Index Option Prices and Stock Market Momentum*

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Abstract

We test the prediction of standard option pricing models that there should be *no relation* between option prices and past stock market movements. Using the Standard and Poor's 100 index options (OEX options) prices from 1983-1995, we document that OEX calls are significantly overvalued relative to OEX puts after large stock price increases. The reverse is true after large stock price decreases. These valuation effects are both economically and statistically significant. Our results suggest that past stock returns exert an important influence on index option prices.

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I. Introduction

Standard option pricing models, such as the Black-Scholes model and binomial model, assume perfect capital markets, a martingale diffusion process for underlying asset returns and replicability of option payoffs using the underlying asset and the risk-free asset. Under these assumptions, options are priced by disallowing arbitrage opportunities. Hence, standard models predict that only six factors enter into the option pricing formulas: the price of the underlying asset, exercise price, time to maturity, risk-free interest rate, volatility and dividends on the underlying asset. Other factors which may affect the price of the underlying asset, such as expected future stock returns and investors' preferences about the higher moments of the underlying asset return distributions, are not priced. However, when the perfect market assumption is relaxed, it becomes difficult to replicate option payoffs. Consequently, option prices can deviate from the prices of the replicating portfolios, and to some extent, become non-redundant securities [Figlewski (1989), Figlewski and Webb (1993) and Grossman (1995)]. Prices of the non-redundant securities are then determined both by the supply and demand for these securities as well as limited arbitrage considerations in imperfect markets. This approach opens up the possibility that additional factors could enter into option pricing. Specifically, stock market momentum can change investors' risk aversion and their perceptions about the mean, volatility, or the higher moments of the underlying stock market return distribution and thereby affect the supply and demand for options. In this paper, we test the predictions of the standard option pricing models that there should be *no relation* between the option prices and the stock market momentum.[1]

While there is a large literature on the importance of momentum in pricing of stocks, the relation between momentum and option pricing has not been examined. In imperfect markets, option prices can be affected by the momentum of the underlying asset through a number of channels, such as investors' expectations about future stock returns, their demand for portfolio insurance, or their attitude towards the higher moments of stock return distributions. First, investors' expectations about future stock returns can depend on past stock returns. Lo and MacKinlay (1988) show that the value-weighted market index shows strong positive auto-correlation of returns up to four-month horizons. Hence, if past returns are strongly positive, positive auto-correlation suggests that future stock returns will also be greater than average. Investors can exploit this expectation by buying call options on the market index, thereby creating an upward pressure on call prices. Similarly, if past returns are negative, then future stock returns will be projected to be below average. Investors can exploit this expectation by buying put options on the market index, creating an upward pressure on put prices. Second, portfolio insurance consideration suggests that the degree to which market participants want exposure to stock prices can depend on recent stock market movements, which then affects the supply and demand for calls and puts. An easy way of changing the exposure to the stock market is by buying call and put options on a stock market index. If after market prices have risen, an increased number of market participants demand greater exposure to equities, they can purchase call options on a market index, thereby putting upward pressure on call prices. In this case, call prices will rise to increase the supply of call writers. If after market prices have fallen, an increased number of market participants demand smaller exposure to equities, they can purchase put options on a market index, thereby putting upward pressure on put prices. In this case, put prices will rise to increase the supply of put writers. Finally, past stock returns can change investors' expectations about the higher moments of stock prices. If investors care about higher moments, then their demand for call and put options can change as their expectations about higher moments change, again creating pressures in call and put prices. For instance, previous research in the stock market has found that investors prefer skewness in stock returns. Once again, changes in market momentum can affect the supply and demand for options by changing investors' skewness expectations.

Our study is related to Stein (1989) and Lo and Wang (1995). Stein (1989) shows that long-term calls and puts overreact to volatility shocks, relative to short-term options. Our study differs from Stein (1989) in that we examine if investors bid up prices of call options after market advances and bid up prices of put options after market declines. Lo and Wang (1995) consider the implications of the predictability of stock returns on the estimates of historical volatility and on option pricing. Our objective differs from that of Lo and Wang in that we do not constrain the pricing effects to occur through the overall volatility estimates. Instead, we look for relative *divergence* between call and put option prices as a function of past stock returns.

At first glance, options market may seem to be an inappropriate place to look for price distortions.[2] Standard arbitrage considerations dictate that option prices must be closely tied both to each other and to the underlying stock prices. Any large deviations from "fair values" should be quickly eliminated. However, under real-world market conditions, option values can deviate from fair values by significant amounts without creating riskless-arbitrage opportunities

[Evnine and Rudd (1985), Figlewski (1989) and Canina and Figlewski (1993)]. Buying and selling stocks and options in the real world are subject to large transactions costs. Volatility is not known but must be estimated. Borrowing rates do not equal lending rates, and there are margin requirements and taxes. The effects of the transactions costs, up-tick rules and constraints on the use of short-sale proceeds make it difficult to buy or short sell the 100 stocks comprising the OEX index in exact proportions.[3] Arbitrage with futures is subject to basis risk since a futures contract on the OEX does not exist. An arbitrageur would have to trade futures on the S&P 500 index contract, further increasing the uncertainty of the arbitrage profit. Dividends on the index are not known but must be estimated, which introduces additional uncertainty. Cash settlement based on not-yet-known end-of-day closing stock prices also make arbitrage difficult. In fact, an investor can exercise an in-the-money OEX index option during the day and end up with a loss because of the subsequent adverse movements in the index at the end of the day. Moreover, the assigned option writers learn about the exercise the next day. This introduces an additional risk in covering short-option positions since the long position in the index can only be sold the next day. Again, if the market declines from the previous close, the assigned option writers will also experience losses even if they own the underlying index. These market imperfections introduce sufficient risk into any arbitrage strategy and prevent arbitrageurs from immediately eliminating the price distortions in OEX options.

