IS INVESTOR MISREACTION ECONOMICALLY SIGNIFICANT? EVIDENCE FROM SHORT- AND LONG-TERM S&P 500 INDEX OPTIONS

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Several recent studies present evidence of investor misreaction in the options market. Although the interpretation of their results is still controversial, the important question of economic significance has not been fully addressed. Here this gap is addressed by formulating regression-based

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tests to identify misreaction and its duration and constructing trading strategies to exploit the empirical patterns of misreaction. Regular S&P 500 index options and long-dated S&P 500 LEAPS are used to find an underreaction that on average dissipates over the course of 3 trading days and an increasing misreaction that peaks after four consecutive daily variance shocks of the same sign. Option trading strategies based on these findings produce economically significant abnormal returns in the range of 1–3% per day. However, they are not profitable in the presence of transaction costs. Jrl Fut Mark 25:717–752, 2005

INTRODUCTION

Investor misreaction has recently been proposed as an explanation of certain empirically confirmed stock market anomalies such as momentum effects in the intermediate horizon and return reversals in the long horizon.[1] For example, Barberis, Shleifer, and Vishny (1998, BSV hereafter) argue that investors initially tend to underreact to new information because of a conservatism bias, but will eventually overreact to a series of similar information. This latter effect, the so-called representativeness bias, interacts with conservatism bias to generate the observed temporal patterns in stock returns. The empirical implications of these behavioral models have been examined in the context of the stock market by Hong, Lim, and Stein (2000), among others.

An important implication of these behavioral theories is that investor misreaction should be pervasive and not necessarily restricted to the stock market. In this respect, the options market is also a natural candidate for testing this sort of theory. However, to date there are few studies that deal with the subject of investor misreaction in the options market. In an early article, Stein (1989) finds evidence that 2-month options overreact to shocks to volatility implied from 1-month options. Poteshman (2001) finds that options maturing 1 month after the short-maturity ones respond less than short-maturity options to current variance shocks, but the difference in response is reduced or even reversed when the current variance shock is preceded by a sequence of similar shocks. These findings provide evidence in support of predictions of the BSV model.

[1]For evidence on short-run momentum effects, see Jegadeesh and Titman (1993) and Chan, Jegadeesh, and Lakonishok (1997). For evidence on long-run return reversal, see Fama and French (1988), Poterba and Summers (1988), and De Bondt and Thaler (1985). The list of behavioral explanations includes Barberis, et al. (1998), Daniel, Hershleifer, and Subrahmanyam (1998), and Hong and Stein (1999).

In spite of these important developments, there is still a concern as to whether the extent of misreaction in the options market is economically significant after accounting for transaction costs. To address this issue, option trading strategies based on the identified misreaction patterns are constructed. After all, momentum and contrarian effects in the stock market were first discovered through buy-and-hold strategies, and investor misreactions in the options market would seem vacuous if they do not result in similar profit patterns. Significant abnormal returns, after accounting for transaction costs, would strengthen the claim of "anomaly" and lead to future efforts to understand the economic sources of such returns. On the contrary, the absence of abnormal returns would suggest that even if investor misreaction is taken at its face value, it is still not exploitable.

The focus on the economic significance of investor misreaction in the options market suggests several important ways to extend the existing literature. First, it is necessary to search for misreactions in options with a much wider range of maturities than those used in existing studies. Stein (1989) suggests that

> In order for such ignorance of mean reversion in volatility to translate into large pricing errors, the options involved would have to be quite long-lived. Thus, it would be very interesting to know whether investors in long-dated options also tend to overreact to changes in short-term implieds. If they do, the mispricings involved are likely to be much more economically significant.

Consequently, options with a distinct maturity structure are used—regular S&P 500 index options with maturities less than 1 year and long-dated S&P 500 LEAPS with maturities up to 3 years, to study the economic significance of investor misreaction.

Second, regression-based tests of investor misreaction are formulated with an eye toward the design of trading strategies that exploit such patterns. In contrast to the tests in Stein (1989) and Poteshman (2001), which focus on the contemporaneous differences between short- and long-term implied variances, the result of these tests allows one to trade long-term options with the history of implied variances from short-term options used as a trading signal. Specifically, in these tests the variance shocks implied from a set of short-term options are used as a benchmark to see how they predict the prices (volatilities) of longer-term options. Short-run underreaction implies that information is impounded into prices slowly. This necessitates the inclusion of lagged variance shocks as explanatory variables, which would then tell us how fast new information is impounded into option prices. Separately, a sequence of daily variance shocks of the same sign tends to increase the response of longer-term option prices to a contemporaneous variance shock. This path-dependent effect, which may generate overreaction to persistent information, can only be captured through the use of carefully designed interaction terms in a regression. Because variance shocks occur daily in the options market, the observed data represent a constant interaction between underreaction and overreaction as new information develops and old information decays. A joint formulation is important because it takes into account the richness of this information structure and is necessary for properly identifying and trading on the two biases in the BSV model.

The regression tests yield two major results. First, it is found that both medium-term regular S&P 500 index options (those with maturities between 180 and 365 days) and long-term S&P 500 LEAPS (those with maturities greater than 365 days) underreact to short-term variance shocks. The evidence indicates that the effect of these shocks dissipates over the course of 3 days, lending support to the slow incorporation of new information into longer-term option prices. Second, the response of longer-term options to a contemporaneous short-term variance shock is found to increase in the extent of past similar shocks. Specifically, the strongest response appears when there is a string of four consecutive variance shocks (the contemporaneous shock included), all of which have the same sign. Although this indicates increasing misreaction, the evidence for eventual overreaction is rather weak and does not survive robustness checks.

Two momentum-type trading rules in the S&P 500 index options markets are studied—one based on all signals and the other on strong signals. Specifically, a long (short) position in the longer-term option portfolio is entered into each day (1) when the unexpected change in the short-term variance is positive (negative), or (2) when the relative unexpected change in the short-term variance is sufficiently positive (negative). The position is liquidated the next day and the daily average return is used to assess the profitability of these trading strategies. Several option portfolios are considered, including ones that consist of all long-term LEAPS, only in-the-money, at-the-money, or out-of-the-money LEAPS. A similar test is implemented with the use of medium-term S&P 500 index options. For each trading rule, both unhedged and delta-hedged option portfolios are examined. Overall, the findings can be summarized as follows.

Trading rules that exploit investor underreaction lead to positive abnormal returns between 1 and 3% per day if long-term LEAPS are traded. The trading profits are statistically and economically significant trading costs are taken into account. The abnormal returns are the largest if out-of-the-money LEAPS are traded. Next, a qualitatively similar conclusion can be drawn when medium-term index options are used instead of long-term LEAPS. Last, the robustness of the trading results is considered with different trading signals, extended holding periods, more complex versions of the stochastic variance model, and different regression tests for misreaction. The results remain qualitatively the same.

Although these results are consistent with the predictions of the BSV model, trading mechanisms based on investor underreaction in the index options market are unable to generate an excess return that outperforms rule-of-thumb measures of option market transaction costs. The momentum-style strategy based on the finding of initial underreaction yields a highly significant average excess return on the order of 1–3% per day. This is, nevertheless, dwarfed by bid–ask spreads that could easily be as much as 5% of the option price even for the most liquid contracts.

It should be emphasized that this lack of economic significance is limited to investor misreaction in the index options market. It is possible that this conclusion does not extend to similar trading strategies implemented in other markets. However, even for the stock market, where bid–ask spreads are much lower, whether momentum profits can survive transaction costs is still widely debated. For example, Lesmond, Schill, and Zhou (2003) find that most of the momentum profits come from trading stocks with disproportionately large transaction costs (which include bid–ask spreads, commissions, price impact of trades, short sale costs, etc.). Korajczyk and Sadka (2004) estimate the price impact of trades and find the largest momentum fund size before trading profits disappear to be around $5 billion. Although the quantitative results may differ across markets, it appears that the economic significance of market anomalies is a universal concern.

The rest of the article is organized as follows. First regression-based tests for investor misreactions are formulated. This is followed by a description of the options data and the estimation method for the instantaneous variances. A detailed analysis of investor misreaction based on the regression results is next presented, followed by an examination of the profitability of trading strategies that exploit quantitative findings in the preceding sections. Concluding remarks are then offered.

TESTS FOR INVESTOR MISREACTION IN THE OPTIONS MARKET

This section concentrates on the formulation of regression-based tests used to examine initial underreaction, eventual overreaction and the process through which the transition takes place. For simplicity, assume that there are two daily time series of instantaneous variances, one inferred from short-term options, V_t^S, the other from long-term options, V_t^L. Given any option pricing model, the unexpected daily change in variance is defined as $\Delta V_t^{S,\text{unexpected}}$ and $\Delta V_t^{L,\text{unexpected}}$, respectively for the short-term and the long-term series.

Assume that the instantaneous variances follow the stochastic volatility (SV) model of Heston (1993):

$$dV_t^i = (\theta_V^* - \kappa_V^* V_t^i)\,dt + \sigma_V^* \sqrt{V_t^i}\,dW_t, \quad i = S, L \tag{1}$$

where κ_V^*, θ_V^*/κ_V^*, and σ_V^* are the speed of adjustment, long-run mean and variation coefficient of the volatility V_t. W_t is a standard Brownian motion under the physical measure, and the superscript i denotes short (S) or long (L) term options. The unexpected change in variance over time period τ is given by

$$\Delta V_t^{i,\text{unexpected}} = (V_t^i - V_{t-1}^i) - \left(\frac{\theta_V^*}{\kappa_V^*} - V_{t-1}^i\right)(1 - e^{-\kappa_V^* \tau}), \quad i = S, L \tag{2}$$

If the Heston model correctly describes the true volatility process, then $V_t^S = V_t^L$ and $\Delta V_t^{S,\text{unexpected}} = \Delta V_t^{L,\text{unexpected}}$.

