Is Investor Misreaction Economically Significant? Evidence from Short- and Long-term S&P 500 Index Options[1]

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Abstract

Several recent studies present evidence of investor misreaction in the options market. While the interpretation of their results is still controversial, we note that the important question of economic significance has not been fully addressed. We fill in this gap by formulating regression-based tests to identify misreaction and its duration and constructing trading strategies to exploit the empirical patterns of misreaction. Using regular S&P 500 index options and long-dated S&P 500 LEAPS, we find an underreaction that on average dissipates over the course of three 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 one to three percent per day. However, they are not profitable in the presence of transaction costs.

JEL Classification: G13, G14

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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 due to 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) and Lee and Swaminathan (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.[2] In an early paper, Stein (1989) finds evidence that two-month options overreact to shocks to volatility implied from one-month options.[3] He works with the Black-Scholes implied volatility from at-the-money options because the true instantaneous volatility is unobservable. A recent paper by Poteshman (2001) examines investor underreaction, overreaction, and increasing misreaction in the options market. It extends the work of Stein in both scope and methodology. Using the Heston (1993) stochastic volatility model (as well as other more involved variants), the exact meaning of a "variance shock" is clarified—it is the unexpected change in the instantaneous variance, which can be calculated given a set of estimated structural model parameters. Given the history of variance shocks, one can then investigate how the prices of various options, long-term or short-term, respond to these shocks. Poteshman finds that options maturing one month after the short maturity ones (those with the shortest maturity greater than 10 days) 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.

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.

[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, Shleifer and Vishny (1998), Daniel, Hershleifer and Subrahmanyam (1998) and Hong and Stein (1999).

[2]In addition to the two papers mentioned below, Poteshman and Serbin (2003) show that customers of discount brokers often exercise stock options suboptimally, while 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.

[3]This early evidence is by no means conclusive. For example, Diz and Finucane (1993) apply a different econometric test and show that the evidence for overreaction largely disappears. Campa and Chang (1995) demonstrate the absence of overreaction in the foreign exchange options market.

To address this issue, we construct option trading strategies based on the identified misreaction patterns. 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 perhaps would 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 we take investor misreaction at its face value, it is still not exploitable.

Our focus on the economic significance of investor misreaction in the options market suggests several important ways in which we can 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. Notably, existing studies focus on the short-end of the implied volatility term structure. In these studies, the words "long-term" and "short-term" are used in a relative sense because both refer to options with maturities less than three months. This has in fact led Stein (1989) to suggest 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."[4]

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

Second, we formulate regression-based tests of investor misreaction 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 our tests allows one to trade long-term options using the history of implied variances from short-term options 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

[4]There is another reason to believe that the addition of longer-term options may enrich our understanding of options market misreactions. Recently, Bollerslev and Mikkelsen (1996, 1999) and Bakshi, Cao and Chen (2000) show that the implied volatilities from short-term and longer-term options behave quite differently, and the longer-term implied volatility decays much more slowly and has a long memory feature. The fact that short- and long-term implied volatilities have different dynamics suggests that there is no reason a priori to believe that these options are characterized by the same type of investor misreaction.

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.[5] Since 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.

Our regression tests yield two major results. First, we find 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 three days, lending support to the slow incorporation of new information into longer-term option prices. Second, we find that the response of longer-term options to a contemporaneous short-term variance shock is increasing 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.

After showing that the longer-term options underreact to short-term variance shocks, the next step is to formulate trading strategies to exploit this pattern. Toward this goal, we study two "momentum"-type trading rules in the S&P 500 index options markets—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 using medium-term S&P 500 index options. For each trading rule, both unhedged and delta-hedged option portfolios are examined. Overall, our findings can be summarized as follows.

Trading rules that exploit investor underreaction lead to positive abnormal returns between one and three percent per day if we trade long-term LEAPS. The trading profits are statistically and economically significant before taking trading costs into account. The abnormal returns are the largest if we trade out-of-the-money LEAPS. Next, a qualitatively similar conclusion can be drawn

[5] Other effects can also be studied within our flexible regression framework. For instance, Lee and Swaminathan (2000) document an asymmetric stock market misreaction to positive and negative earnings shocks. This effect can be incorporated into our regressions.

when medium-term index options are used instead of long-term LEAPS. Lastly, we consider the robustness of our trading results using 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.