In this paper, we test to see if S&P 100 index option prices (OEX) depend on past market returns. Market imperfection considerations suggest that call option prices would be bid up after increases in the stock market while put option prices should be bid up after declines in the stock market. Our methodology consists of two distinct tests. First, we examine if the put-call parity boundary conditions for American options are systematically violated more frequently after stock price increases or decreases. These relations are completely model independent. If there exist systematic violations of these arbitrage bounds as a function of past stock price returns, this indicates strong evidence of systematic pricing pressure on calls and puts.

Our results suggest that violations of the American put-call boundary conditions depend on past stock market momentum. Strongly positive past market returns lead to violations of the American call-put boundary conditions by increasing the call option prices. Strongly negative past market returns lead to violations of the American call-put boundary conditions by increasing the put option prices. Also, both the probability and the magnitude of the violations are important.

For the sample period, 1983 to 1995, a shift in stock prices from a past 60-day return of -5% to +5% more than doubles the probability of a boundary condition violation and produces a mispricing that varies from 1.3% to 30.0% of the average option price. Hence, our results are not only statistically significant, but also economically significant.

Our results also suggest that the price pressures on call and put option prices are important both before and after the crash of 1987. Hence, our findings are general and cannot be attributed solely to the crash. Others have found a structural shift around the crash.[4] It is true that the option prices during the immediate post-crash period exhibit larger violations of the boundary conditions. However, our findings are not driven by the crash. If we exclude the three-month period after the crash in computing the shift in option prices described in the previous paragraph, we obtain similar overall results, and pre- and post-crash results.

The American option boundary condition violations demonstrate a general relation between call and put option price divergence and past stock returns. However, the boundary conditions are in the form of inequalities, which do not impose an exact relationship between put and call prices. With an exact parametric form, we can quantify the magnitude of the price distortions and separate the sources of the distortions. For example, since the finance literature documents a strong negative correlation between volatility and stock returns, we can separate the effects of past stock returns from historical volatility changes. To address these issues, we conduct a parametric test.

In our parametric test, we measure the overpricing of calls relative to puts by the difference between their implied volatilities, or volatility spread. Implied volatility is now an accepted paradigm for empirical tests of option valuation [Jarrow and Wiggins (1989)]. Under the perfect market framework and for a given maturity date, the volatility implicit in call prices must be equal to the volatility implicit in put prices on each date. On the other hand, higher call-implied volatilities relative to put-implied volatilities indicate that calls are overpriced relative to puts. Similarly, higher put-implied volatilities relative to call-implied volatilities indicate that puts are overvalued relative to calls. Therefore, we measure the relative overpricing or underpricing of call and put options by their implied volatilities. A similar procedure is used by Figlewski and Webb (1993) to demonstrate price pressures in the options market as a function of short interest.

We show that the volatility spread increases after stock market increases and decreases after stock market decreases. Therefore, call options are again relatively overpriced immediately following large stock market increases, and put options are relatively overpriced immediately following large stock market declines. Moreover, these results are unaffected when we control for moneyness and term structure effects in the implied volatilities. These results corroborate our non-parametric tests, and they are consistent with market momentum hypothesis.

Our findings have a number of important implications. First, our evidence suggests that past stock returns exert an important influence on option prices. This pressure is strong enough to result in systematic boundary condition violations, which are independent of any particular model of option pricing. Consequently, our findings suggest that efforts to account for the observed biases in option prices through no-arbitrage based option pricing models are not likely to be successful. Second, our findings indicate that it would be worthwhile to examine how taking past stock returns into account affects various documented biases in different option pricing models [Bakshi, Cao and Chen (1997)]. Third, implied volatility is frequently used to explore arbitrage opportunities [Manaster and Rendleman (1982)], to proxy the market's volatility [Schwert (1989, 1990), Canina and Figlewski (1993), and Lamoureux and Lastrapes (1993)], or to measure the market's risk premia [Merton (1980), Poterba and Summers (1986)]. Therefore, our results demonstrating the systematic variation in implied volatilities of calls and puts as a function of past stock returns can also be used to improve the quality of the implied volatility estimates used for these purposes. For example, put and call implied volatilities each provide separate information about market risk premia not contained in the other implied volatility estimate. Finally, our findings have investment implications. Following large stock market increases, bets on further stock market increases are more expensive to implement using call options. Hence, traders wanting to place such bets may be better off using the futures contracts or underlying stocks. Conversely, following large price increases, certain strategies, such as covered call writing is likely to be more profitable.

A summary of the paper is as follows. In Section 2, we describe the data. In Section 3, we describe the methodology used for analyzing boundary condition violations and present empirical tests. The implied volatilities are analyzed in detail in Section 4. Potential sources of price pressure are explored in Section 5. Section 6 concludes.

II. Data

For this study, we use Berkeley transactions data set for call and put options on the Standard and Poor's 100 Index (also called OEX options) traded on the Chicago Board Options Exchange (CBOE) for the period March 11, 1983, to December 29, 1995. OEX options have been traded on the CBOE since March 11, 1983. For each trade, the data record contains the option's type (call or put), its transaction price, strike price, maturity, trading volume, and the contemporaneous value of the index.

The Berkeley transaction database contains a number of well-known data entry errors, especially concentrated in early years [Evnine and Rudd (1985)]. These typically involve the miscoding of the index value, which we correct. We also delete all transactions with missing or negative option prices. In addition, all transactions where option prices are below their intrinsic values are deleted.