Investor misreaction leads to a departure from these equalities. In this article, *misreaction* is taken to mean investors under- or overadjust long-term option volatility in response to a change in short-term option volatility. There are several reasons for using short-term options as the benchmark, or the source of information. First, short-term options have the highest volume and the best liquidity among all options, and sophisticated traders often use information extracted from short-term options to price medium- and long-term options. This suggests a special information role for short-term options. Second, it is common in the existing literature on the information content of implied volatilities to extract true volatility estimates from short-term options. The choice of short-term options as the source of information would be consistent with this practice. Finally, in results not presented here, the variances implied from long-term and medium-term options contain roughly the same information (with a correlation coefficient close to 90%). The information contained in short-term options, however, is rather distinctive.

One of the possible misreactions is an underreaction of V_t^L to new information contained in the benchmark V_t^S. This phenomenon would be consistent with the conservatism bias in the BSV model and the empirically observed return continuation after an earnings announcement. As this implies that new information is slowly incorporated into prices, a regression-based test can be formulated as

$$\Delta V_t^{L,\text{unexpected}} = \alpha + \sum_{k=0}^{K} \beta_k \Delta V_{t-k}^{S,\text{unexpected}} + \varepsilon_t \tag{3}$$

where K is a predetermined number. Specifically, β_k measures the effect of a variance shock that occurred k days ago, or alternatively, the effect of a current variance shock k days into the future. Underreaction and the subsequent catching up is confirmed when the leading term $\beta_0 < 1$ and $\beta_k > 0$ for $k \geq 1$.

The purpose of this test is to shed light on the question of how fast new information is fully incorporated into prices. The understanding of this question is of critical importance to the design of trading strategies that seek to earn abnormal returns by exploiting momentum effects. For instance, in the stock market it is known that return continuation typically lasts from 3–12 months. This test would yield insight into the same question for the options market. For that one can simply look for the largest number n for which the estimate of β_n is statistically significant. This provides an upper bound on the length of return continuation in the options market.

Another ingredient of the BSV model is the representativeness bias, which suggests that option investors would overreact to the current variance shock when it is preceded by a string of similar shocks. *Similar shocks* is interpreted to mean unexpected changes in variance that are of the *same sign*. Assuming that representativeness bias is the cause of investor overreaction, its impact is likely to be the greatest when investors face a long sequence of consecutive daily variance shocks of the same sign. A test for the representativeness bias can then be formulated as follows:

$$\Delta V_t^{L,\text{unexpected}} = \alpha + \sum_{m=0}^{M} \gamma_m 1_{\{\omega \in A_{m,t}\}} \Delta V_t^{S,\text{unexpected}} + \varepsilon_t \tag{4}$$

where M is a predetermined number. Here ω represents the state of the world and

$$A_{m,t} = \left\{ \begin{array}{l} \Delta V_t^{S,\text{unexpected}}, \Delta V_{t-1}^{S,\text{unexpected}}, \ldots, \Delta V_{t-m}^{S,\text{unexpected}} \text{ are all of the same sign} \\ \text{and } \Delta V_{t-m-1}^{S,\text{unexpected}} \text{ has a different sign} \end{array} \right\} \quad 1 \leq m \leq M-1 \quad (5)$$

and

$$A_{M,t} = \{\Delta V_t^{S,\text{unexpected}}, \Delta V_{t-1}^{S,\text{unexpected}}, \ldots, \Delta V_{t-M}^{S,\text{unexpected}} \text{ are all of the same sign}\} \quad (6)$$

Two things are noted about these sets. First, they are exhaustive and also mutually exclusive. Second, the number $m + 1$ can be simply interpreted as the length of the sequence of shocks with the same sign, going backward in time starting with the current shock. An easier way to understand these sets is to rewrite them in terms of the signs of the realized variance shocks (assuming that $M = 3$):

$$\begin{aligned} A_{0,t} &= \{+ - \cdots, - + \cdots\} \\ A_{1,t} &= \{+ + - \cdots, - - + \cdots\} \\ A_{2,t} &= \{+ + + - \cdots, - - - + \cdots\} \\ A_{3,t} &= \{+ + + + \cdots, - - - - \cdots\} \end{aligned} \quad (7)$$

When this test is conducted, the existence of conservatism bias would suggest that $\gamma_0 < 1$, indicating an initial underreaction to new information when the preceding information is dissimilar. However, there may exist a smallest number n such that

$$\gamma_n > 1 \quad (8)$$

which would indicate that after n consecutive variance shocks of the same sign as the current shock, long-term options would start to overreact to new information. In fact, a sequence of γ_n that is increasing in n (which may or may not eventually exceed 1) can be interpreted as increasing misreaction to information in the framework of Poteshman (2001). This result, which may be insufficient by itself to generate overreaction to the cumulative effect of a sequence of similar shocks (see Stein, 1989), is nonetheless evidence supporting the price-formation process suggested by BSV.

Now combine Equations (3) and (4) into a single regression-based test of investor misreaction:

$$\Delta V_t^{L,\text{unexpected}} = \alpha + \sum_{m=0}^{M} \gamma_m 1_{\{\omega \in A_{m,t}\}} \Delta V_t^{S,\text{unexpected}} + \sum_{k=1}^{K} \beta_k \Delta V_{t-k}^{S,\text{unexpected}} + \varepsilon_t \quad (9)$$

The above equation captures both ingredients in the BSV model. First, investors underreact to new information and information is impounded into prices slowly. Second, investors overreact to new information when it is preceded by a sequence of similar information. These would generate testable hypotheses regarding the coefficients β_k and γ_m as outlined above. Such a joint formulation (with the included lag structure and indicator functions) is necessary because variance shock occurs daily in the options market and the time series of variance represents a constant interplay between investor underreaction and overreaction. For example, suppose that on a given day there is a positive variance shock followed by more positive shocks. The BSV theory predicts that investors will initially underreact but later overreact to new information. Because the overall variance process is mean reverting, a sequence of positive shocks is bound to be followed by negative shocks at some point. This turns investor overreaction to positive shocks into underreaction to negative shocks. As time goes on, this generates a mean-reverting process of investor sentiment.

Note that the formulation above can be generalized by including the effect of similar information from lagged variance shocks:

$$\Delta V_t^{L,\text{unexpected}} = \alpha + \sum_{k=0}^{K}\left(\sum_{m=0}^{M} \gamma_{km} 1_{\{\omega \in A_{m,t-k}\}}\, \Delta V_{t-k}^{S,\text{unexpected}}\right) + \varepsilon_t \quad (10)$$

If overreaction in long-term instantaneous variance is followed by a reversal to the correct level, a test based on the above equation would reveal negative coefficients γ_{km}, where k is some integer greater than or equal to 1 and m is an integer large enough for overreaction to occur according to previous tests such as that based on Equation (9). This would be valuable information for the design of a contrarian strategy. Finally, the asymmetric response across positive and negative shocks is studied with the use of

$$\begin{aligned}\Delta V_t^{L,\text{unexpected}} = \alpha &+ \sum_{k=0}^{K}\left(\sum_{m=0}^{M} \gamma_{km}^{+} 1_{\{\omega \in A_{m,t-k}\}} (\Delta V_{t-k}^{S,\text{unexpected}})^{+}\right) \\ &- \sum_{k=0}^{K}\left(\sum_{m=0}^{M} \gamma_{km}^{-} 1_{\{\omega \in A_{m,t-k}\}} (\Delta V_{t-k}^{S,\text{unexpected}})^{-}\right) + \varepsilon_t \quad (11)\end{aligned}$$

where $(\Delta V_{t-k}^{S,\text{unexpected}})^{+}$ and $(\Delta V_{t-k}^{S,\text{unexpected}})^{-}$ are, respectively, the positive and negative part of the variance shock. These generalizations are pursued in a later section.

ESTIMATION OF OPTION-IMPLIED VARIANCES

Data

Two types of option contracts with distinctive maturity structures are studied. Both are written on the S&P 500 index: (1) regular S&P 500 index options with maturities up to 1 year at inception, and (2) S&P 500 long-term equity anticipation securities (LEAPS), which are long-dated options expiring approximately 2–3 years from the date of initial listing. Unlike regular S&P 500 index options, the underlying security of a LEAPS contract is 1/10th of the S&P 500 index. Thus a LEAPS contract is one-tenth the size of a regular contract. Because of this difference, LEAPS are not convertible to regular S&P 500 contracts even when they have the same number of days to maturity (less than 1 year to expiration).

The sample period is from September 1, 1993 through August 31, 1994.[2] Bid and ask quotes were obtained from the Berkeley Options Database (BODB). For each contract on each trading day, the last reported bid–ask quote that occurred prior to 3 PM Central Standard Time is retained. The S&P 500 index value recorded in the BODB is the index level at the moment when the option bid–ask quote is recorded. Following a standard practice, the two Treasury-bill (or Treasury-note) rates straddling an option's expiration date are used to obtain the interest rate corresponding to the option's maturity. This is done for each contract and on each day.

Several filters are applied to the raw data. First, only puts are retained, because the trading volume of LEAPS is concentrated in put options. Among LEAPS contracts, long-term puts are particularly popular among investors and are actively traded. During the sample period, there are 10,363 (4,558) LEAPS put (call) bid–ask prices recorded in the BODB. In addition, 5,511 puts and 162 calls are actually traded, respectively. In the analysis, the midpoint between bid and ask prices as a representation of the true market value of a put is used. Quotes on options with less than 6 days to expiration are eliminated, to avoid possible expiration-related price effects. Finally, to minimize the impact of price discreteness, quotes with prices less than $3/8 are excluded.

[2]Prior to 1993, the trading volume of LEAPS is thin relative to that of regular S&P 500 index options. Furthermore, more recent intradaily options data from U.C. Berkeley and CBOE could not be obtained because of the Justice Department's investigation of collusion on the CBOE.

The final sample contains 4,074 LEAPS (with time to expiration greater than 365 days) and 8,018 regular put quotes. The regular put-option sample is further divided into two time-to-expiration categories—those with maturity less than 60 days and those between 180 and 365 days. Let T be the days to expiration. A put option is said to be short term if $T < 60$, medium term if $180 \leq T < 365$, and long-term if $T \geq 365$. There are 4,772, 3,246 and 4,074 short-, medium-, and long-term put quotes, respectively, in the sample. A put is said to be at-the-money (ATM) if $0.97 < K/S < 1.03$, out-of-the-money (OTM) if $K/S \leq 0.97$, and in-the-money (ITM) if $K/S \geq 1.03$, where S is the index level and K the strike price. The average price of a short-term ATM put is \$6.68, whereas the average price of a long-term ITM LEAPS put is \$36.57.