While these results are largely 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-the-thumb measures of option market transaction costs. For example, our "momentum-style" strategy based on the finding of initial underreaction yields a highly significant average excess return on the order of one to three percent per day. This is, nevertheless, dwarfed by bid-ask spreads that could easily be as much as five percent 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, and 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. While the quantitative results may differ across markets, it appears that the economic significance of market "anomalies" is a universal concern.

The rest of the paper is organized as follows. We formulate regression-based tests for investor misreactions in Section 1. Section 2 describes our options data and the estimation method for the instantaneous variances. In Section 3, we present a detailed analysis of investor misreaction based on our regression results. Section 4 examines the profitability of trading strategies that exploit quantitative findings in the preceding sections. Concluding remarks are offered in Section 5.

1 Tests for Investor Misreaction in the Options Market

In this section, we concentrate on the formulation of regression-based tests that we use to examine initial underreaction, eventual overreaction and the process through which the transition takes place. For simplicity, we 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):

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

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:

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

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

Investor misreaction leads to a departure from these equalities. In this paper, "misreaction" is taken to mean investor under- or over-adjust 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. Our 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 percent). 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 we know that return continuation typically lasts from three to twelve months. Our test would yield insight into the same question for the options market. For that we 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. We interpret "similar shocks" as 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

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

and

$$A_{M,t} = \left\{ \Delta V_t^{S,\text{unexpected}}, \Delta V_{t-1}^{S,\text{unexpected}}, \ldots, \Delta V_{t-M}^{S,\text{unexpected}} \text{ are all of the same sign} \right\}. \tag{6}$$

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 $M = 3$):

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

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

$$\gamma_n > 1, \tag{8}$$

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 one) 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.

We now combine equations (3) and (4) into a single regression-based test of investor misreaction:

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

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 we outline 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. Since 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.

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

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

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 one 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, we study the asymmetric response across positive and negative shocks using

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

where $\left(\Delta V_{t-k}^{S,\text{unexpected}}\right)^{+}$ and $\left(\Delta V_{t-k}^{S,\text{unexpected}}\right)^{-}$ are respectively the positive and negative part of the variance shock. These generalizations are subsequently pursued in Section 3.

2 Estimation of Option-Implied Variances

2.1 Data

We study two types of option contracts with distinctive maturity structures. Both are written on the S&P 500 index: (1) regular S&P 500 index options with maturities up to one year at inception, and (2) S&P 500 Long-Term Equity Anticipation Securities (LEAPS) which are long-dated options expiring in approximately two to three 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. Due to this difference, LEAPS are not convertible to regular S&P 500 contracts even when they have the same days-to-maturity (less than one year to expiration).

Our sample period is from September 1, 1993 through August 31, 1994.[6] We obtain bid and ask quotes from the Berkeley Options Database (BODB). For each contract on each trading day, we retain the last reported bid-ask quote that occurs prior to 3 PM Central Standard Time. 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, we use the two Treasury-bill (or Treasury-note) rates straddling an option's expiration date 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 our raw data. First, we retain only puts 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 due to their role in portfolio insurance. During our 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, we use the mid-point between bid and ask prices as a representation of the true market value of a put. Second, we eliminate quotes on options with less than six days to expiration to avoid possible expiration

[6]Prior to 1993, the trading volume of LEAPS is thin relative to that of regular S&P 500 index options. Furthermore, we are unable to obtain more recent intradaily options data from U.C. Berkeley and CBOE due to Justice Department's investigation of collusion on the CBOE.

related price effects. Finally, to minimize the impact of price discreteness, we exclude quotes with prices less than \$3/8.

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 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. In Section 4, we investigate the economic implication of investor misreaction by reporting returns from trading options in different moneyness categories. 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 in the sample is \$6.68, whereas the average price of a long-term ITM LEAPS put is \$36.57.

2.2 Estimation Method

In Section 1 we have formulated our tests for investor misreaction based on a sequence of instantaneous variances. 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 we have a reasonable degree of confidence in a given model, there could still be many different estimation techniques to choose from.