Table 1 describes our options data. For American option put-call parity boundary condition violations, the value of the underlying S&P 100 index must be identical when the call and the put trades. To identify put-call pairs with identical index levels, we take each day of call and put trades and conduct a combined sort by strike, maturity, index level, and time-of-day. We then select from this any put-call pair that appears consecutively within the sort, thereby extracting only pairs with identical contract specifications and index levels. To ensure that our first-traded price is relatively fresh, we also require that no more than *ten* minutes pass when the first-option trade is observed and the second-matching-option trade is observed. Otherwise, we throw away the initial option trade and conclude that no matching trade was identified.[5]

Panel A of Table 1 shows the characteristics of the options we have included for boundary violation tests. Our overall sample period from March 11, 1983, to December 29, 1995, contains 2,935,923 matched call-put pairs. The average price of options equals $4.85 for calls and $4.27 for puts (giving an overall average of $4.56). Call prices increase from $4.45 to $8.43 while put prices increase from $3.84 to $6.52 as maturity increases from less than one month to more than three months. Our overall sample contains, on average, 912.3 matched option pair trades per day. Also, short maturity options trade most frequently, while trading volume falls uniformly with maturity. For the short maturity options, daily trade averages 827.7, falling to 8.54 for the longest maturity options. Since long maturity options trade somewhat less frequently, it becomes more difficult to match them on the value of the index, which gives rise to the sharp fall in matched volume.

For our parametric tests, we do not need to match the options on index value and exercise price. Instead, we can compute implied volatility from each of the call put trades. The advantage of this approach is that it increases the sample size substantially. However, to avoid our sample from being dominated by options that are skewed with respect to moneyness or maturity, we first group all option trades according to whether the options are in the money, at the money or out of money, as well as according to maturity. We then randomly match options by moneyness and maturity to ensure that we have equal representation of all options. Any excess options that are not matched are thrown away. This pre-selection avoids introducing subtle biases due to sample selection criterion. For instance, if the past market returns are positive, most of the call options will be in the money, while most puts will be out of the money. Since we would like to measure the effects of past stock returns on volatility independently of moneyness, we need to ensure in-the-money as well as out-of-the-money options are equally well represented.

Panel B of Table 1 shows the characteristics of the options we have included for implied volatility tests. Our sample period now contains 6,398,795 matched option pairs, which more than doubles the sample size for the boundary condition tests. The average price of options in this sample equals $3.85 for calls and $3.49 for puts (giving an overall average of $3.67). Call prices increase from $3.41 to $7.76 while put prices increase from $3.13 to $7.14 as maturity increases from less than one month to more than three months. Our overall sample contains, on average, 2025.6 matched option pair trades per day. Again, short maturity options trade most frequently, while trading volume falls uniformly with maturity. The daily average number of trades equals 1584.1 for shortest-maturity options and 20.4 for the longest-maturity options.

Both boundary condition valuation and the computation of implied volatilities require information about interest rates and dividends. We obtained daily bid and ask prices for Treasury Bills for the period 1983-1995 from Smith Barney. The original source of this data is DRI. For each Treasury Bill, the discount yield corresponding to its maturity is computed from the average of its bid and ask prices. The appropriate maturity interest rate for each option maturity and dividend payment date is obtained by linearly interpolating between these discount yields.

Following standard practice in the literature, we assume that investors know the dividends on the OEX index in advance. The realized dividends are used to compute the present value of dividends during the remaining life of each option. The dividend data are described in detail in

Harvey and Whaley (1992).

III. Boundary Condition Tests based on Put-Call Parity for American Options

We first study if the put-call parity boundary conditions for American options are systematically violated as a function of past market returns. These conditions are model independent. The absence of arbitrage opportunities implies that for a fixed maturity date and strike price, the following boundary conditions must hold for American options:

$$\begin{aligned} \mathit{B1} &= \mathit{CallPrice} - \mathit{PutPrice} - \mathit{Index} + PV[\mathit{StrikePrice}] \leq 0, \\ \mathit{B2} &= \mathit{PutPrice} - \mathit{CallPrice} + \mathit{Index} - PV[\mathit{Dividends}] - \mathit{StrikePrice} \leq 0, \end{aligned}$$

where PV is the present value operator and *Dividends* corresponds to all the dividends paid during the remaining life of the option [see Jarrow and Rudd (1983), pages 68-74 for similar conditions].

Suppose the first boundary condition, (*B1*), is violated. We can make arbitrage profits by buying the put, selling the call, buying the index and borrowing the present value of the exercise price. This strategy yields an initial positive cash inflow equal to the amount of the boundary violation. In the future, there will be no cash outflows. To demonstrate the arbitrage opportunity and simplify the discussion, consider the following four possibilities: 1) Short call is exercised before the first dividend; 2) Short call is exercised after the first dividend, but prior to maturity; 3) Short call is exercised at maturity; and 4) Short call is never exercised.

In the first case, we can deliver the cash equivalent of the underlying index. The receipt of the strike price is always greater than the value of our initial loan. The second case is similar. However, this time our profits are increased by the dividend received. The third case is again similar. This time our profits are increased by the cumulative dividends received. In the fourth case, if the call is never exercised, our borrowing position can be covered by the cash flow from the long positions in the put and the index at option maturity. At maturity, the put and the index have a combined value greater than or equal to the exercise price. Moreover, since we own the index, any realized dividends on the long index position will again increase our arbitrage profit. Therefore, in the absence of transaction costs, this strategy will yield an arbitrage profit greater than or equal to the amount of the initial boundary violation.

Similarly, one can show that a violation of the second boundary condition is also inconsistent with the absence of arbitrage. If (*B2*) is ever violated, we can make arbitrage profits by buying the call, selling the put, shorting the index and lending the exercise price and the present value of the dividends. This strategy yields an initial positive cash flow equal to the amount of the boundary violation and no future cash outflows. To demonstrate the arbitrage opportunity, once again consider the following four possibilities: 1) Short put is exercised before the first dividend; 2) Short put is exercised after the first dividend, but prior to maturity; 3) Short put is exercised at maturity; and 4) Short put is never exercised.