Estimation Method

The tests for investor misreaction based on a sequence of instantaneous variances were formulated in the previous section. This raises the issues of model selection and volatility estimation. Across the vast literature of option pricing, models range from the simple Black-Scholes to sophisticated jump-diffusion stochastic volatility models. Even when there is a reasonable degree of confidence in a given model, there could still be many different estimation techniques to choose from.

The starting point of this analysis is the Heston (1993) stochastic volatility model, which represents the first-order improvement upon the Black-Scholes model as judged by the out-of-sample pricing and hedging performance. This is true for both regular S&P 500 index options and S&P LEAPS (see Bakshi, Cao, and Chen, 1997, 2000). This article uses the method of simulated moments (MSM) to estimate the structural parameters of the SV model. Compared to methods that imply out the structural parameters jointly with the instantaneous variances on a daily basis, this methodology is computationally more intensive, though superior, because it uses the time-series information contained in option prices in a way that is consistent with the model's assumptions. For completeness, a brief explanation of the option pricing framework as well as the MSM technique is included in Appendix A. The interpretation of structural parameters of the stochastic volatility model (e.g., κ_V, θ_V, σ_V, and ρ) is also provided in the Appendix A.

The estimation provides the following structural parameters: $\kappa_V = 1.1325$, $\theta_V = 0.0305$, $\sigma_V = 0.202$, $\rho = -0.249$. As in Poteshman (2001), it is assumed that the market price of volatility risk parameter

$\lambda = -\kappa_V/2$. As a result, the relevant structural parameters under the physical measure are: $\kappa_V^* = 1.69875$ and $\theta_V^* = 0.0305$ (see the Appendix). These parameters are used to compute the unexpected change in variance following Equation (2), using the instantaneous variances extracted with the procedure described later. It is noted that the choice of the volatility risk premium λ makes little difference for subsequent results. For example, experimentation with different values of volatility risk premia (e.g., $\lambda = -0.25\kappa_V$, $\lambda = -0.50\kappa_V$, $\lambda = -0.75\kappa_V$, and $\lambda = -1.0\kappa_V$) showed that the conclusions were qualitatively similar. One reason for this result is that because unexpected changes are computed on a 1-day horizon when the estimated mean reversion half life is on the order of a year ($\kappa_V = 1.1325\ \mathrm{Yr}^{-1}$), the expected changes are virtually zero.

Assuming that structural parameter estimates have been obtained via the MSM estimation, the instantaneous variance V_t on any given day can be obtained with the use of all available put prices on that day. Specifically, let N be the total number of observed puts on day t, $\hat{P}_n(t, \tau_n, K_n)$ and $P_n(t, \tau_n, K_n; \Phi, V_t)$ be the observed and theoretical price of the nth put, respectively, and Φ the collection of structural parameters. With the use of the MSM estimates of Φ as input, V_t can be found by minimizing the sum of squared pricing errors:

$$\min_{V_t} \sum_{n=1}^{N} (\hat{P}_n(t, \tau_n, K_n) - P_n(t, \tau_n, K_n; \Phi, V_t))^2 \qquad (12)$$

This procedure yields a time series of instantaneous variances based on all observed option prices. The same procedure can also be implemented using options from a given maturity category. This results in the time series of instantaneous variances implied from short-term, medium-term, and long-term options, which are used in the formulation of the empirical tests in the previous section.

DO LEAPS INVESTORS MISREACT TO NEW INFORMATION?

Although the focus of the article is the economic implication of investor misreaction in the S&P 500 LEAPS market, it is important to understand whether investors underreact or overreact to new information before examining profits from trading strategies that exploit investor misreaction. Furthermore, the design of trading strategies relies on how long the underreaction/overreaction (if any) persists. This section presents evidence of investor underreaction and overreaction by examining the

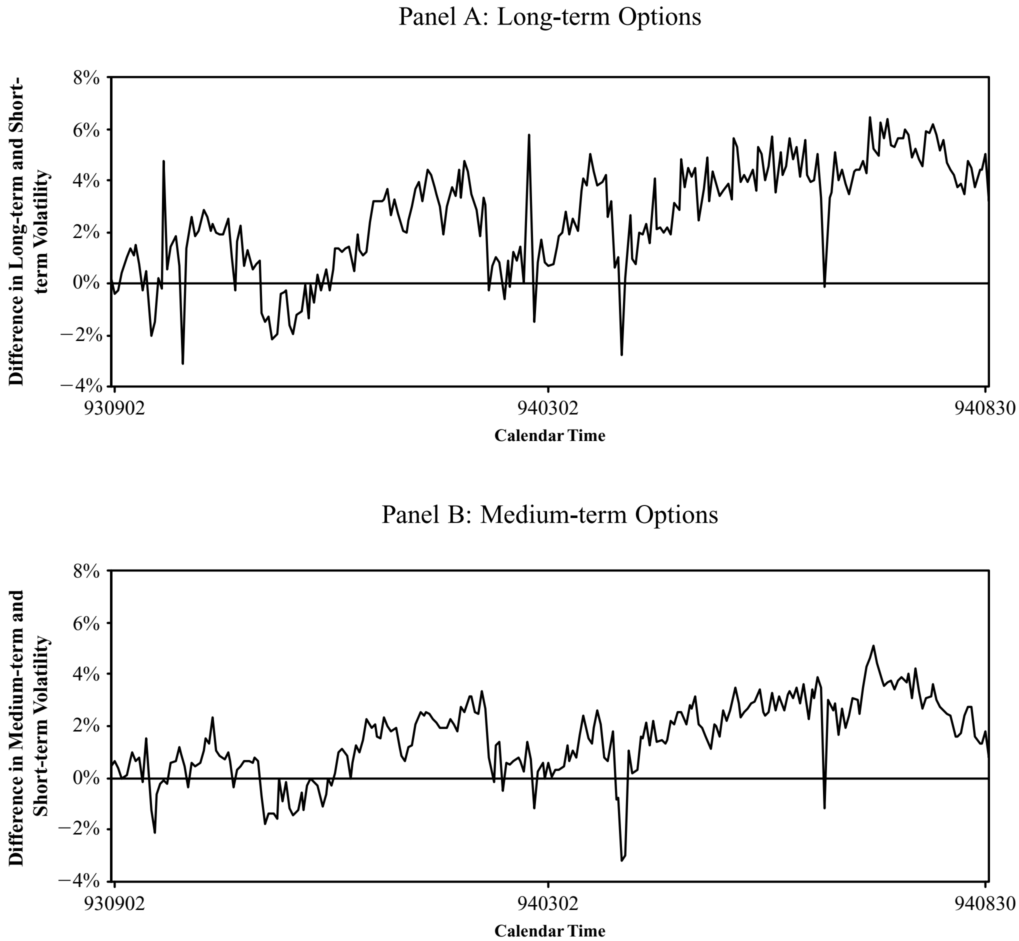

FIGURE 1
Difference between short-term and longer-term implied volatility. This figure plots the difference between long-term (medium-term) and short-term instantaneous volatility implied from the Heston stochastic volatility model for the sample period of September 1, 1993 to August 31, 1994.

relationship between unexpected changes in short- and longer-term instantaneous variances.

To appreciate the differential information contained in long-term (medium-term) and short-term options, Figure 1 plots the difference between long-term (medium-term) and short-term instantaneous volatilities estimated with the use of the Heston (1993) model. There are substantial differences between longer-term and short-term volatilities (as large as 6%), and the differences are consistently positive. On the other hand, the two plots are similar during most of the sample period, suggesting a high correlation between long- and medium-term volatilities.

Table I presents results of the regression test for investor underreaction. The test is based on Equation (3), where the daily unexpected

TABLE I
Tests for Investor Underreaction to New Information

Parameters	*Medium-term options*	*Long-term options*
α	0.000 (0.14)	0.000 (0.30)
β_0	0.186* (5.72)	0.271* (3.17)
β_1	0.148* (4.45)	0.267* (3.04)
β_2	0.032 (0.95)	−0.060 (−0.68)
β_3	0.014 (0.43)	0.122 (1.38)
β_4	−0.022 (−0.67)	−0.047 (−0.54)
β_5	0.028 (0.87)	−0.037 (−0.44)
R^2	0.159	0.083

Note. Regression tests for investor underreaction to new information in the S&P 500 index options market. The regression results are based on the following equation:

$$\Delta V_t^{i,\text{unexpected}} = \alpha + \sum_{k=0}^{5} \beta_k \, \Delta V_{t-k}^{S,\text{unexpected}} + \varepsilon_t, \quad i = M, L$$

where $\Delta V_t^{i,\text{unexpected}}$ is the daily unexpected change in instantaneous variance and the superscript i denotes short-term (S), medium-term (M), or long-term (L) options. The instantaneous variance is obtained from the Heston stochastic volatility model, which is estimated by the method of simulated moments. The sample period extends from September 1, 1993 to August 31, 1994. An option is said to be short term, medium term, or long term if it has less then 60 days, between 180 and 365 days, or longer than 365 days to expiration. t statistics are in parentheses.

*Denotes significance at the 5% level.

change in long-term (or medium-term) instantaneous variance is regressed on the unexpected change in short-term instantaneous variance and its lags. The maximum lag, K, is chosen as 5 trading days. In the case of medium-term options, a contemporaneous short-term variance shock generates a 19% response in the unexpected change in medium-term instantaneous variance. In response to the first lag of short-term variance shock, the unexpected change in medium-term variance is 15%. Subsequent lagged short-term variance shocks have no significant impact on the unexpected change in medium-term instantaneous variance. The results are similar for long-term options. The coefficient of the contemporaneous short-term variance shock is 27%, and the coefficient of its first lag also 27%. This evidence is largely consistent with the slow incorporation of new information into medium-term and LEAPS option prices and the presence of a conservatism bias. The effect of daily variance shocks decays completely by the third trading day.