The starting point of our 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)]. In this paper, we use the method of simulated moments (MSM) to estimate the structural parameters of the SV model. We need to generate the moment conditions using simulation because the marginal distribution of the unobservable variance process cannot be expressed in closed-form. Compared to methods that imply out the structural parameters jointly with the instantaneous variances on a daily basis, our 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, we include a brief explanation of our option pricing framework as well as the MSM technique 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 Appendix A.

Our 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), we assume 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 Appendix A). These parameters are used to compute the unexpected change in variance following equation (2), using the instantaneous variances extracted with the procedure described below. It is noted that the choice of the volatility risk premium λ makes little difference for subsequent results. For example, we experimented 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 $\lambda = -1.0\kappa_V$) and found our conclusions were qualitatively similar. One reason for this result is that since we are computing unexpected changes on a one-day horizon when the estimated mean reversion half life is on the order of a year ($\kappa_V = 1.1325$ Yr^{-1}), the expected changes are virtually zero.

Assuming that we have obtained structural parameter estimates via the MSM estimation, the instantaneous variance V_t on any given day can be obtained using all available put prices on that day. Specifically, let N be the total number of observed puts on day t, $\widehat{P}_n(t, \tau_n, K_n)$ 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. Using the MSM estimates of Φ as input, V_t can be found by minimizing the sum of squared pricing errors:

$$\min_{V_t} \sum_{n=1}^{N} \left(\widehat{P}_n(t, \tau_n, K_n) - P_n(t, \tau_n, K_n; \Phi, V_t) \right)^2 . \tag{12}$$

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 our empirical tests in Section 1.

3 Do LEAPS Investors Misreact to New Information?

While the focus of the paper 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 we examine profits from trading strategies that exploit investor misreaction. Furthermore, the design of trading strategies relies on how long the underreaction/overreaction (if any) persists. In this section we present evidence of investor underreaction and overreaction by examining the 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, we plot, in Figure 1, the difference between long-term (medium-term) and short-term instantaneous volatilities estimated using the Heston (1993) model. There are substantial differences between longer-term and short-term volatilities (as large as 6 percent), and the differences are consistently positive. On the other hand, the two plots are similar during most of our sample period, suggesting a high correlation between long- and medium-term volatilities.

Table 1 presents results of the regression test for investor underreaction. The test is based on equation (3), where the daily unexpected 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 percent 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 percent. 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 percent, and the coefficient of its first lag also 27 percent. 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.

Our 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, we choose the maximum m as 3. The various scenarios of the sequence of short-term variance shocks are summarized in equation (7).

We report estimation and test results in Table 2. 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 concurrent shock in short-term instantaneous variance is only 5 percent and insignificant when the current shock and the preceding shock are of opposite sign. However, the coefficient increases to 27 percent when the preceding shock is of the same sign, and 45 percent when the preceding shocks over a three-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, we find supporting evidence that the initial underreaction eventually becomes overreaction. For instance, the coefficients γ_0 and γ_1 are 9 and 40 percent, 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 percent which is close to one standard deviation greater than one. 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 our understanding of misreaction, we perform a joint test of both underreaction and increasing misreaction. 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 multiplied by dummy variables described in Table 2. The results reported in Table 3 show that, after we control for investor underreaction, the effect of increasing misreaction remains significant. Take long-term options as an example. The coefficient γ_1 is 33 percent and significantly less than one, indicating initial underreaction, whereas the coefficient γ_3 is 105 percent, indicating marginal overreaction when four consecutive shocks of the same sign are observed.

We perform an additional test to examine the persistence of the effect of a string of similar variance shocks.[7] The test is based on equation (10), and the explanatory variables are current and lagged unexpected change in short-term instantaneous variances multiplied by dummy variables described in Table 2. It is clear from Table 4 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, we do not find any negative γ_{km} coefficients with $k \geq 1$ that would indicate a reversal in the level of long-term implied variances. 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.