In the first case, we need to pay the exercise price and receive the cash equivalent of the underlying index, which we can use to cover our short position in the index. We use our exercise price escrow account to pay the exercise price and keep the interest earned on the exercise price, the call and the dividend escrow account as extra profits. The second case is similar, except that we use part of the funds in our dividend escrow account to pay the first dividends. The third case is again similar, except that we use all of the funds in our dividend escrow account to pay the entire dividends. In the fourth case, we can always use our call (which must be in the money) to buy the index (again using our exercise price escrow account to pay the exercise price) and deliver it against our short index position. Again, we keep the interest on the exercise price as extra profit.[6]

An important caveat is that the above boundary conditions can never be perfectly tested using transactions data due to the various market imperfections discussed in the introduction. Our aim here is not to argue that there are unexploited arbitrage opportunities, but simply identify pressures on option prices. The absence of textbook arbitrage implies that *B1* and *B2* should be negative for every strike price and maturity combination. Market momentum hypothesis predicts that call prices will tend to be relatively high following stock price increases. Therefore, if investors significantly bid up call prices after stock price run-ups, then the probability that *B1* is greater than zero (a violation) should be higher during periods after large stock price increases than during periods after large stock price decreases. Similarly, following stock price declines, put prices will tend to be relatively high, increasing the probability that *B2* is greater than zero.

In Table 2, we report the probability of boundary condition violations and the average value of violations conditional on a violation, as a function of the prior 60-day market return. The probability of boundary condition violations (that $B1 > 0$) is computed as the number of observations of *B1* for which $B1 > 0$ divided by the number of total observations of *B1*. The market returns are computed using the value-weighted index of NYSE, AMEX, and NASDAQ stocks.

Boundary conditions are evaluated on date t, while the past stock returns are computed from date $t-60$ to date $t-1$. We leave a one-day separation to facilitate the potential implementability of our strategy. This one-day window makes our tests realistic, since market participants can evaluate the past stock returns and implement the tests. We also experimented with computing returns from $t-61$ to $t-2$. Our results are not affected by the choice of stock market return horizons.

In Panel A, we report the results for the entire sample period. Later, we redo our tests both before and after the crash. The immediate aftermath of the crash of 1987 is problematic since liquidity problems resulted in unreliable prices. For contrast, we also report in Panel B, the results by focusing entirely on the pre-crash period. In panel C, we focus on the post-crash period after eliminating observations from the three-month period immediately following the crash. Since the magnitude of the boundary condition violations increased significantly in the immediate aftermath of the crash, we infer that arbitrage activity was much lower immediately after the crash. Consequently, the difference in the results in Panels A and C provides some evidence on the effect of arbitrage activity in keeping prices in line with fundamentals.

Panel A of Table 2 shows the average value of *B1* and *B2*, the probability of boundary condition violations and the dollar magnitude of the violations for the entire sample, which contains 2,935,923 option pairs. Our results indicate average value of *B1* and *B2*, the probability of boundary condition violations and the dollar magnitude of the violations all depend on past stock returns. First, there is a positive relation between past stock returns and the mean value of *B1*. Going from -5% to +5% past returns increases the mean value of *B1* from -\$0.69 to -\$0.35, or a \$0.34 difference. In contrast, there is a negative relation between mean value of *B2* and past stock returns. Going from -5% to +5% past returns decreases the mean value of *B2* from -\$0.53 to -\$0.94, or a \$0.41 difference.

The relation between past stock returns and probability of boundary condition violations is especially strong. An increase in past stock returns (going from -5% to +5%) causes the probability of *B1* violations to almost double (an increase from 18 percent to 34 percent). Similarly, an increase in past stock returns (going from -5% to +5%) causes the probability of *B2* violations to decline by more than half (a decline from 19 percent to 8 percent).

Conditional on a violation, the magnitude of the arbitrage violation is about \$0.30 and varies between \$0.24 and \$1.37. Given an average option price of \$4.56, these mispricings represent 6.6%, 5.3%, and 30.0% of the average option price, respectively. Going from -5% to +5%, average *B1* violations change from \$0.31 to \$0.37, a \$0.06 change, while the average *B2* violations change from \$0.64 to \$0.24, a \$0.40 change. These shifts represent 1.3% and 8.8% mispricing of the average option price, respectively.

Panel B of Table 2 examines the pre-crash period only (March 11, 1983, to October 16, 1987). While there are no days before the crash when the 60-day return to the value-weighted index is less than -10%, the results from this sample are still consistent with our market momentum hypothesis. With negative stock returns, *B2* violations are almost twice as likely as *B1* violations. With positive returns, *B1* violations are three to four times as likely as *B2* violations. Similarly, when past returns switch from negative to positive, the probability of *B1* violations more than double from 14% to 39%. When past returns switch from negative to positive, the probability of *B2* violations fall by about two-thirds, from 25% to 9%. Once again, both the mean value of the boundary conditions as well as the mean value conditional on a violation depend on past stock returns.

Panel C of Table 2 examines the post-crash period (January 19, 1988, to December 29, 1995) after excluding the three-months immediately following the crash.[7] The post-crash period in fact shows somewhat weaker results compared to the pre-crash period. Conditional on a violation, the magnitude of *B1* equals \$0.27 as compared with \$0.32 during the pre-crash period. Similarly, conditional on a violation, the magnitude of *B2* equals \$0.21 as compared with \$0.31 during the pre-crash period. In most cases, the dollar magnitude of violations conditional on violation go down for both *B1* and *B2* after the crash as compared with pre-crash.