The test for increasing misreaction is based on Equation (4), where the unexpected change in long-term (or medium-term) instantaneous variance is regressed on the unexpected change in short-term instantaneous variance multiplied by dummy variables. Each dummy variable $1_{\{\omega \in A_{m,t}\}}$ indicates whether on day t the sequence of current and past short-term instantaneous variance shocks of the same sign has length $m + 1$. The coefficient is expected to increase with respect to m if the representativeness bias in the BSV model exists in the options market. To ensure that there are sufficient observations for each m, the maximum m is chosen as 3. The various scenarios of the sequence of short-term variance shocks are summarized in Equation (7).

Estimation and test results are reported in Table II. In general, the coefficient increases as m changes from 0 to 3, with the exception of γ_2. For medium-term options, the response of instantaneous variance to the

TABLE II

Tests for Increasing Investor Misreaction to a Series of Similar Information

Parameters	*Medium-term options*	*Long-term options*
α	0.000 (−0.09)	0.000 (0.30)
γ_0	0.054 (1.23)	0.091 (0.80)
γ_1	0.270* (5.10)	0.400* (2.91)
γ_2	0.136 (1.19)	−0.291 (−0.98)
γ_3	0.452* (3.33)	1.244* (3.53)
R^2	0.140	0.084

Note. Regression tests for increasing investor misreaction to new information in the S&P 500 index options market. The regression results are based on the following equation:

$$\Delta V_t^{i,\text{unexpected}} = \alpha + \sum_{m=0}^{3} \gamma_m 1_{\{\omega \in A_{m,t}\}} \Delta V_t^{S,\text{unexpected}} + \varepsilon_t, \quad i = M, L$$

where $\Delta V_t^{i,\text{unexpected}}$ is the daily unexpected change in instantaneous variance and the superscript i denotes short-term (S), medium-term (M), or long-term (L) options. The sets $A_{m,t}$ are exhaustive and mutually exclusive and describe the property of the sequence of past variance shocks (current shock $\Delta V_t^{S,\text{unexpected}}$ inclusive). Specifically, $\omega \in A_{m,t}$ if the sequence of past variance shocks with the same sign is of length $m + 1$ ($\omega \in A_{3,t}$ if the length is 4 or longer). The instantaneous variance is obtained from the Heston stochastic volatility model, which is estimated by the method of simulated moments. The sample period extends from September 1, 1993 to August 31, 1994. An option is said to be short term, medium term, or long term if it has less then 60 days, between 180 and 365 days, or longer than 365 days to expiration. t statistics are in parentheses.

*Denotes significance at the 5% level.

concurrent shock in short-term instantaneous variance is only 5% and insignificant when the current shock and the preceding shock are of opposite sign. However, the coefficient increases to 27% when the preceding shock is of the same sign, and 45% when the preceding shocks over a 3-day period are of the same sign as the current shock. These coefficient estimates are highly significant, with p values less than 0.01. This result can be construed as strong evidence of increasing misreaction to new information. For long-term options, supporting evidence is found that the initial underreaction eventually becomes overreaction. For instance, the coefficients γ_0 and γ_1 are 9 and 40%, respectively. As the number of consecutive daily shocks with the same sign increases to four or more, the coefficient of the unexpected change in short-term instantaneous variance grows to 124%, which is close to one standard deviation greater than 1. Therefore, overreaction to a current shock does occur after investors observe a sufficiently long series of shocks in the same direction. It is worthwhile to point out that increasing misreaction is path dependent. Depending on the signs of subsequent variance shocks, an initial underreaction can change to overreaction.

The preceding evidence indicates that long-term option investors underreact to new information as measured by the unexpected change in short-term instantaneous variance. Yet the evidence also suggests that there is an increasing misreaction. To enrich the understanding of misreaction, a joint test of both underreaction and increasing misreaction is performed. The test is based on Equation (9), where the unexpected change in long-term (or medium-term) instantaneous variance is regressed on lagged unexpected changes in short-term instantaneous variance, and the unexpected change in short-term instantaneous variance is multiplied by dummy variables described in Table II. The results reported in Table III show that, after investor underreaction is controlled for, the effect of increasing misreaction remains significant. Take long-term options as an example. The coefficient γ_1 is 33% and significantly less than 1, indicating initial underreaction, whereas the coefficient γ_3 is 105%, indicating marginal overreaction when four consecutive shocks of the same sign are observed.

An additional test is performed to examine the persistence of the effect of a string of similar variance shocks.[3] The test is based on

[3]With results not shown here, a further test based on Equation (11) was conducted to examine asymmetric underreaction and increasing misreaction to positive and negative variance shocks. Lee and Swaminathan (2000) provide evidence that firm-specific bad news is incorporated into stock prices more slowly than good news, a result consistent with Hong et al. (2000). However, asymmetries are not found in the index options market.

TABLE III

Joint Tests for Underreaction and Increasing Misreaction

Parameters	*Medium-term options*	*Long-term options*
α	0.000 (0.09)	0.000 (0.48)
γ_0	0.134* (2.57)	0.292* (2.15)
γ_1	0.241* (4.51)	0.326* (2.35)
γ_2	0.069 (0.60)	−0.459 (−1.53)
γ_3	0.375* (2.75)	1.052* (2.97)
β_1	0.111* (2.83)	0.278* (2.73)
R^2	0.168	0.112

Note. Joint regression tests for investor underreaction and increasing misreaction in the S&P 500 index options market. The regression results are based on the following equation:

$$\Delta V_t^{i,\text{unexpected}} = \alpha + \sum_{m=0}^{3} \gamma_m 1_{\{\omega \in A_{m,t}\}}\, \Delta V_t^{S,\text{unexpected}} + \beta_1\, \Delta_{t-1}^{S,\text{unexpected}} + \varepsilon_t, \quad i = M, L$$

where $\Delta V_t^{i,\text{unexpected}}$ is the daily unexpected change in instantaneous variance and the superscript i denotes short-term (S), medium-term (M), or long-term (L) options. The sets $A_{m,t}$ are exhaustive and mutually exclusive and describe the property of the sequence of past variance shocks (current shock $\Delta V_t^{S,\text{unexpected}}$ inclusive). Specifically, $\omega \in A_{m,t}$ if the sequence of past variance shocks with the same sign is of length $m + 1$ ($\omega \in A_{3,t}$ if the length is 4 or longer). The instantaneous variance is obtained from the Heston stochastic volatility model, which is estimated by the method of simulated moments. The sample period extends from September 1, 1993 to August 31, 1994. An option is said to be short term, medium term, or long term if it has less then 60 days, between 180 and 365 days, or longer than 365 days to expiration. t statistics are in parentheses.

*Denotes significance at the 5% level.

Equation (10), and the explanatory variables are current and lagged unexpected change in short-term instantaneous variances multiplied by dummy variables described in Table II. It is clear from Table IV that the effect of a string of similar shocks is largely dissipated by the next day, and entirely gone by the third trading day. Notably, no negative γ_{km} coefficients with $k \geq 1$ that would indicate a reversal in the level of long-term implied variances are found. An implication of this result is that increasing misreaction/overreaction cannot be exploited by trading strategies that buy and hold long-term options for just a few trading days.

TABLE IV

Tests for the Effect of a Lagged Sequence of Similar Variance Shocks

Parameters	*Medium-term options*	*Long-term options*
α	0.000 (−0.01)	0.000 (0.24)
γ_{00}	0.121 (2.04)*	0.189 (1.23)
γ_{01}	0.235 (4.36)*	0.296 (2.12)*
γ_{02}	0.088 (0.70)	−0.184 (−0.56)
γ_{03}	0.254 (1.63)	0.501 (1.24)
γ_{10}	0.230 (3.87)*	0.297 (1.93)
γ_{11}	0.006 (0.09)	0.057 (0.34)
γ_{12}	0.206 (1.53)	1.102 (3.15)*
γ_{13}	0.003 (0.02)	0.338 (0.82)
γ_{20}	0.044 (0.89)	−0.142 (−1.11)
γ_{21}	0.162 (2.46)*	0.184 (1.08)
γ_{22}	0.134 (0.97)	−0.561 (−1.57)
γ_{23}	−0.058 (−0.40)	−0.293 (−0.79)
R^2	0.217	0.173

Note. Regression tests for the effect of a lagged sequence of similar variance shocks in the S&P 500 index options market. The regressions are based on the following equation:

$$\Delta V_t^{i,\text{unexpected}} = \alpha + \sum_{k=0}^{2}\left(\sum_{m=0}^{3}\gamma_{km}1_{\{\omega\in A_{m,t-k}\}}\,\Delta V_{t-k}^{S,\text{unexpected}}\right) + \varepsilon_t, \quad i = M, L$$

where $\Delta V_t^{i,\text{unexpected}}$ is the daily unexpected change in instantaneous variance and the superscript i denotes short-term (S), medium-term (M), or long-term (L) options. The sets $A_{m,t-k}$ are exhaustive and mutually exclusive and describe the property of the sequence of past variance shocks (counting backward from the kth lagged shock $\Delta V_{t-k}^{S,\text{unexpected}}$). Specifically, $\omega \in A_{m,t}$ if the sequence of past variance shocks with the same sign is of length $m + 1$ ($\omega \in A_{3,t-k}$ if the length is 4 or longer). The instantaneous variance is obtained from the Heston stochastic volatility model, which is estimated by the method of simulated moments. The sample period extends from September 1, 1993 to August 31, 1994. An option is said to be short term, medium term, or long term if it has less then 60 days, between 180 and 365 days, or longer than 365 days to expiration. t statistics are in parentheses.

*Denotes significance at the 5% level.

IS THERE MONEY TO BE MADE BY EXPLOITING INVESTOR MISREACTION?

In light of the investor misreaction documented by Stein (1989), Poteshman (2001) and this article, an important question that remains unanswered is whether misreaction leads to practical and profitable trading strategies.[4] The answer to this question will provide an economic measure of the size of investor misreaction. As Stein (1989) points out,

[4]In addition to the two articles mentioned above, Poteshman and Serbin (2003) show that customers of discount brokers often exercise stock options suboptimally, and institutional investors do not exhibit this behavior. Poteshman and Mahani (2004) find that unsophisticated investors load up on growth stocks using options prior to earnings announcements, even though growth stocks underform value stocks at such times.

long-lived options are ideal contracts to examine the economic significance of investor misreaction. The preceding analysis suggests that one trading strategy that can be implemented is a momentum-type strategy, which is based on the intuition that long-term option investors underreact to new information, and that new information is incorporated only slowly. Although a statistically significant relationship between $\Delta V_t^{L,\text{unexpected}}$ and $\Delta V_t^{S,\text{unexpected}}$ is found, this relation cannot be exploited, because when forming positions at time $t-1$, one only have access to the information available at that time. As a result, one can only utilize investor misreactions that persist for at least another trading day. Although investor underreaction qualifies because it lasts for 2 days, overreaction must be ruled out, because Table IV shows no perceptible pattern of reversal following a recent overreaction. Here trading strategies are formulated, returns from various strategies are examined.