4 Is There Money to be Made by Exploiting Investor Misreaction?

In light of the investor misreaction documented by Stein (1989), Poteshman (2001) and this paper, an important question that remains unanswered is whether misreaction leads to practical and profitable trading strategies. The answer to this question will provide an economic measure of the size of investor misreaction. As Stein (1989) points out, long-lived options are ideal contracts to examine the economic significance of investor misreaction. Our preceding analysis suggests that one trading strategy we can implement 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 we find a statistically significant relationship between $\Delta V_t^{L,\text{unexpected}}$ and $\Delta V_t^{S,\text{unexpected}}$, we cannot exploit this relation because when forming our positions at time $t-1$, we have access to only the information available at that time. As a result, we can only utilize investor

[7] In results not shown here, we conduct a further test based on equation (11) to examine asymmetric underreaction and increasing misreaction to positive and negative variance shocks. Lee and Swaminathan (2000) provide evidence that firm-specific bad news are incorporated into stock prices more slowly than good news, a result consistent with Hong, Lim and Stein (2000). However, we do not find asymmetries in the index options market.

misreactions that persist for at least another trading day. While investor underreaction qualifies because it lasts for two days, we have to rule out overreaction because Table 4 shows no perceptible pattern of reversal following a recent overreaction. In this section, we formulate trading strategies and examine returns from various strategies.

4.1 Short-Term Momentum Strategies

We consider momentum-type trading strategies based on instantaneous variances implied from short-term options. For simplicity, we use LEAPS to illustrate the implementation. Specifically, on each trading day t, we examine the sign of the unexpected change in short-term instantaneous variance $\Delta V_t^{S,\text{unexpected}}$. 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.[8] Once trades are executed, the positions are held for one day and liquidated on day $t+1$. Two option positions are considered: (1) a delta-hedged portfolio which eliminates the risk exposure to the underlying S&P 500 index, and (2) an unhedged portfolio. To isolate the effect associated with investor underreaction, we report the holding period return on the option portfolio in excess of the theoretical expected return according to Heston's stochastic volatility model.

To make the point precise, we use Heston's model to demonstrate how investor underreaction can be translated into a trading strategy. Extension of the following analysis to other models is straightforward. Let P be the price of an option portfolio, and Q the value of the corresponding delta-hedged portfolio where

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

From Ito's lemma,

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

Substituting the dynamics of V into the above equation and using 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. Using equation (14), the abnormal return on portfolio Q is:

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

[8] We also consider holding an equally-weighted option portfolio and find that the results are slightly stronger.

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 we long (short) 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 $\Delta Q_t = Q_t - Q_{t-1}$. We report results by using $\Delta V_t^{M,\text{unexpected}}$ and $\Delta V_t^{L,\text{unexpected}}$ 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 $\Delta V_{t-1}^{S,\text{ unexpected}}$, our trading strategy will yield an expected return above $E_{t-1}\left(\Delta Q_t/Q_{t-1}\right)$. This is the essence of our "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, we set λ to be $-\kappa_V/2$ in all subsequent analyses. To check the robustness of results, we set λ to different values and recalculate option returns. Results show that different values of λ have no significant impact on the abnormal return from our trading strategy.[9]

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

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

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 our strategy is similar to momentum strategies for stocks in the sense that we also form our positions 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 our time scale is much shorter—option return momentum persists for just a few trading days while stock return momentum can last for up to a few months.

We implement the trading strategy in the spirit of out-of-sample tests. We divide the entire sample period into two equal-length sub-periods: the first half is used to estimate the structural parameters of the SV model, while the second half is used to calculate option portfolio returns. Table 5 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

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

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, we report results based on all signals (i.e., we enter a trade whenever $\left|\Delta V_t^{S,\text{unexpected}}\right| > 0$) or strong signals (i.e., we trade only when $\left|\Delta V_t^{S,\text{unexpected}}/V_{t-1}^S\right| > 0.1$). Approximately, $\left|\Delta V_t^{S,\text{unexpected}}/V_{t-1}^S\right| > 0.1$ for half of the sample days.

Several interesting results emerge from Panel A of Table 5 where the option portfolios are delta-hedged. First, all abnormal returns are positive, ranging from 0.36 to 2.79 percent per day. This is true regardless of whether we trade ITM, ATM, or OTM options. 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 percent 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 two to three times larger than that from trading ITM options, irrespective of whether we take long or short positions. Take long-term options and long plus short positions as an example. Daily abnormal returns are 0.59, 1.18, and 1.36 percent, respectively, for trading ITM, ATM and OTM options when the unexpected change in short-term variance is different from zero. Fourth, using strong signals often leads to larger abnormal returns. This is true for 23 out of 24 cases presented in Table 5. Finally, the return differential between long and short positions appears to be small, suggesting that the asymmetric response towards positive and negative unexpected change in instantaneous variance is insignificant. This is consistent with our regression results in Section 3.