During the post-crash period, the probability of *B1* violations are higher than those of *B2* violations for all groups shown. This is partially due to a smaller number of observations with negative stock returns. However, comparing days when past stock returns are moderately negative (-5% or less), with those when the past stock returns are moderately positive (+5% or more), mean values of *B1* are positively related to past stock returns while the mean value of *B2* is negatively related to past stock returns. Also, when past stock returns go from negative to positive, the probability of *B1* violations increase from 17% to 29%. When past returns switch from negative to positive, the probability of *B2* violations fall from 10% to 7%.

To get a clearer picture for the entire range of stock returns, we plot the relation between past stock returns and probability of boundary condition violations in Figure 1 after grouping the past stock returns into percentiles. Once again, past stock returns are measured from day -60 to day -1. Visual examination of Figure 1 shows a strong positive relation between *B1* violations and past stock returns for the entire range of returns. Similarly, there is a strong negative relation between *B2* violations and past stock returns. Hence, our evidence in Table 2 cannot be attributed to a particular grouping procedure.

Our results so far ignore any transactions costs. As argued before, we would not expect investors to forego riskless, costless arbitrage opportunities. However, the fact that more violations occur, as implied by the market momentum hypothesis, is significant. The model independence of these boundary conditions provides initial support for the market momentum hypothesis.

To formalize this relation, we also present two-way classification Chi-square tests[8] of the relation between violations of *B1* and *B2* boundaries and the past stock returns (Table 3, Panel A). Here we again focus on each matched option trade. Our purpose here is two-fold. First, we would like to demonstrate that patterns shown in Table 2 are not due to outliers when few options are trading. Second, the Chi-square tests formalize the informal information presented in Table 2 without imposing any structure on the relationship.

Our evidence indicates that the relation between the past stock returns and boundary condition violations is statistically significant (Table 3). When past stock returns are negative, violations of *B2* are more likely relative to their expected number if there was no relationship between past stock returns and *B2* violations. When past stock returns are positive, violations of *B1* are now more likely.

While not shown in Table 3, results are significant for both the pre-crash and post-crash subsamples. Based on Chi-square tests, our evidence also suggests that boundary condition violations, as a result of movements in stock prices, are somewhat more significant for the pre-crash period.

We also examine whether the boundary condition violations are meaningful after taking into account one type of transaction costs. To test this idea, we require that purchase transactions take place at the market makers' ask price, and sale transactions take place at the market makers' bid price.[9] This way investors pay the bid-ask spreads in the options markets before they realize any arbitrage profits. For instance, to execute an arbitrage transaction based on *B1* violation requires that investors buy the put option and sell the call option. Taking transactions costs into account in this case, we record the put price at the market makers' ask price and record the call price at the market makers' bid price. This approach penalizes any arbitrage profits by the bid-ask spread. A violation is found if either *B1* or *B2* is positive after taking into account the bid-ask spreads.

Our results hold up even after taking into account the bid-ask spreads [Table 3, Panel B]. While both the magnitude and the significance of the violations decline after transactions costs, nevertheless, the overall results are similar. Even after paying the transactions costs, violations of the boundary conditions are related to past stock returns. These findings suggest that our results are not only statistically significant but also economically significant.

While not shown here, we conducted additional sensitivity tests of the relations shown in Table 2. Specifically, we regressed *B1* and *B2* values on 10- to 100-day past stock returns. In all cases, we have a significant positive relation between *B1* and past stock returns and significant negative relation between *B2* and past stock returns. All regressions are significant at the 1% level.

As a second sensitivity test, we first averaged the probability of boundary condition violations for each day, and then examined the relation between average probability of violations and past stock returns by using time-series regressions, after taking into account the autocorrelation structure of residuals. These results are consistent with Tables 2 and 3 and are not shown. The regressions of probability of *B1* boundary condition violations on past stock returns yield all positive coefficients that are significant at the 1% level. The regressions of probability of *B2* boundary condition violations on past stock returns yield all negative coefficients that are significant at the 1% level. Moreover, some of the regression coefficients generally are close to 1.0, suggesting that a 10% shift in stock return changes both *B1* and *B2* violations by about 10%. This finding is consistent with the results shown in Table 2. We also repeated this analysis for the pre-crash and post-crash periods. Once again, our evidence is consistent with Tables 2 and 3.[10]

IV. Implied Volatility and Past Stock Returns

While the evidence presented so far is convincing, it leaves at least four questions unanswered. First, market momentum hypothesis does not require boundary violations. By examining only the boundary violations so far, we have restricted our sample to extreme observations only. We would like to find out whether the pressure on option prices occurs in general or only in extreme situations. Second, our tests in Tables 2 and 3 focus mostly on the probability of boundary violations and ignore the magnitude of the violations. We need to examine whether the dollar magnitude of *B1* and *B2* violations are also affected by past stock returns. Third, we would like to know whether market momentum hypothesis continues to hold for parametric specifications of the option prices. Fourth, by parameterizing the degree of mispricing, we can separate the influences of different factors caused by changes in market momentum, such as changes in expected future market returns and portfolio insurance. To answer these questions, we formulate a parametric approach instead of the non-parametric boundary condition violations.

Our parametric measure of the price pressures in option markets is the implied volatility of call and put prices. The implied volatility is computed using the escrowed dividend modification of the binomial model as employed in Harvey and Whaley (1992). We assume that the dividend on the index is known in advance and escrowed. This approach also explicitly takes into account that the OEX calls and puts are American options subject to early exercise. We begin by calculating an implied volatility for every transaction in our dataset.