Short-Term Momentum Strategies

Momentum-type trading strategies based on instantaneous variances implied from short-term options are considered. For simplicity LEAPS are used to illustrate the implementation. Specifically, on each trading day t, the sign of the unexpected change in short-term instantaneous variance, $\Delta V_t^{S,\text{unexpected}}$, is examined. A long (short) position in long-term option portfolio is entered into if the sign is positive (negative). In other words, whenever a buy signal is observed, all LEAPS puts with maturities greater than 365 days are bought in equal quantity (i.e., one contract for each LEAPS put), and the resulting portfolio is a value-weighted portfolio.[5] Once trades are executed, the positions are held for 1 day and liquidated on day $t+1$. Two option positions are considered: (1) a delta-hedged portfolio that eliminates the risk exposure to the underlying S&P 500 index, and (2) an unhedged portfolio. To isolate the effect associated with investor underreaction, the holding period return on the option portfolio in excess of the theoretical expected return is reported, according to Heston's stochastic volatility model.

To make the point precise, Heston's model is used to demonstrate how investor underreaction can be translated into a trading strategy. Extension of the following analysis to other models is straightforward.

[5]Holding an equally weighted option portfolio was also considered, and the results were slightly stronger.

Let P be the price of an option portfolio, and Q be the value of the corresponding delta-hedged portfolio, where

$$Q = P - \frac{\partial P}{\partial S}S \tag{13}$$

From Ito's lemma,

$$dQ = \frac{\partial P}{\partial V}\,dV + \left(\frac{\partial P}{\partial t} + \frac{1}{2}\frac{\partial^2 P}{\partial S^2}VS^2 + \frac{1}{2}\frac{\partial^2 P}{\partial V^2}\sigma_V^2 V + \rho\sigma_V VS\frac{\partial^2 P}{\partial S\partial V}\right)dt \tag{14}$$

Substitute the dynamics of V into the above equation and use the fact that the instantaneous return in the absence of a market price for volatility risk is equal to the constant risk-free rate R; the expected return on portfolio Q is

$$E\left(\frac{dQ}{Q}\right) = R\,dt + \frac{\partial P/\partial V}{P - (\partial P/\partial S)S}\lambda V\,dt \tag{15}$$

where λ is the constant market price of volatility risk as defined in Appendix A. With the use of Equation (14), the abnormal return on portfolio Q is

$$\frac{dQ}{Q} - E\left(\frac{dQ}{Q}\right) = \frac{\partial P/\partial V}{P - (\partial P/\partial S)S}\,dV^{\text{unexpected}} \tag{16}$$

The above equation shows that the instantaneous abnormal return on an option portfolio is proportional to the unexpected change in variance over the next instant. When one longs (shorts) a put portfolio, the proportionality constant in Equation (16) is positive (negative) because $\partial P/\partial V > 0$ and $\partial P/\partial S < 0$ for puts. In the implementation of trading strategies, Equation (16) should hold approximately for daily abnormal returns:

$$\frac{\Delta Q_t}{Q_{t-1}} - E_{t-1}\left(\frac{\Delta Q_t}{Q_{t-1}}\right) \approx \left.\frac{\partial P/\partial V}{P - (\partial P/\partial S)S}\right|_{t-1} \Delta V_t^{\text{unexpected}} \tag{17}$$

where $\Delta Q_t = Q_t - Q_{t-1}$. Results are reported with $\Delta V_t^{M,\text{unexpected}}$ and $\Delta V_t^{L,\text{unexpected}}$ used in the above equation. To the extent that $\Delta V_t^{M,\text{unexpected}}$ and $\Delta V_t^{L,\text{unexpected}}$ can be predicted from $\Delta V_{t-1}^{S,\text{unexpected}}$, this trading strategy will yield an expected return above $E_{t-1}(\Delta Q_t/Q_{t-1})$. This is the essence of the momentum option strategy.

As shown in Equation (15), the expected option return depends on the market price of volatility risk λ, which can take on a wide range of possible values. Following a standard practice, λ is set to be $-\kappa_V/2$ in all subsequent analyses. To check the robustness of results, λ is set to different values and option returns are recalculated. The results show that different values of λ have no significant impact on the abnormal return from this trading strategy.[6]

To reduce the impact of the model-dependent hedge ratio and theoretical expected return, an alternative implementation of the above strategy is also pursued. In this approach, $\Delta V_t^{S,\text{unexpected}}$ is used as a trading signal, but the option positions are unhedged. For an unhedged option portfolio P, its abnormal return is given by

$$\frac{\Delta P_t}{P_{t-1}} - E_{t-1}\left(\frac{\Delta P_t}{P_{t-1}}\right) = \left.\frac{\partial P/\partial S}{P}\right|_{t-1} \Delta S_t^{\text{unexpected}} + \left.\frac{\partial P/\partial V}{P}\right|_{t-1} \Delta V_t^{\text{unexpected}} \qquad (18)$$

If $\Delta S_t^{\text{unexpected}}$ and $\Delta V_t^{\text{unexpected}}$ are negatively correlated, the abnormal return of an unhedged portfolio will be larger than that of a delta-hedged portfolio.

Note that this strategy is similar to momentum strategies for stocks in the sense that positions are also formed based on the sign of past returns [Equation (17) shows that a positive $\Delta V_t^{M,\text{unexpected}}$ or $\Delta V_t^{L,\text{unexpected}}$ implies a positive abnormal return on a portfolio of longer-term options]. The difference is that this time scale is much shorter—option return momentum persists for just a few trading days, whereas stock return momentum can last for up to a few months.

The trading strategy is implemented in the spirit of out-of-sample tests. The entire sample period is divided into two equal-length subperiods: The first half is used to estimate the structural parameters of the SV model, and the second half is used to calculate option portfolio returns. Table V presents the time-series average of daily abnormal option portfolio returns and the corresponding t statistics. Results from trading medium-term or long-term options, and from long, short, and long-plus-short positions are reported. Within a given maturity category, option returns are presented for trading all options, only ITM, ATM, or OTM options (under the abbreviation ALL, ITM, ATM, or OTM). Furthermore, results based on all signals are reported (i.e., a trade is entered whenever $|\Delta V_t^{S,\text{unexpected}}| > 0$) or strong signals (i.e., trading only when $|\Delta V_t^{S,\text{unexpected}}/V_{t-1}^S| > 0.1$). Approximately, $|\Delta V_t^{S,\text{unexpected}}/V_{t-1}^S| > 0.1$ for half of the sample days.

[6] For brevity, these results are not reported but are available upon request.

TABLE V
Momentum Effects in Option Returns

	Medium-term options				Long-term options			
	ALL	*ITM*	*ATM*	*OTM*	*ALL*	*ITM*	*ATM*	*OTM*
Panel A: Delta-Hedged Option Portfolios								
All signals								
Long	0.50%	0.36%	0.51%	0.87%	0.72%	0.51%	1.06%	1.29%
	(0.78)	(0.72)	(0.62)	(0.76)	(1.83)	(1.53)	(2.04)	(1.86)
Short	0.67%	0.45%	0.79%	0.72%	0.84%	0.64%	1.26%	1.40%
	(1.77)	(1.53)	(1.65)	(1.08)	(4.20)	(3.43)	(4.55)	(3.44)
Long + short	0.60%	0.42%	0.67%	0.78%	0.79%	0.59%	1.18%	1.36%
	(1.75)	(1.56)	(1.55)	(1.28)	(3.98)	(3.36)	(4.41)	(3.66)
Strong signals								
Long	0.80%	0.51%	0.99%	0.38%	1.40%	0.96%	2.16%	2.42%
	(0.91)	(0.71)	(0.87)	(0.26)	(2.37)	(1.84)	(2.92)	(2.55)
Short	1.08%	0.54%	1.38%	1.36%	1.30%	0.94%	1.91%	2.79%
	(1.81)	(1.14)	(1.86)	(1.19)	(4.07)	(3.18)	(4.01)	(5.58)
Long + short	0.96%	0.53%	1.21%	0.92%	1.34%	0.95%	2.02%	2.63%
	(1.87)	(1.27)	(1.86)	(1.00)	(4.26)	(3.36)	(4.80)	(5.22)
Panel B: Naked Option Portfolios								
All signals								
Long	1.16%	0.93%	1.11%	2.06%	0.99%	0.61%	1.82%	2.35%
	(1.13)	(0.96)	(1.01)	(1.54)	(1.70)	(1.10)	(1.91)	(2.16)
Short	0.79%	0.63%	0.76%	1.39%	0.67%	0.41%	1.48%	1.60%
	(1.30)	(1.12)	(1.14)	(1.63)	(2.15)	(1.30)	(3.02)	(1.75)
Long + short	0.94%	0.76%	0.90%	1.66%	0.80%	0.49%	1.48%	1.90%
	(1.71)	(1.46)	(1.52)	(2.25)	(2.67)	(1.69)	(3.02)	(2.72)
Strong signals								
Long	1.52%	1.09%	1.61%	1.38%	1.67%	1.10%	3.14%	2.74%
	(1.03)	(0.76)	(1.01)	(0.78)	(1.86)	(1.27)	(2.02)	(2.25)
Short	1.40%	1.06%	1.51%	1.59%	1.04%	0.65%	1.45%	3.22%
	(1.51)	(1.19)	(1.48)	(1.13)	(2.27)	(1.44)	(1.95)	(2.51)
Long + short	1.46%	1.07%	1.55%	1.49%	1.32%	0.85%	2.19%	3.01%
	(1.77)	(1.35)	(1.74)	(1.37)	(2.81)	(1.87)	(2.74)	(3.38)