The above conclusions generally hold when option portfolios are unhedged. Panel B of Table 5 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 our estimation result shows that the unexpected change in variance and the unexpected change in index return are negatively correlated ($\rho = -0.25$).

Two comments are noted 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 will tend to underadjust to that shock. If this were true, then our "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, we 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 five percent of the option price. Since 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.

4.2 Trading Strategies with Extended Holding Periods

Up to this point we have conducted trading tests that are based on the observation that long-term options underreact to changes in the variance implied from short-term options. We have ruled out overreaction as a source of potential trading profits because the evidence for overreaction in the data is weak, and our 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 our regression tests ineffective at detecting these patterns. In this case, trading profits should increase as we lengthen the holding period 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.

We repeat the above "momentum" trading strategy with holding periods of three, five, ten or twenty trading days. We find that as the holding period extends from one to three (or five) 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 percent. Collectively, this evidence suggests that holding the option portfolio for longer periods is unable to generate additional profits that are necessary to overcome transaction costs.

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

4.3 Trading Strategies Based on Implied Variance Levels

Next we address the question of whether other formulations of the regression tests for investor overreaction could have led to more profitable trading strategies. In this paper we have 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 short-term variance is, the more mispriced are 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 pre-determined threshold value, and liquidating the positions when short-term variance reverts to a level close to its long-run mean.

While this strategy is straightforward to implement, first it is worthwhile to explain the relationship between the above level-based test and our previous test for overreaction. For this we note that our definition of "similar information" leads to the strongest form of overreaction according to the behavioral hypotheses that are the focus of this paper. 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. Since our 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, we do not further examine trading tests based on overreaction in variance levels.

4.4 Alternative Option Pricing Models

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

We first check 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 $\Delta V_t^{\text{unexpected}}$. Our result shows that the autocorrelation is non-zero—the partial autocorrelations suggest that they should be modeled as an AR(2) process.

We apply the Durbin-Watson test to the regressions in Section 3. The hypothesis of no autocorrelation is rejected at the five percent 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 our 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 our estimates and make it easier to interpret them.

In Table 6, we reproduce the joint test of underreaction and increasing misreaction (previously in Table 3) 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 qualitatively the same. The only change is that we can no longer conclude 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, we extract implied variances using the stochastic volatility with jumps (SVJ) model. This model has received considerable attention and been tests in the context of index options and index futures options (Bakshi, Cao and Chen (1997) and 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. Since we rely on short-term implied variances for both regression tests and as a trading signal for our 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.

In Table 7, we repeat the joint test on the time series of instantaneous variances implied from the SVJ model. The variance estimation follows the two-step procedure outlined in Section 2. 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:

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

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, we work with only the diffusion part of instantaneous variances 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, using 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 7 reflect this correction. The estimated coefficients show that our finding of investor misreaction is quite robust.

We implement the trading analysis discussed above using stochastic variances extracted from the SVJ model and report results in Table 8. 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.

5 Conclusion

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

Due to this focus, we take the behavioral interpretation of Stein (1989) and Poteshman (2001)'s results as given. However, we note that there is a lack of trading tests based on the empirically identified misreaction patterns. To construct suitable trading strategies, we formulate regression-based tests 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 our regression tests, we find that investors underreact to new information contained in short-term options when pricing longer-term options. It takes on average three 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, we find 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, we construct "momentum" strategies for option portfolios. We show that the average daily return of this strategy is about one to three percent 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. We perform several variations of our trading strategies including using a stronger trading signal and holding the option portfolios for extended periods. However, we are unable to further increase the trading profit. 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 taking trading costs 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. While this paper 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. Particularly, some individual stocks may have characteristics that cause them to be more susceptible to investor sentiment. In those cases, the economic significance of investor misreaction in option pricing is worth further examination. We leave this to future research.