We estimate the implied volatility using the Newton-Raphson search procedure similar to the one suggested by Manaster and Koehler (1982). Given an i^{th} estimate of σ_i, the procedure suggests estimate $i+1$ should be:

$$\sigma_{i+1} = \sigma_i - \frac{[C(\sigma_i) - C(\sigma^*)]}{vega}, \text{ where} \tag{1}$$

$C(\sigma_i)$ is the price of the given option with an implied volatility of σ_i computed from the binomial model, $C(\sigma^*)$ is the observed option price, and vega is the partial derivative of the binomial option price with respect to σ_i. For each transaction, we iterate on this procedure until the implied volatility has converged, and the predicted option price is equal to the observed price.[11]

By going to binomial model implied volatilities, we give up the model independent generality of Tables 2 and 3. However, by examining implied volatilities, we can now quantify and relate the effects of price distortions to previously established biases of the standard option pricing models. Specifically, we can measure the magnitude of the shifts in option prices and whether they are related to the systematic differences in implied volatility estimates by maturity and moneyness.

Previous literature suggests that the option pricing models systematically misprices options with respect to moneyness and maturity [see Whaley (1982) and Stein (1989), and Bakshi, Cao, and Chen (1997)]. Short-term options are typically underpriced by Black-Scholes relative to long-term options. Similarly, deep in-the-money and deep out-of-the-money options are underpriced relative to at-the-money options. Hence, we need to control for option moneyness and maturities when we examine the relation between implied volatilities and past stock returns.

We show the implied volatilities of call and put prices as a function of past 60-day stock returns separated by the strike price and maturity of the options [Table 4]. Panel A shows the implied call volatilities when past 60-day stock returns are positive (greater than 0.05), and Panel B shows the implied call volatilities when past stock returns are negative (less than -0.05). A decline in stock prices increases call-implied volatilities regardless of the maturity and strike price. On average, a switch in returns, from 5% to -5%, increases the call-implied volatilities by about 4.6 percentage points, from 18.3% to 22.9%. Negative stock returns increase implied volatility estimates across the board, while affecting the short-maturity options (one month or less), deep-out-of-the-money and deep-in-the-money options the most. For short-maturity calls, implied volatility increases from 20.7% to 27.6%, an increase of 6.9 points. For deep-in-the-money calls, the increase equals 13.9 points (38.5% minus 24.6%) while for deep-out-of-the-money calls, the increase equals 6.1 points (23.9% minus 17.8%). Long-maturity and at-the-money options are affected to a smaller extent.

For put options, the patterns are similar (Panels C and D of Table 4). A shift from rising to declining stock prices increases put-implied volatilities by 6.1 percentage points, from 17.5% to 23.6%. All implied volatility estimates increase with declining stock prices. Once again, most pronounced volatility increases are observed in short maturity (one month or less), deep in-the-money puts and deep out-of-the-money puts.

The evidence in Table 4 is consistent with that in Tables 2 and 3. Declines in stock prices increase both call and put option volatilities; however, put-implied volatilities increase more than call-implied volatilities (6.1 points versus 4.6 points). As a result, put options become relatively more expensive when stock prices decline. Given an increase in stock prices, investors bid up the relative prices of call options above those of the put options. Given a decline in stock prices, investors bid up the relative prices of put options above those of the call options.

A. Implied Volatility Smiles

Volatility smile refers to the U-shaped implied volatility estimates as a function of the exercise price. Previous option pricing studies have shown that both in-the-money and out-of-the-money calls and puts have higher implied volatilities as compared with the at-the-money calls and puts. Moreover, short-maturity (less than 60 days), deep-in-the-money calls and deep-out-of-money puts have the highest estimated implied volatilities giving rise to a skew-shaped implied volatility patterns [see

Bakshi, Cao, Chen (1997)]. We document a similar relation in Table 4. Generally, deep-in-the-money calls and deep-out-of-money puts have the highest estimated implied volatilities.

Table 4 also allows us to examine the impact of past stock returns on the volatility smiles. When stock returns are positive, the smile measures 8.7 percentage points (24.6% minus 15.9%) for deep in-the-money calls and 1.9 percentage points for deep out-of-the-money calls (17.8% minus 15.9%). When stock returns are negative, the call-smile more than doubles: 20.2 percentage points (38.5% minus 18.3%) for deep in-the-money calls and 5.6 percentage points for deep out-of-the-money calls (23.9% minus 18.3%).

A similar picture emerges for put options. For puts, a decline in market returns more than triples the volatility smile. When stock returns are positive, the smile averages 4.1 points. When stock returns are negative, the smile jumps to 13.7 points.[12] Hence, the effect of past stock returns on volatility smiles is even more pronounced for puts than for calls.

Our evidence suggests that declines in stock prices more than double the volatility smiles. An interpretation of this finding in market momentum context suggests that price pressure is especially effective for options away-from-the-money since these are the least liquid options. Second, our evidence suggests that investors highly value these away-from-the-money options especially in strong bull and bear markets. Hence, our evidence uncovers an important new factor that affects not only option prices but also the volatility smile. Our evidence also suggests that modeling past stock returns into equilibrium option pricing models is likely to have strong explanatory power for volatility smiles.

To further compare call and put implied volatilities as a function of past stock returns, we plot in Figure 2 the average difference between call and put implied volatility, defined as the volatility spread, as a function of maturity and percent moneyness. Percent moneyness is defined as the percent by which the option's strike price is in-the-money relative to the opening level of the index. The two graphs offer several insights. First, the increase in put-implied volatilities relative to call-implied volatilities (decline in the volatility spread) that follows declines in stock prices is robust with respect to moneyness. The effect is present for most categories and most pronounced for deep out-of-the-money options. Market momentum effect uniformly declines with increasing moneyness. While it is also present for at-the-money options, it mostly disappears for deep in-the-money options. Hence, market momentum most strongly affects options that have higher degrees of leverage. Market momentum does not appear to be a complete explanation for the volatility smiles, which are present whether stock prices increase or decrease. However, the market momentum factor does exaggerate the deep out-of-the-money volatilities in bear markets. Hence, to get a better measure of the volatility smiles, it is necessary to control for past stock return effects.

