past 60-day S&P 500 indices, RM(t-60, t-1), in which there are five categories: (1) RM<-10%, (2) -10% ≤ RM<-5%, (3) -5% ≤ RM<5%, (4) 5% ≤ RM<10%, and (5) 10% ≤ RM.

Days to Maturity	10 - 29			30 - 89			90 - 180			
Moneyness	OTM	NTM	ITM	OTM	NTM	ITM	OTM	NTM	ITM	Total
				Panel A. RM < -10%						
GARCH	1.67	1.71	2.67	5.27	4.49	3.33	9.28	6.48	4.86	4.89
EGARCH	2.42	1.97	2.12	3.66	2.64	2.77	3.89	2.09	5.11	3.09
GJR-GARCH	0.93	2.91	4.18	4.89	11.80	9.58	10.07	23.91	18.32	7.83
NGARCH	4.40	4.07	1.87	10.79	9.66	3.95	17.06	14.29	7.54	9.48
TGARCH	3.66	3.26	1.85	7.41	6.16	2.70	9.74	6.95	3.27	6.06
NGARCH-Jump	2.42	2.08	5.42	4.15	3.41	4.47	3.81	6.01	13.38	4.08
TGARCH-Jump	1.78	5.65	7.13	4.99	12.25	10.33	8.53	21.54	20.71	8.18
				Panel B. -10% ≤ RM < -5%						
GARCH	2.44	2.68	1.51	4.16	4.33	3.41	6.27	5.43	4.47	4.08
EGARCH	3.58	3.61	1.26	4.48	3.99	2.78	5.54	3.23	3.60	3.97
GJR-GARCH	0.51	2.12	2.46	4.09	9.78	7.67	9.79	23.02	16.62	7.10
NGARCH	4.22	4.38	1.38	7.35	7.07	3.07	12.25	11.10	4.61	6.92
TGARCH	4.44	4.66	1.41	6.57	6.26	2.88	9.81	7.88	3.26	6.02
NGARCH-Jump	1.63	2.46	4.97	2.36	4.22	4.33	4.35	10.93	13.90	4.04
TGARCH-Jump	1.01	4.43	6.53	3.87	9.83	8.30	8.38	21.51	20.48	7.41
				Panel C. -5% ≤ RM < 5%						
GARCH	1.59	2.25	2.96	3.74	5.07	4.37	6.49	10.14	9.72	4.56
EGARCH	2.22	2.21	2.83	3.53	4.46	4.20	5.15	8.56	9.56	4.14
GJR-GARCH	0.78	2.43	3.34	3.85	9.97	7.15	11.88	26.19	17.71	7.62
NGARCH	2.65	2.44	2.83	5.32	5.48	4.38	8.92	11.19	9.18	5.41
TGARCH	2.63	2.43	2.79	4.81	4.82	4.08	7.19	9.19	8.56	4.79
NGARCH-Jump	1.25	2.19	3.63	2.51	5.63	4.88	5.98	16.03	16.20	4.93
TGARCH-Jump	1.53	2.18	3.54	2.42	4.66	5.23	5.49	14.71	17.16	4.65
				Panel D. 5% ≤ RM < 10%						
GARCH	1.84	2.86	2.89	3.45	4.03	4.19	5.91	7.35	7.18	4.19
EGARCH	2.30	2.83	2.79	3.36	3.65	4.14	4.62	5.59	7.47	3.83
GJR-GARCH	0.81	3.53	3.40	4.32	10.29	7.10	11.87	25.44	17.68	8.52
NGARCH	2.50	3.22	2.94	4.94	5.18	4.36	8.87	10.23	6.88	5.43
TGARCH	2.80	3.23	2.89	4.78	4.35	4.07	7.22	7.89	6.19	4.80
NGARCH-Jump	0.81	2.60	3.44	1.72	5.51	4.63	6.20	16.50	18.55	5.18
TGARCH-Jump	1.20	2.80	4.28	3.31	5.44	5.76	6.65	17.51	19.93	5.89
				Panel E. 10% ≤ RM						
GARCH	2.49	2.02	0.94	5.06	3.45	—	8.11	4.04	—	3.85
EGARCH	2.84	2.51	0.71	5.34	3.90	—	7.43	3.16	—	3.96
GJR-GARCH	0.52	2.59	2.78	4.65	12.14	—	14.32	31.13	—	6.54
NGARCH	3.33	3.17	0.42	7.73	6.77	—	15.60	13.27	—	6.55
TGARCH	3.48	3.38	0.41	7.51	6.59	—	13.19	10.34	—	6.10
NGARCH-Jump	0.76	1.94	6.49	1.20	4.31	—	6.10	16.29	—	3.46
TGARCH-Jump	0.91	4.65	7.71	4.07	12.05	—	11.42	25.69	—	6.89