Appendix

A Estimation Procedure for Stochastic Volatility Models

This appendix summarizes the procedure we use to estimate the stochastic volatility model and stochastic volatility model with random jumps. Bates (1996) and Bakshi, Cao and Checn (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:

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

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 our 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 $(-\infty, 0)$.[10]

[10]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. Since our estimate of κ_V is positive, the negativity of λ guarantees the positivity of κ_V^*.

With this setup, option prices can be computed analytically as a function of the assumed structural parameters, which collectively are denoted by Φ. Using these pricing formulas, we estimate the structural parameters using the method of simulated moments (MSM) [see Duffie and Singleton (1993), Gouriéroux and Monfort (1996), and Bakshi, Cao and Chen (2000)], the detail of which is illustrated below using the Heston model as a special case.

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

Let $\widehat{P}^j(t, \tau_{tj}, K_{tj})$ 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 price P^j also depends on the level of the index, S_t, and the variance V_t. However, since the variance is unobservable, P^j is unknown as well and only its expectation can be computed. We do this by simulation below. 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 $G_T(\Phi) = (1/T)\sum_{t=1}^{T} g_t(\Phi)$,

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

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

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

$$\begin{aligned} S(t+1) - S(t) &= (R-\delta) S(t) \Delta t + \sqrt{V(t)} S(t) \varepsilon_S(t) \sqrt{\Delta t}, && \text{(A7)} \\ V(t+1) - V(t) &= (\theta_V - \kappa_V V(t)) \Delta t + \sigma_V \sqrt{V(t)} \varepsilon_V(t) \sqrt{\Delta t}, && \text{(A8)} \end{aligned}$$

  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 $V(t)$, $t = 1, 2, \ldots, T$ using the random variables generated in the previous step. We set the initial index level $S(1)$ to be the observed index level on the first day of the sample, and the initial variance $V(1)$ 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 $E\left(P^j(t, \tau_{tj}, K_{tj}; \Phi)\right)$, which is used in the construction of the moment conditions in equation (A6).

We set $M = 1,000$ in the simulation which provides more than a sufficient level of efficiency [10 simulations alone would provide an efficiency of 90% according to Gouriéroux and Monfort (1996)]. To generate the optimal weighting matrix W_T which requires a higher degree of accuracy, we use $10,000$ simulations. The above procedure can be easily modified to accommodate stochastic volatility model with jumps.

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Table 1
Tests for Investor Underreaction to New Information

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:

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

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 using 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 five percent level.

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

Table 2
Tests for Increasing Investor Misreaction to a Series of Similar Information

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:

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

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 using 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 five percent level.

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

Table 3
Joint Tests for Underreaction and Increasing Misreaction

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:

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

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 using 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 five percent level.

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

Table 4
Tests for the Effect of a Lagged Sequence of Similar Variance Shocks

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:

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

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 *k*th 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 using 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 five percent level.

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

Table 5
Momentum Effects in Option Returns

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, $\left|\Delta V_t^{S,\text{unexpected}} / V_{t-1}^S\right| > 0.1$. 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, 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.

Panel A: Delta-Hedged Option Portfolios

		Medium-Term Options				Long-Term Options			
		ALL	ITM	ATM	OTM	ALL	ITM	ATM	OTM
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)

Table 5
Momentum Effects in Option Returns
(Continued)

Panel B: Naked Option Portfolios

		Medium-Term Options				Long-Term Options			
		ALL	ITM	ATM	OTM	ALL	ITM	ATM	OTM
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)

Table 6
Effect of Autocorrelated Regression Residuals on the Joint Tests of Underreaction and Increasing Misreaction

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:

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

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

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 using 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 five percent level.

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

Table 7
Effect of Jumps in the S&P 500 Index on the Joint Tests of Underreaction and Increasing Misreaction

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:

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

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

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 using 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 five percent level.

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

Table 8
Momentum Effects in Option Returns Using the Stochastic Volatility Jump Model

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, $\left|\Delta V_t^{S,\text{unexpected}} / V_{t-1}^{S}\right| > 0.1$. 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.