To further quantify the relation between past stock returns and volatility smiles, we defined a measure of volatility smile as the difference between implied volatility of away-from-the-money options and at-the-money options, separately for each day, calls and puts and maturities. Volatility smile was then averaged for each day. We then examined the relation between volatility smile and past stock returns, by taking into account the autocorrelation structure of the time-series measure of volatility smile. Our evidence (not shown here for brevity), shows significant negative relations between volatility smiles and past stock returns. The relations are generally significant at or near the 1% level for holding periods 10 days to 100 days for past stock returns. Hence, past stock returns do have a significant impact on volatility smiles as well.

The relation between volatility spreads past stock returns is also robust with respect to maturity [lower panel of Figure 2]. For all options, the volatility spread declines following declining stock prices. Moreover, the volatility spreads exhibit an overall term-structure effect, with near-term maturities exhibiting lower spreads than those with longer maturities. However, this feature is only present when the index level has declined. To properly account for the term-structure in implied volatility spreads, this suggests it is important to control for past stock returns.

B. Implied Volatility Spread

Our results so far suggest that call and put implied volatilities respond differently to past stock returns. We now focus on the overall volatility spread to precisely quantify this differential response. As discussed earlier, to compute the volatility spreads, we require the sets of call and put options used in calculating the spread to have the same maturity and moneyness on each day. That is, due to moneyness or term structure effects, our results may become biased if certain strike prices and maturities trade more on one side of the spread than the other (Table 4). For example, following a run-up in the index, there will be more in-the-money calls and out-of-the-money puts available to be traded. Since we have already documented an interaction between moneyness and market momentum, our results could be affected by the type of options we include in our tests. To avoid any potential interaction effects, we match options according to maturity and moneyness.[13] We then randomly throw out any excess calls or puts at each maturity and moneyness level. In this way, our implied volatility spread is calculated from a set of call and put transactions identically matched in terms of maturity, moneyness, and number.

Each day, for the given set of calls and puts, the implied volatility spread is computed four different ways. The purpose of this exercise is to first explore the sensitivity of various options to the market momentum hypothesis and also ensure that our results are general. We first weight each option-implied volatility equally, averaging across all call and put volatilities and taking the difference, resulting in an equally-weighted estimate of the implied volatility spread.

Second, we compute "vega"-weighted volatility spreads. The vega-weighted spread takes a weighted average of all call and put volatilities based on the partial derivative of each option's price with respect to the volatility. This scheme weights at-the-money options more than out-of-the-money options. If at-the-money options are not affected by market momentum factor, then there should be little or no relation between past stock returns and vega-weighted average spreads.

Our third measure is the elasticity-weighted scheme, which weights by the elasticity of each option with respect to the value of the underlying index. This weighting scheme is similar to the one used by Chiras and Manaster (1978) and Franks and Schwartz (1991) and incorporates leverage constraints. For example, an investor with limited capital who wishes to gain exposure to directional changes in the stock price will typically invest in options with high elasticities. Since the elasticity is a decreasing function of how much the option is in-the-money, this procedure weights out-of-the-money options more than in-the-money options.

Our final weighting scheme uses only the at-the-money options. This scheme is used by Harvey and Whaley (1991) and Figlewski and Webb (1993). At-the-money options are most sensitive to changes in volatility and typically have the most liquidity. At-the-money options are defined as the call-put pairs with exercise prices immediately bracketing the index value prior to option trade. Available options are weighted equally within strike prices and then interpolated based on their distance from the opening index level. The difference between the call and put measures is referred to as the at-the-money implied volatility spread. At-the-money option volatility usually throws away a lot of the option data.

C. Relation to Past Stock Returns

Table 5 documents the sample statistics for the volatility spreads averaged for each trading day for each of the four weighting schemes. First, typically the mean and median weighted-average volatility spread is small and negative, on the order -1%. Negative estimates of the volatility spread means that the put-implied volatility exceeds the call-implied volatility for our sample period. Standard deviations of the volatility spread tend to be between 2% and 3%. Also, 80% of the volatility spreads fall between -4% and 2%.

The minimum value of the volatility spread equals -45% while the maximum value of the volatility spread is about 27%. Most of the negative outliers occur during a short period after the crash of October 1987. The post-crash sub-period analysis excludes this period to avoid the large outliers. Table 5 also shows the partial autocorrelation coefficients for average daily volatility spreads. All four series exhibit significantly positive, partial serial correlations. The first-order partial serial correlations for all weighting schemes are between 0.77 and 0.80. Second-order and third-order partial serial correlations for all weighting schemes are smaller, between 0.11 and 0.21.

Large and positive first-order autocorrelation suggests that the implied volatility spread follows a slow-moving diffusion process. This finding is again consistent with a situation where the innovations in volatility spread (and hence relative valuation of call and put options) arise from sustained price pressure on either call or put options. The positive serial correlation makes it less likely that the volatility spread arises either from temporary measurement errors or asynchronous trading between the options market and the underlying equity market. The slow-moving nature of the volatility spread is taken into account in the subsequent time-series regressions.

Our four weighting schemes produce estimates that are highly correlated (Panel B of Table 5). All estimates cross-correlations are greater than 0.94 and some as high as 0.99. Given the high degree of correlation between our four measures of volatility spread, we are not likely to get vastly different estimates using each of these schemes.

In subsequent tests, we focus mainly on the volatility spread computed using elasticity-weighting. This measure utilizes all options and incorporates leverage constraints. We have, nevertheless, replicated our tests using the other three measures as well.

The relation between past stock returns and volatility spreads is examined next (Table 6). Market momentum hypothesis predicts a positive relation between past stock returns and volatility spreads. Past stock returns are computed using past 2-week to 20-weeks of returns for the value-weighted index of NYSE, AMEX, and NASDAQ stocks. Once again, we use a 1-day window between the ending day for computing stock returns and the computation of the volatility spread to prevent unintended distortions. This procedure guarantees that potential investors have the necessary information on hand to actually implement the tests conducted in this paper.