Table 8
Mean Absolute Dollar Forecast Errors by Maturities and Moneyness in the During-Crash Period under Market Momentum

This table reports mean absolute forecast errors of S&P 500 index call options traded on the CBOE from January 1996 to December 2005 in the during-crash period under market momentum for three financial crises: Russian debt default (August 17, 1998), 9/11 attack (September 11, 2001), and the WorldCom scandal (July 21, 2002). Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. The during-crash period is defined as three months after the crisis event occurred. Call options are classified into three days-to-maturity categories of 10-29, 30-89, and 90-180 days, and three moneyness categories of out-of-the-money (OTM, if $(S-K)/K <$ -0.03), near-the-money (NTM, if $-0.03 \le (S-K)/K < 0.03$), and in-the-money (ITM, if $(S-K)/K \ge 0.03$). The market momentum is defined as the cumulative returns of past 60-day S&P 500 indices, RM(t-60, t-1), in which there are five categories: (1) RM<-10%, (2) -10%≤RM<-5%, (3) -5%≤RM<5%, (4) 5%≤RM<10%, and (5) 10%≤RM.

Days to Maturity	10 - 29			30 - 89			90 - 180			
Moneyness	OTM	NTM	ITM	OTM	NTM	ITM	OTM	NTM	ITM	Total
Panel A. RM < -10%										
GARCH	4.03	4.45	3.67	9.65	9.46	7.70	15.94	13.09	11.72	9.20
EGARCH	2.09	2.57	3.59	3.29	6.77	7.90	4.27	11.76	12.44	4.94
GJR-GARCH	1.85	2.97	4.28	5.36	13.51	12.54	12.51	30.07	23.21	9.37
NGARCH	5.91	5.32	2.99	11.16	10.23	6.85	18.70	16.09	11.01	10.34
TGARCH	4.29	3.89	3.05	6.74	7.11	6.31	8.72	8.93	8.19	6.45
NGARCH-Jump	3.45	3.20	6.07	5.24	6.97	7.17	5.86	11.85	15.85	6.20
TGARCH-Jump	2.73	7.13	9.12	6.10	15.78	14.26	11.95	30.33	27.14	10.91
Panel B. -10% ≤ RM < -5%										
GARCH	7.19	5.15	3.27	8.87	4.29	5.03	12.66	5.89	7.88	7.01
EGARCH	2.25	3.34	4.92	2.85	9.72	11.79	6.29	17.13	18.04	7.20
GJR-GARCH	3.53	3.00	4.53	5.79	15.40	14.27	14.07	32.10	28.00	11.38
NGARCH	6.44	3.99	3.31	6.71	4.10	7.25	10.11	7.59	9.03	6.45
TGARCH	4.20	2.96	4.04	3.59	5.86	9.22	6.28	9.36	12.86	5.84
NGARCH-Jump	5.13	4.08	4.77	4.74	7.55	8.88	7.30	16.51	20.36	7.31
TGARCH-Jump	2.65	5.06	7.24	5.44	15.28	14.44	10.61	28.04	29.53	10.99
Panel C. -5% ≤ RM < 5%										
GARCH	3.19	5.01	3.97	6.22	4.80	5.34	9.31	7.50	11.27	5.91
EGARCH	0.92	3.97	5.51	2.32	8.48	9.76	5.25	15.56	18.06	6.36