Note. Average daily excess returns from a momentum-type trading strategy in the S&P 500 index options market. In the "all signals" implementation, a long (short) position in the option portfolio is entered into each day if the unexpected change in the short-term implied variance $\Delta V_t^{S,\text{unexpected}}$ is positive (negative). In the "strong signals" implementation, a long (short) position in the option portfolio is entered into each day if $\Delta V_t^{S,\text{unexpected}}$ is positive (negative) and in addition, $|\Delta V_t^{S,\text{unexpected}}/V_{t-1}^S| > 0.1$. This position is liquidated on the following day. In Panel A, the portfolios are delta hedged against the S&P 500 index and the daily excess returns are computed with respect to the theoretical daily expected return from the Heston model. In Panel B, the option portfolios are unhedged, and on days when $\Delta V_t^{S,\text{unexpected}}$ is positive (negative), the daily excess returns are computed with respect to the average daily return from always holding a long (short) position in the option portfolio. Data from the first half of the sample period are used to estimate the structural parameters of the stochastic volatility model, and data from the second half of the sample are used to obtain excess returns. Average daily excess returns are presented for days with positive variance shocks (Long), days with negative variance shocks (Short), and all days (L+S). An option is said to be medium term if its time to expiration is between 180 and 365 days, long term if its time to expiration is greater than 365 days, at-the-money (ATM) if its moneyness is between 0.97 and 1.03, out-of-the-money (OTM) if its moneyness is greater than or equal to 1.03, and in-the-money (ITM) if its moneyness is less than or equal to 0.97. t statistics are in parentheses.

Several interesting results emerge from Panel A of Table V, where the option portfolios are delta-hedged. First, all abnormal returns are positive, ranging from 0.36 to 2.79% per day. This is true regardless of whether ITM, ATM, or OTM options are traded. Second, the returns from trading long-term options are consistently higher than those from medium-term options. As a gauge of statistical significance, *t* statistics are reported in parentheses and show that nearly all abnormal returns from trading long-term options are significant at the 5% level. This result indicates that investor underreaction can translate into economic trading profits in the absence of transaction costs. In contrast, trading medium-term options leads to positive but often insignificant abnormal returns. Third, comparing option returns across moneyness categories reveals that trading profits generally increase from ITM to OTM options; the abnormal return from trading OTM options is about 2–3 times larger than that from trading ITM options. Take long-term options and long-plus-short positions as an example. Daily abnormal returns are 0.59, 1.18, and 1.36%, respectively, for trading ITM, ATM, and OTM options when the unexpected change in short-term variance is different from 0. Fourth, using strong signals often leads to larger abnormal returns. This is true for 23 out of 24 cases presented in Table V. Finally, the return differential between long and short positions appears to be small, suggesting that the asymmetric response toward positive and negative unexpected change in instantaneous variance is insignificant. This is consistent with the regression results in the preceding section.

The above conclusions generally hold when option portfolios are unhedged. Panel B of Table V reports abnormal returns from naked option portfolios. In comparison to results from hedged portfolios, the abnormal returns from unhedged portfolios are all positive and generally larger in magnitude. This result is intuitive because the estimation result shows that the unexpected change in variance and the unexpected change in index return are negatively correlated ($\rho = -0.249$).

Two comments are made here. First, the fact that the abnormal returns are consistently positive suggests that the alternative explanation of the documented patterns based on noisy option prices is unlikely to stand. That explanation holds that there is initial underreaction because investors are not sure whether a short-term variance shock is true information or just noise; hence they will tend to underadjust to that shock. If this were true, then the momentum strategy, which goes long in long-term options whenever the short-term shock is positive, will not be expected to generate such a consistently positive abnormal return.

Second, note that the above trading exercise uses bid–ask midpoint as transaction prices, and the magnitude of trading profits is generally smaller than bid–ask spreads in the index options market. For example, for out-of-the-money S&P 500 index LEAPS puts, which are the most liquid contracts in the long-term segment of the market, bid–ask spreads are close to 5% of the option price. Because the option portfolios are bought and then sold the next day, the trading strategies constructed above are unable to generate significant excess returns after accounting for round-trip transaction costs.

Trading Strategies with Extended Holding Periods

Up to this point the trading tests that have been conducted are based on the observation that long-term options underreact to changes in the variance implied from short-term options. Overreaction has been ruled out as a source of potential trading profits, because the evidence for overreaction in the data is weak, and the regression tests do not find a reversal effect following overreaction. It is conceivable, however, that subsequent to an underreaction or overreaction to the current short-term variance shock, the correction to long-term implied variance takes place so slowly that it renders the regression tests ineffective at detecting these patterns. In this case, trading profits should increase as the holding period is lengthened to internalize the predictable pattern in option volatility. Increasing the holding period also has the desirable effect of reducing the impact of transaction costs on daily excess returns, making it more likely to find economic significance for investor misreaction.

The above momentum trading strategy is repeated with holding periods of 3, 5, 10, or 20 trading days. It is found that as the holding period extends from 1 to 3 (or 5) trading days, the average excess return increases slightly. With longer holding periods, the magnitude of the excess return over the holding period is still within the range of 5%. Collectively, this evidence suggests that holding the option portfolio for longer periods cannot generate the additional profits that are necessary to overcome transaction costs.

Similarly, trading strategies based on the overreaction phenomenon are constructed. Specifically, with the use of previous findings, a value-weighted portfolio of longer-term options is sold short (long) whenever a consecutive sequence of four short-term variance shocks with a positive (negative) sign is observed. Irrespective of the holding period, the resulting average excess returns are found to be of no statistical significance. Thus, overreaction is less exploitable than underreaction.

Trading Strategies Based on Implied Variance Levels

Next addressed is the question of whether other formulations of the regression tests for investor overreaction could have led to more profitable trading strategies. This article has worked with regressions formulated with responses to unexpected changes in instantaneous variances. Alternative formulations in the literature have instead examined variance levels. For example, a test of overreaction can be given in terms of variance levels as

$$V_t^L - V_t^S = \alpha + \beta V_t^S + \varepsilon_t \tag{19}$$

with a positive β. The interpretation is that when the overall level of short-term implied variance is high, option investors are likely to be affected by the representativeness bias and as a result overvalue long-term options relative to short-term ones. The higher the short-term variance is, the more mispriced are the long-term options, hence the above relation. This calls for a trading strategy of selling long-term options and buying short-term options whenever short-term implied variance reaches some predetermined threshold value, and liquidating the positions when short-term variance reverts to a level close to its long-run mean.

Although this strategy is straightforward to implement, first it is worthwhile to explain the relationship between the above level-based test and previous tests for overreaction. For this note that the definition of *similar information* leads to the strongest form of overreaction according to the behavioral hypotheses that are the focus of this article. Particularly, if a test based on Equation (9) shows no sign for overreaction, it is unlikely that such evidence will be supplied by a level-based test such as Equation (19)—in short, the former is a necessary condition for the latter. Because the previous tests show only marginally significant overreaction under even the strongest scenario, it is unlikely that there is overreaction in the overall level of implied variance. Indeed, running the above regression test for medium- and long-term options confirms this conjecture. In both cases the β estimate is significantly negative—when short-term implied variance is high, the difference between long-term and short-term implied variance does not seem to be higher. In light of this evidence, trading tests based on overreaction in variance levels are not examined further.

Alternative Option Pricing Models

It is worthwhile to point out that both the regression and trading-rule tests are based on a sequence of instantaneous variances extracted from option prices with the Heston stochastic volatility model. As such, the robustness of the results under alternative specifications of the model is a critical issue.

A first check will determine whether the time series of unexpected change in implied variance is serially independent. This is motivated by the observation that the Heston SV model may not be the best description of the data, even though the SV model provides the first-order improvement in pricing and hedging over the Black-Scholes model. If option prices were generated by the Heston SV model, then autocorrelation should be absent in the sequence of $\Delta V_t^{\text{unexpected}}$. The result shows that the autocorrelation is nonzero—the partial autocorrelations suggest that they should be modeled as an AR(2) process.

The Durbin-Watson test is applied to the regressions in the previous section. The hypothesis of no autocorrelation is rejected at the 5% significance level. The Durbin-Watson statistics are such that the regression residuals are negatively autocorrelated. This result suggests that the autocorrelation in the $\Delta V_t^{M,\text{unexpected}}$ and $\Delta V_t^{L,\text{unexpected}}$ series cannot be fully accounted for by lagged values of $\Delta V_t^{S,\text{unexpected}}$ and other interaction terms designed to capture investor misreactions in the regression equations. Although this does not invalidate the present tests per se, the presence of negatively autocorrelated regression residuals causes the estimated standard errors to be overstated. Therefore, modeling the regression residuals as an autoregressive process can sharpen the precision of the estimates and make it easier to interpret them.

Table VI reproduces the joint test of underreaction and increasing misreaction (previously in Table III) while correcting for the presence of autocorrelation by modeling the residuals as an AR(2) process. The stylized finding of underreaction and increasing misreaction remains

TABLE VI

Effect of Autocorrelated Regression Residuals on the Joint Tests of Underreaction and Increasing Misreaction

Parameters	*Medium-term options*	*Long-term options*
α	0.000 (0.17)	0.000 (0.83)
γ_0	0.143* (3.23)	0.187 (1.86)
γ_1	0.217* (4.44)	0.242* (2.11)
γ_2	0.197 (1.82)	0.074 (0.29)
γ_3	0.328* (2.76)	0.668* (2.46)
β_1	0.118* (3.16)	0.204* (2.24)
ρ_1	0.360* (5.63)	0.501* (8.04)
ρ_2	0.105 (1.64)	0.243* (3.89)
R^2	0.234	0.113
Durbin-Watson	2.04	2.19

Note. This table examines the effect of autocorrelated regression residuals on the joint tests for investor underreaction and increasing misreaction in the S&P 500 index options market. The regression and its residuals are specified through the following equations:

$$\Delta V_t^{i,\text{unexpected}} = \alpha + \sum_{m=0}^{3} \gamma_m 1_{\{\omega \in A_{m,t}\}} \, \Delta V_t^{S,\text{unexpected}} + \beta_1 \, \Delta V_{t-1}^{S,\text{unexpected}} + \varepsilon_t, \quad i = M, L$$

$$\varepsilon_t = \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + e_t$$

where $\Delta V_t^{i,\text{unexpected}}$ is the daily unexpected change in instantaneous variance and the superscript i denotes short-term (S), medium-term (M), or long-term (L) options. The sets $A_{m,t}$ are exhaustive and mutually exclusive and describe the property of the sequence of past variance shocks (current shock $\Delta V_t^{S,\text{unexpected}}$ inclusive). Specifically, $\omega \in A_{m,t}$ if the sequence of past variance shocks with the same sign is of length $m + 1$ ($\omega \in A_{3,t}$ if the length is 4 or longer). The instantaneous variance is obtained from the Heston stochastic volatility model, which is estimated by the method of simulated moments. The sample period extends from September 1, 1993 to August 31, 1994. An option is said to be short term, medium term, or long term if it has less then 60 days, between 180 and 365 days, or longer than 365 days to expiration. t statistics are in parentheses.