Panel A: Delta-Hedged Option Portfolios

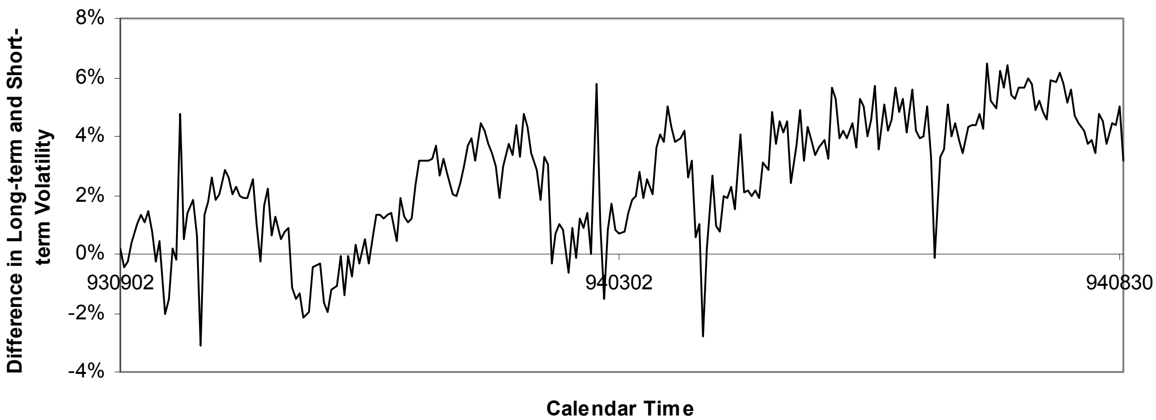
		Medium-Term Options				Long-Term Options			
		ALL	ITM	ATM	OTM	ALL	ITM	ATM	OTM
All Signals	Long	0.50%	0.66%	1.01%	1.23%	0.72%	0.59%	1.30%	1.49%
		(0.78)	(1.31)	(1.26)	(1.13)	(1.83)	(1.68)	(2.45)	(2.12)
	Short	0.67%	0.69%	1.19%	1.03%	0.84%	0.73%	1.50%	1.60%
		(1.77)	(2.18)	(2.31)	(1.38)	(4.20)	(3.67)	(5.20)	(3.65)
	Long+Short	0.60%	0.68%	1.11%	1.11%	0.79%	0.67%	1.41%	1.56%
		(1.75)	(3.28)	(3.37)	(2.47)	(3.98)	(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)

Table 8
Momentum Effects in Option Returns Using the Stochastic Volatility Jump Model (Continued)

Panel B: Naked Option Portfolios

		Medium-Term Options				Long-Term Options			
		ALL	ITM	ATM	OTM	ALL	ITM	ATM	OTM
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)

Panel A: Long-term Options



Panel B: Medium-term Options

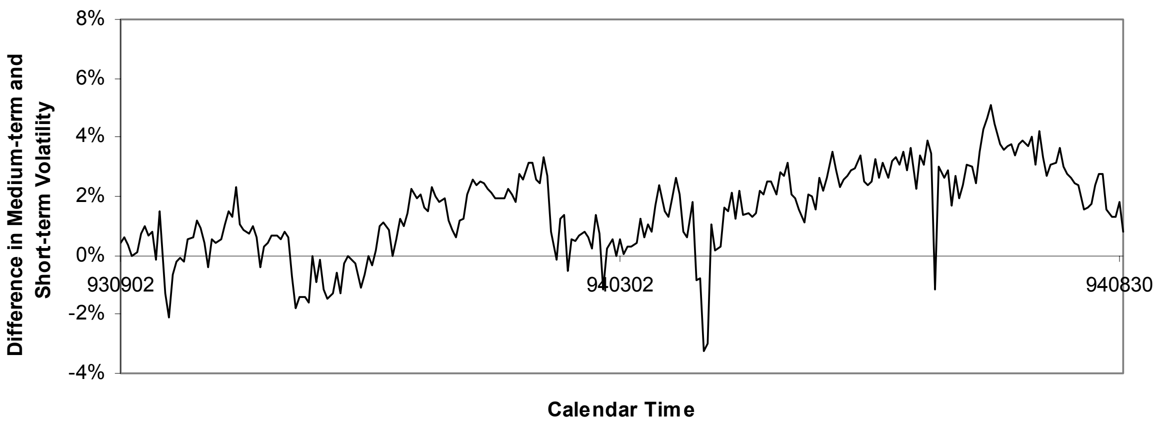


Figure 1
Difference between Short-term and Longer-term Implied Volatility

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