GJR-GARCH	1.41	4.96	5.77	5.47	14.08	12.14	14.65	32.47	27.75	10.63
NGARCH	1.93	2.59	4.70	3.08	5.78	7.88	6.31	10.61	13.87	5.37
TGARCH	1.58	2.99	5.01	2.56	6.51	8.34	4.73	10.84	14.50	5.36
NGARCH-Jump	1.73	4.16	5.24	3.10	7.75	7.76	7.35	20.67	23.18	6.88
TGARCH-Jump	1.31	4.87	6.56	3.88	10.94	10.99	8.72	23.97	26.67	8.63
Panel D. 5% ≤ RM < 10%										
GARCH	2.12	2.82	2.09	7.05	4.81	4.26	8.28	4.18	5.62	4.37
EGARCH	0.49	2.26	3.67	1.69	5.91	9.18	3.96	11.97	13.93	5.14
GJR-GARCH	0.73	2.54	3.54	3.72	11.99	11.77	11.80	28.65	23.91	8.60
NGARCH	0.38	1.70	3.47	2.01	4.39	8.19	5.50	9.50	11.12	4.53
TGARCH	0.51	1.90	3.53	1.94	4.83	8.38	5.16	9.68	11.55	4.67
NGARCH-Jump	0.74	2.58	4.60	1.66	6.09	7.22	6.54	19.43	23.07	6.13
TGARCH-Jump	0.86	3.92	6.62	2.58	9.26	10.37	7.83	20.49	24.79	7.99
Panel E. 10% ≤ RM										
GARCH	—	—	—	12.11	12.08	4.69	26.43	23.29	13.78	13.08
EGARCH	—	—	—	1.55	3.50	6.35	3.38	12.22	16.33	4.85
GJR-GARCH	—	—	—	3.80	13.26	11.13	16.99	35.50	32.95	12.55
NGARCH	—	—	—	9.17	8.22	3.55	19.56	15.64	7.05	9.33
TGARCH	—	—	—	6.39	4.33	2.66	7.26	1.18	5.35	5.04
NGARCH-Jump	—	—	—	4.14	2.44	6.15	3.24	9.47	18.94	5.61
TGARCH-Jump	—	—	—	3.84	13.59	11.26	15.08	32.90	34.52	12.39

Table 9
Mean Absolute Dollar Forecast Errors by Maturities and Moneyness in the Post-Crash Period under Market Momentum

This table reports mean absolute forecast errors of S&P 500 index call options traded on the CBOE from January 1996 to December 2005 in the post-crash period under market momentum for three financial crises: Russian debt default (August 17, 1998), 9/11 attack (September 11, 2001), and the WorldCom scandal (July 21, 2002). Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. The post-crash period is defined as from the fourth month after the crisis event occurred till three months before the next crisis event. Call options are classified into three days-to-maturity categories of 10-29, 30-89, and 90-180 days, and three moneyness categories of out-of-the-money (OTM, if $(S-K)/K <$ -0.03), near-the-money (NTM, if $-0.03 \le (S-K)/K < 0.03$), and in-the-money (ITM, if $(S-K)/K \ge 0.03$). The market momentum is defined as the cumulative returns of past 60-day S&P 500 indices, RM(t-60, t-1), in which there are five categories: (1) RM<-10%, (2) -10%≤RM<-5%, (3) -5%≤RM<5%, (4) 5%≤RM<10%, and (5) 10%≤RM.