*Denotes significance at the 5% level.

qualitatively the same. The only change is that it can no longer be concluded that long-term options eventually overreact to short-term variance shocks. This conclusion is similar to that of Diz and Finucane (1993), who find that the evidence of overreaction documented in Stein (1989) is not robust under an AR(1) specification for the regression residual.

As a second robustness check, implied variances are extracted with the use of the stochastic volatility with jumps (SVJ) model. This model has received considerable attention and has been tested in the context of index options and index futures options (Bakshi et al., 1997; Bates, 2000). It is well known that the jump component adds flexibility in fitting volatility smiles in short-term options, and that the SVJ model has the best performance (relative to the BS and SV models) in pricing short-term options. Because short-term implied variances are relied on for both regression tests and as trading signals for the momentum strategy, it is worthwhile to use a more sophisticated model such as the SVJ to attain a higher level of accuracy for these variables.

Table VII repeats the joint test on the time series of instantaneous variances implied from the SVJ model. The variance estimation follows the two-step procedure outlined previously. A slight difference is that in the SVJ model the instantaneous variance contains two parts:

$$V_t = V_t^D + V_t^J \tag{20}$$

which result from the diffusion and jump term in the variance dynamics, respectively. However, the jump component of variance is a function of structural parameters only and does not vary with time:

$$V_t^J = \lambda_J(\mu_J^2 + (\exp(\sigma_J^2) - 1)(1 + \mu_J)^2) \tag{21}$$

where λ_J, μ_J, and σ_J are the jump frequency per year, and the mean and volatility of the jump size. As a result, only the diffusion part of instantaneous variances is used for the purpose of computing variance shocks and performing subsequent regression analyses. The relevant MSM estimates are $\kappa_V = 1.52$ and $\theta_V = 0.0304$. Again, with the use of a market price of volatility risk parameter $\lambda = -\kappa_V/2$, the structural parameters under the physical measure are $\kappa_V^* = 2.28$ and $\theta_V^* = 0.0304$. These are then used to compute the unexpected change in variance for the three time-to-expiration categories: $\Delta V_t^{S,\text{unexpected}}$, $\Delta V_t^{M,\text{unexpected}}$, and $\Delta V_t^{L,\text{unexpected}}$.

Summary statistics show that these series are very similar to their counterpart extracted from the SV model, with a correlation of 93%. Furthermore, the rate of jump parameter λ_J is estimated to be 0.78, which implies that jumps occur about once a year on average, and its impact on daily changes in stochastic variance is small. Diagnostic tests show that the autocorrelation in these series can also be adequately modeled as an AR(2) process and the estimates in Table VII reflect this

TABLE VII
Effect of Jumps in the S&P 500 Index on the Joint Tests of Underreaction and Increasing Misreaction

Parameters	*Medium-term options*	*Long-term options*
α	0.000 (0.87)	0.000 (1.08)
γ_0	0.172* (3.47)	0.218 (1.73)
γ_1	0.249* (4.53)	0.235 (1.63)
γ_2	0.126 (1.30)	0.135 (0.52)
γ_3	0.684* (4.16)	0.363 (0.89)
β_1	0.143* (3.59)	0.346* (3.11)
ρ_1	0.325* (5.07)	0.523* (8.41)
ρ_2	0.077 (1.20)	0.249* (4.01)
R^2	0.259	0.102
Durbin-Watson	2.07	2.16

Note. This table examines the effect of jumps in the underlying S&P 500 index on the joint regression tests for investor underreaction and increasing misreaction in the S&P 500 index options market. The regression and its residuals are specified through the following equations:

$$\Delta V_t^{i,\text{unexpected}} = \alpha + \sum_{m=0}^{3} \gamma_m 1_{\{\omega \in A_{m,t}\}} \Delta V_t^{S,\text{unexpected}} + \beta_1 \Delta V_{t-1}^{S,\text{unexpected}} + \varepsilon_t, \quad i = M, L$$

$$\varepsilon_t = \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + e_t$$

where $\Delta V_t^{i,\text{unexpected}}$ is the daily unexpected change in instantaneous variance and the superscript i denotes short-term (S), medium-term (M), or long-term (L) options. The sets $A_{m,t}$ are exhaustive and mutually exclusive and describe the property of the sequence of past variance shocks (current shock $\Delta V_t^{S,\text{unexpected}}$ inclusive). Specifically, $\omega \in A_{m,t}$ if the sequence of past variance shocks with the same sign is of length $m + 1$ ($\omega \in A_{3,t}$ if the length is 4 or longer). The instantaneous variance is obtained from the SVJ model, which is estimated by the method of simulated moments. The sample period extends from September 1, 1993 to August 31, 1994. An option is said to be short term, medium term, or long term if it has less then 60 days, between 180 and 365 days, or longer than 365 days to expiration. t statistics are in parentheses.

*Denotes significance at the 5% level.

correction. The estimated coefficients show that the finding of investor misreaction is quite robust.

The trading analysis discussed above is implemented with the use of stochastic variances extracted from the SVJ model, and the results are reported in Table VIII. The average abnormal returns are slightly higher, in most cases, than those obtained under the Heston SV model. However, they still fall far short of the level sufficient to overcome transaction costs in the options market.

TABLE VIII
Momentum Effects in Option Returns with the Use of the Stochastic Volatility Jump Model

	Medium-term options				*Long-term options*			
	ALL	*ITM*	*ATM*	*OTM*	*ALL*	*ITM*	*ATM*	*OTM*
Panel A: Delta-Hedged Option Portfolios								
All signals								
Long	0.92%	0.66%	1.01%	1.23%	0.82%	0.59%	1.30%	1.49%
	(1.45)	(1.31)	(1.26)	(1.13)	(2.02)	(1.68)	(2.45)	(2.12)
Short	1.00%	0.69%	1.19%	1.03%	0.95%	0.73%	1.50%	1.60%
	(2.47)	(2.18)	(2.31)	(1.38)	(4.53)	(3.67)	(5.20)	(3.65)
Long + short	0.97%	0.68%	1.11%	1.11%	0.89%	0.67%	1.41%	1.56%
	(3.71)	(3.28)	(3.37)	(2.47)	(5.36)	(4.65)	(6.47)	(5.35)
Strong signals								
Long	1.53%	1.09%	1.96%	0.81%	1.71%	1.24%	2.60%	2.73%
	(1.80)	(1.55)	(1.86)	(0.50)	(2.86)	(2.38)	(3.49)	(2.74)
Short	1.13%	0.53%	1.47%	2.13%	1.31%	0.98%	1.99%	2.55%
	(2.14)	(1.27)	(2.21)	(2.04)	(4.27)	(3.47)	(4.42)	(4.97)
Long + short	1.29%	0.75%	1.67%	1.61%	1.47%	1.08%	2.23%	2.62%
	(3.78)	(2.67)	(3.95)	(2.48)	(6.12)	(5.18)	(7.47)	(6.58)
Panel B: Naked option portfolios								
All signals								
Long	1.71%	1.41%	1.69%	1.56%	1.20%	0.82%	2.08%	2.34%
	(1.74)	(1.50)	(1.60)	(2.14)	(2.12)	(1.54)	(2.23)	(2.19)
Short	1.20%	0.99%	1.19%	2.56%	0.84%	0.58%	1.46%	1.64%
	(1.97)	(1.73)	(1.78)	(2.14)	(2.68)	(1.81)	(2.93)	(1.77)
Long + short	1.41%	1.16%	1.40%	2.12%	0.99%	0.68%	1.72%	1.93%
	(2.61)	(2.28)	(2.39)	(2.93)	(3.34)	(2.36)	(3.57)	(2.76)
Strong signals								
Long	2.40%	1.93%	2.56%	1.83%	2.14%	1.57%	4.18%	2.61%
	(1.76)	(1.45)	(1.76)	(1.00)	(2.58)	(1.96)	(3.15)	(1.99)
Short	1.48%	1.04%	1.63%	2.72%	1.00%	0.68%	1.61%	2.44%
	(1.87)	(1.42)	(1.83)	(2.18)	(2.33)	(1.63)	(2.05)	(2.15)
Long + short	1.85%	1.40%	2.00%	2.37%	1.46%	1.04%	2.64%	2.51%
	(2.57)	(2.03)	(2.55)	(2.29)	(3.46)	(2.55)	(3.66)	(2.94)

Note. Average daily excess returns from a "momentum"-type trading strategy based on the stochastic volatility jump model (SVJ). In the "all signals" implementation, a long (short) position in the option portfolio is entered into each day if the unexpected change in the short-term implied variance $\Delta V_t^{S,\text{unexpected}}$ is positive (negative). In the "strong signals" implementation, a long (short) position in the option portfolio is entered into each day if $\Delta V_t^{S,\text{unexpected}}$ is positive (negative) and in addition, $|\Delta V_t^{S,\text{unexpected}}/V_{t-1}^S| > 0.1$. This position is liquidated on the following day. In Panel A, the portfolios are delta-hedged against the S&P 500 index and the daily excess returns are computed with respect to the theoretical daily expected return from the SVJ model. In Panel B, the option portfolios are unhedged and on days when $\Delta V_t^{s,\text{unexpected}}$ is positive (negative), the daily excess returns are computed with respect to the average daily return from always holding a long (short) position in the option portfolio. Data from the first half of the sample period are used to estimate the structural parameters of the SVJ model, while data from the second half of the sample are used to obtain excess returns. Average daily excess returns are presented for days with positive variance shocks (Long), days with negative variance shocks (Short), and all days (L+S). An option is said to be "medium-term" if its time-to-expiration is between 180 and 365 days, "long-term" if its time-to-expiration is greater than 365 days, "at-the-money" (ATM) if its moneyness is between 0.97 and 1.03, "out-of-the-money" (OTM) if its moneyness is greater than or equal to 1.03, and "in-the-money" (ITM) if its moneyness is less than or equal to 0.97. t statistics are in parentheses.

CONCLUSION

The economic significance of investor misreactions in the S&P 500 index options market is examined with the use of both medium-term regular options and long-term LEAPS options. The fundamental question is whether investor misreactions can be exploited to generate economically measurable profit. The choice of long-dated LEAPS data is motivated by the Stein (1989) concluding remark that longer-term options may be necessary for investor misreactions to make an economic impact.

Because of this focus, the behavioral interpretation of the Stein (1989) and Poteshman (2001) results are taken as given. However, it is noted that there is a lack of trading tests based on the empirically identified misreaction patterns. To construct suitable trading strategies, regression-based tests are formulated for the price-formation process conjectured by Barberis, Shleifer, and Vishny (1998), which reconciles short-horizon underreaction with long-horizon overreaction. This can be regarded as an effort to extend the empirical tests in Stein (1989) and Poteshman (2001) so that they yield valuable information for the construction of potentially profitable trading strategies.

From the regression tests, it is found that investors underreact to new information contained in short-term options when pricing longer-term options. It takes on average 3 trading days for shocks to short-term implied variances to be completely absorbed by longer-term option prices. This can be interpreted as evidence supportive of the conservatism bias. Furthermore, it is found that investors' reaction to the current variance shock grows when it is preceded by a string of similar variance shocks. For both medium-term and long-term options, the largest response occurs when there is a sequence of four daily variance shocks (current shock inclusive) of the same sign. Although the evidence for eventual overreaction to the current shock is weak, this is nevertheless evidence in support of the representativeness bias.

Based on these results, momentum strategies are constructed for option portfolios. It is shown that the average daily return of this strategy is about 1–3% higher than a suitably defined benchmark return. This is statistically and economically significant in the absence of transaction costs. However, the trading profit can be easily swamped by transaction costs, in particular the bid–ask spread, in the options market. Several variations of the trading strategies were performed, including using a stronger trading signal and holding the option portfolios for extended periods. However, the trading profit could not be increased. Therefore, except for market makers and professional traders who can effectively avoid paying transaction costs, investor misreaction in the S&P index options market cannot yield economically significant trading profits after trading costs are taken into account.

The exploration of investor misreactions using options data is a new research area that promises to generate additional insights into the role of investor psychology in the price-formation process. Its importance parallels the recent development in the empirical tests of behavioral theories using stock market returns. Although this article extends the existing literature by examining the profitability of trading strategies that exploit misreactions in longer-term index options, another potentially fruitful exercise is to study misreactions in individual stock options. Some individual stocks may have characteristics that cause them to be more susceptible to investor sentiment. In those cases, the significance of investor misreaction in options market is worth further examination. This is left to future research.

APPENDIX A

Estimation Procedure for Stochastic Volatility Models

This appendix summarizes the procedure used to estimate the stochastic volatility model and stochastic volatility model with random jumps. Bates (1996) and Bakshi et al. (1997) establish option pricing formulas under a fairly general stochastic volatility model that nests the popular Black-Scholes (BS) model, the Heston stochastic volatility (SV) model, and the stochastic volatility with jump (SVJ) model. In this setting, the underlying security has the following dynamics under the risk-neutral measure:

$$\frac{dS_t}{S_t} = (R - \delta - \lambda_J \mu_J)\, dt + \sqrt{V_t}\, dW_{S,t} + J_t\, dq_t \tag{A1}$$

where R is the constant spot interest rate, δ is the continuously compounded dividend yield, $W_{S,t}$ is a Wiener process, V_t is the instantaneous variance attributed to the diffusion component $W_{S,t}$, q_t is a Poisson jump process with rate λ_J, and J_t is the random percentage jump size with a lognormal distribution:

$$\ln(1 + J_t) \sim N\left[\ln(1 + \mu_J) - \tfrac{1}{2}\sigma_J^2, \sigma_J^2\right] \tag{A2}$$

where μ_J and σ_J are constants.

The diffusion component of return variance follows a square-root process:

$$dV_t = (\theta_V - \kappa_V V_t)\,dt + \sigma_V \sqrt{V_t}\,dW_{V,t} \tag{A3}$$

where κ_V, θ_V/κ_V, and σ_V are the speed of adjustment, long-run mean and variation coefficient of the volatility V_t, and $W_{V,t}$ is a Wiener process. The correlation between W_V and W_S is ρ, and the jump process q and jump size J are uncorrelated and both assumed to be independent of W_V and W_S.

As the empirical tests are conducted under the physical measure, it is necessary to adjust some of these processes for the market prices of various sources of risk. One can specify the market price of volatility risk such that under the physical measure:

$$dV_t = (\theta_V^* - \kappa_V^* V_t)\,dt + \sigma_V^* \sqrt{V_t}\,d\widetilde{W}_{V,t} \tag{A4}$$

where $\theta_V^* = \theta_V$, $\kappa_V^* = \kappa_V - \lambda$, $\sigma_V^* = \sigma_V$, and $\widetilde{W}_{V,t}$ is a Wiener process. The constant λ parametrizes the market price of volatility risk and is within the range of $(-\infty, 0)$.[7]

With this setup, option prices can be computed analytically as a function of the assumed structural parameters, which collectively are denoted by Φ. With the use of these pricing formulas, the structural parameters are estimated by the method of simulated moments (MSM) (see Bakshi et al., 2000; Duffie & Singleton, 1993; Gouriéroux & Monfort, 1996) the details of which are now illustrated with the Heston model used as a special case.

Recall that the sample of option prices is divided into three time-to-expiration categories: short term, medium term, and long term. Each is further divided into three categories according to the moneyness of each option. As a result, there are nine categories of options according to their time-to-expiration and moneyness. On each day, one option is randomly chosen from each category. This results in nine option price time series, each with $T = 252$ observations.

Let $\hat{P}^j(t, \tau_{tj}, K_{tj})$ be the observed price of the put option from the jth category on day t, and $P^j(t, \tau_{tj}, K_{tj}; \Phi)$ be the corresponding theoretical price given a set of structural parameters Φ, where τ_{tj} and K_{tj} are, respectively, the time to maturity and strike price of the option. The theoretical

[7]The range of possible values for λ results from two considerations. First, investors prefer less variance *ceteris paribus*. Within the current setup this implies that the variance process has a higher long-run mean under the risk-neutral measure, hence the negativity of λ. Second, the variance process must not explode under either the physical or the risk-neutral measure. Because the estimate of κ_V is positive, the negativity of λ guarantees the positivity of κ_V^*.

price P^j also depends on the level of the index, S_t, and the variance V_t. However, because the variance is unobservable, P^j is unknown as well, and only its expectation can be computed. This is now done by simulation. The MSM estimator of Φ is obtained by minimizing the following quadratic form:

$$J_{T,M} = \arg\min_{\Phi} G_T' W_T G_T \tag{A5}$$

where $G_T(\Phi) = (1/T)\sum_{t=1}^{T} g_t(\Phi)$,

$$g_t(\Phi) = \begin{pmatrix} \dfrac{\hat{P}^1(t, \tau_{t1}, K_{t1})}{K_{t1}} - \dfrac{E(P^1(t, \tau_{t1}, K_{t1}; \Phi))}{K_{t1}} \\ \vdots \\ \dfrac{\hat{P}^9(t, \tau_{t9}, K_{t9})}{K_{t9}} - \dfrac{E(P^9(t, \tau_{t9}, K_{t9}; \Phi))}{K_{t9}} \end{pmatrix} \tag{A6}$$

W_T is the optimal weighting matrix, and $E[P^j(t, \tau_{tj}, K_{tj}; \Phi)]$ is approximated by M simulations. The simulation is conducted as follows:

- Discretize the time dimension of the processes governing the underlying index and the variance:

$$S(t+1) - S(t) = (R - \delta)\, S(t)\, \Delta t + \sqrt{V(t)}\, S(t)\varepsilon_S(t)\sqrt{\Delta t} \tag{A7}$$

$$V(t+1) - V(t) = (\theta_V - \kappa_V V(t))\, \Delta t + \sigma_V \sqrt{V(t)}\, \varepsilon_V(t)\sqrt{\Delta t} \tag{A8}$$

  where Δt is the length of a trading day, or 1/252.
- Generate two time series of i.i.d. standard normal random variables, $\varepsilon_S(t)$ and $\varepsilon_V(t)$, $t = 1, 2, \ldots, T$, where the correlation between $\varepsilon_S(t)$ and $\varepsilon_V(t)$ is ρ.
- Simulate the time series of $S(t)$ and $V(t)$, $t = 1, 2, \ldots, T$ with the use of the random variables generated in the previous step. The initial index level $S(1)$ is set to be the observed index level on the first day of the sample, and the initial variance $V(1)$ is set to be the long-run mean value. The risk-free rate R is chosen to be the daily average of the 30-day T-bill rate during the sample period.
- Repeat above steps M times to generate M different sample paths for $S(t)$ and $V(t)$. For each sample path, compute $P^j(t, \tau_{tj}, K_{tj}; \Phi)$ for each category j and each day t. Its average across the M sample paths provides an approximation to the expectation $E[P^j(t, \tau_{tj}, K_{tj}; \Phi)]$, which is used in the construction of the moment conditions in Equation (A6).

M is set equal to 1000 in the simulation, which provides a sufficient level of efficiency (according to Gouriéroux and Monfort, 1996, 10 simulations alone would provide an efficiency of 90%.). To generate the optimal weighting matrix W_T, which requires a higher degree of accuracy, 10,000 simulations are used. The above procedure can be easily modified to accommodate a stochastic volatility model with jumps.

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