Days to Maturity	10 - 29			30 - 89			90 - 180			
Moneyness	OTM	NTM	ITM	OTM	NTM	ITM	OTM	NTM	ITM	Total
				Panel A. RM < -10%						
GARCH	3.01	4.33	3.82	9.25	10.75	5.59	14.78	14.79	9.12	8.13
EGARCH	2.73	3.46	3.65	5.07	4.47	3.72	4.81	4.25	5.52	4.21
GJR-GARCH	1.62	4.05	4.39	4.64	11.44	9.47	13.32	27.34	19.78	7.89
NGARCH	4.94	5.75	3.86	13.78	14.87	6.72	21.14	20.17	11.66	11.41
TGARCH	4.35	5.06	3.71	10.14	10.51	4.64	12.46	10.72	5.97	7.97
NGARCH-Jump	1.85	4.03	8.36	4.16	5.91	6.82	5.11	13.42	17.40	5.54
TGARCH-Jump	3.28	6.35	8.05	6.84	14.92	14.26	12.33	23.74	23.66	10.04
				Panel B. -10% ≤ RM < -5%						
GARCH	3.41	3.73	3.38	5.88	5.93	5.16	9.51	11.73	9.84	6.14
EGARCH	2.29	2.39	2.94	3.37	3.84	5.12	4.62	9.01	10.23	4.13
GJR-GARCH	1.46	3.82	3.98	5.69	13.71	9.89	15.84	32.06	24.63	10.14
NGARCH	3.89	3.45	2.71	7.70	6.18	4.30	11.36	11.58	7.94	6.71
TGARCH	3.25	2.89	2.69	5.74	4.63	4.30	7.37	8.63	6.97	5.13
NGARCH-Jump	1.49	3.74	7.63	3.04	8.83	10.05	9.12	22.74	23.19	7.50
TGARCH-Jump	3.09	6.53	7.66	6.95	11.74	10.12	13.02	24.42	24.56	10.05
				Panel C. -5% ≤ RM < 5%						
GARCH	3.53	2.99	2.04	5.65	4.71	3.46	8.35	7.28	6.81	4.75
EGARCH	3.01	2.91	1.96	4.84	4.91	3.36	6.89	7.69	7.27	4.50
GJR-GARCH	1.47	2.35	2.66	4.08	8.43	7.34	11.88	23.76	18.08	7.30
NGARCH	3.93	3.10	1.92	6.90	5.79	3.12	11.04	9.29	5.96	5.54
TGARCH	3.71	3.19	1.89	6.31	5.57	3.00	9.19	8.12	5.85	5.12
NGARCH-Jump	1.70	2.86	5.56	3.30	6.02	7.35	6.97	15.37	18.35	6.05
TGARCH-Jump	2.98	3.39	3.60	5.20	6.34	6.08	8.46	12.16	16.48	6.19
				Panel D. 5% ≤ RM < 10%						
GARCH	2.75	2.25	2.14	3.73	3.71	3.46	6.29	6.35	6.16	3.75
EGARCH	1.97	2.04	2.23	2.98	4.06	3.68	6.39	7.88	6.46	3.80
GJR-GARCH	1.42	3.04	2.98	4.95	9.66	7.18	12.28	24.05	16.90	7.98
NGARCH	2.57	2.09	2.22	3.87	4.19	3.42	8.11	8.39	5.58	4.09
TGARCH	2.59	2.19	2.14	3.85	4.17	3.31	7.50	8.03	5.51	4.00
NGARCH-Jump	1.33	3.51	5.84	3.34	7.17	7.52	7.84	16.75	17.83	6.85
TGARCH-Jump	2.37	3.56	3.85	4.40	7.32	6.26	9.25	15.12	16.52	6.68
				Panel E. 10% ≤ RM						
GARCH	2.79	3.44	2.44	3.88	4.94	5.27	6.58	8.81	10.18	4.97
EGARCH	1.45	2.52	3.00	2.55	6.05	7.08	5.75	11.97	13.41	5.47
GJR-GARCH	1.76	4.23	3.52	6.67	15.28	10.64	15.76	32.62	23.19	11.42
NGARCH	1.73	2.59	2.93	2.87	5.60	6.56	6.22	10.33	11.53	5.19
TGARCH	1.58	2.43	2.94	2.50	5.34	6.61	5.37	10.15	11.88	5.00
NGARCH-Jump	1.74	4.66	5.75	4.63	12.53	11.78	11.04	25.51	23.23	10.23
TGARCH-Jump	1.96	4.30	4.51	4.84	11.14	9.79	10.54	23.21	24.44	9.41

Table 10

Regression Results of Absolute Dollar Forecast Errors

The sample contains S&P 500 index call options traded on the CBOE from January 1996 to December 2005. Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. The dependent variable is the absolute forecast error ($AE_{i,t}^{GH}$) defined as the absolute difference between the observed market price and the model price of option i at time t. Independent variables include the cumulative returns of past 60-day market indices *(RM(t-60, t-1)),* implied volatilities ($IMPLYvol_{i,t}$) derived using the Black-Scholes formula, days to maturity ($TM_{i,t}$), moneyness ($(S_t - K_i)/K_i$), and the three-month US Treasury bill middle rate as the surrogate for risk-free rate (rf_t) at time *t*. Standard errors based on White's (1980) heteroskedasticity consistent estimators are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

$$AE_{i,t}^{GH} = w_0 + w_1 RM_{t-60,t-1} + w_2 IMPLYvol_{i,t} + w_3 TM_{i,t} + w_4 \frac{S_t - K_i}{K_i} + w_5 rf_t + e_{i,t}^{GH}.$$

	GARCH	EGARCH	GJR-GARCH	NGARCH	TGARCH	NGARCH-Jump	TGARCH-Jump
Intercept	-2.361***	-1.443***	-10.254***	-1.351***	0.304***	-8.24***	-7.133***
	(0.05)	(0.07)	(0.09)	(0.06)	(0.06)	(0.09)	(0.08)
$RM_{t-60,t-1}$	-0.082***	0.023***	0.121***	-0.143***	-0.066***	0.144***	0.032***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$IMPLYvol_{i,t}$	0.175***	0.122***	0.445***	0.121***	0.061***	0.339***	0.429***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$TM_{i,t}$	0.043***	0.041***	0.129***	0.056***	0.042***	0.084***	0.088***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$(S_t - K_i)/K_i$	-0.092***	0.028***	0.001	-0.100***	-0.028***	0.119***	0.042***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
rf_t	0.266***	0.204***	0.306***	0.321***	0.206***	0.682***	0.078***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adj. R^2	0.240	0.213	0.503	0.303	0.213	0.403	0.392

Table 11

Regression Results of Adjusted Absolute Dollar Forecast Errors

The sample contains S&P 500 index call options traded on the CBOE from January 1996 to December 2005. Sample data in which maturity days are less than 10 days or greater than 180 days are excluded. The dependent variable is the adjusted absolute dollar forecast error ($ADJ\_AE_{i,t}^{GH}$) which is the regression error from equation (17). The independent variables include the lagged S&P 500 composite dividend yield (DIV_{t-1}), the lagged default spread (DEF_{t-1}) which is the yield spread between Moody's Baa and Aaa bonds, and lagged term spread ($TERM_{t-1}$) which is the yield spread between ten year bond and six-month T-bill. Standard errors based on White's (1980) heteroskedasticity consistent estimators are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

$$ADJ\_AE_{i,t}^{GH} = c_0 + c_1 DIV_{t-1} + c_2 DEF_{t-1} + c_3 TERM_{t-1} + \eta_{i,t}\,.$$

	GARCH	EGARCH	GJR-GARCH	NGARCH	TGARCH	NGARCH-Jump	TGARCH-Jump
Intercept	1.248***	0.779***	8.101***	1.305***	1.242***	5.529***	2.943***
	(0.10)	(0.08)	(0.13)	(0.10)	(0.08)	(0.13)	(0.13)
DIV_{t-1}	-2.442***	-0.434***	-6.101***	-2.25***	-1.516***	-4.434***	-2.555***
	(0.05)	(0.04)	(0.07)	(0.05)	(0.04)	(0.07)	(0.06)
DEF_{t-1}	3.713***	0.863***	1.017***	3.505***	2.276***	1.113***	0.626***
	(0.07)	(0.06)	(0.09)	(0.07)	(0.06)	(0.08)	(0.09)
$TERM_{t-1}$	-0.368***	-0.537***	0.355***	-0.486***	-0.516***	0.287***	0.331***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Adj. R^2	0.057	0.023	0.072	0.05	0.042	0.046	0.014