The properties of the volatility spread suggest a slow-moving time-series. Hence, if daily average spreads are used as the dependent variable in OLS regressions, the residuals will exhibit strong autocorrelations, leading to potential biases in the estimated regression coefficients. We found that an AR(5) error model eliminates the correlation structure of the residuals, as judged by the Box-Pierce statistics. We have also replicated our tests by sampling once a week and once a month. For the weekly interval, an AR(2) error model was sufficient to eliminate the residual correlations. For the monthly sampling interval, ordinary least-squares regressions had well behaved residuals. All three methods produced qualitatively similar results with increasing t-statistics and decreasing adjusted R-square values with more frequent sampling.

We report the results of the regression of the daily volatility spread against stock returns over the past 2- to 20- weeks for the entire sample period [Table 6]. For the overall period, as well as the pre-crash and post-crash subperiods, the relation between volatility spread and past stock returns is positive and significant. Comparing the pre-crash subperiod with post-crash subperiod again shows that the post-crash subperiod results generally indicate smaller regression coefficients. This finding is consistent with Table 2.

While not shown here, we observe the same positive relation between past stock returns and volatility spreads across the other weighting schemes. Hence, our relations are not produced by a particular weighting scheme. Comparing the four weighting schemes suggests that while all four estimates are still positive and significant, elasticity-weighted options yield stronger results while at-the-money options yield somewhat weaker results (consistent with Table 4 and Figure 2). Overall, our results indicate that the price pressure on deep-out-of-money and deep-in-the-money options is the most, while the price pressure on at-the-money options appears to be the least. These findings are intuitive since at-the-money options tend to be most liquid. If price pressure leads to arbitrage boundary violations for these options, arbitrageurs are more likely to exploit this mispricing. In contrast, trading volume in deep-out-of-money options tends to be less, thereby making it more difficult to exploit mispricing.

As a sensitivity test, we have also computed implied volatilities using only options with maturities less than 30 days. Limiting our data set to the short maturity options resulted in elimination of about one-third of the data set. Using only shortest-maturity options results in much stronger positive relations between volatility spreads and past stock returns. In most cases, both the coefficient estimates and t-statistics double in comparison with all maturity options. These results are not surprising given Figure 2, which shows that the effects of past stock returns is strongest in the shortest-maturity options, falling uniformly with maturity.

V. Sources of Price Pressure

So far, we have established that past stock market returns affect option prices. Positive market returns increase the price of call options. Negative market returns increase the price of put options. Both price changes lead to boundary condition violations that are inconsistent with frictionless, arbitrage-free markets. There are a number of potential interpretations of our findings, and in this section, we will attempt to distinguish between them.

One possible explanation for the results documented so far is that investors simply project past stock returns into future stock returns. As documented by Lo and MacKinlay (1988), the value-weighted market index exhibits strong positive autocorrelation over intermediate horizons of less than one year. Hence, given positive past market returns, investors expect the positive returns to continue, and bid up the prices of call options. Given negative past market returns, investors expect the negative returns to continue, and bid up the prices of put options. We call this the market momentum hypothesis. This hypothesis predicts that past stock returns will exhibit an independent positive influence of volatility spread.

A second explanation for our findings is that past stock returns may be proxying for an omitted variable that affects call and put options differently. For instance, the finance literature documents a negative relation between stock returns and volatility [Schwert (1989)]. When stock prices fall, volatility increases. When stock prices rise, volatility decreases. We also replicate this finding in Table 4. This idea suggests that if a separate estimate of the volatility is included as a regressor in Table 6, it would show up with a negative coefficient, and it would also drive away the significance of the past market returns.

Another possibility is that investors' supply and demand for options is not only affected by their return expectations from market momentum but also by portfolio insurance considerations, and both effects are present. When the volatility of stock returns increases, a greater number of investors seek reduced exposure to the stock market and bid up the prices of put options. When the volatility of stock returns decreases, a greater number of investors seek increased exposure to the stock market and bid up the prices of call options. This idea suggests that if a separate estimate of the volatility is included as a regressor in Table 6, it would show up with a negative coefficient but it would not necessarily drive away the significance of the past stock returns. Both past stock returns and volatility would show up with significant influences.

Obviously, similar ideas can apply to higher moments of the stock return distributions. If investors care about higher moments and their perceptions of higher moments are affected by changes in past stock prices, then once again, option prices would be affected. Studies in the stock market have found that both stock returns are right skewed and that investors have a preference for (systematic) right skewness [Arditti (1967), Kraus and Litzenberger (1976)]. Holding all else constant, if investors expect an increase in right skewness, they will bid up prices of call options relative to put options. This logic suggests a positive relation between changes in skewness and volatility spread.

Finally, the kurtosis measure captures probability of extreme events separately from the volatility measure when stock returns are not normally distributed. We include an estimate of kurtosis to determine if changes in expectations about rare events (both positive and negative) affect the valuation of options. Since kurtosis measure affects both left and right tails of stock return distributions, there is no ex-ante prediction of a sign of the relation between kurtosis and volatility spread. We leave the sign of this potential relation to be determined by the estimation procedure.

We test these ideas with a regression analysis using past stock returns, expectations about volatility, skewness, and kurtosis as independent variables. We estimate a four-equation joint system using GMM to take into account potential cross-equation dependencies as well as potential heteroscedasticity issues. To estimate the future expectations about volatility, skewness and kurtosis, we fit an AR(5) model for each of these variables. For volatility spread, we use elasticity-weighted implied volatilities as in Table 6. Historical stock return volatility is estimated as the standard deviation of realized returns for the value-weighted index of NYSE, AMEX and NASDAQ stocks over the same 2-week to 20-week horizons as the stock returns. Skewness and kurtosis of past stock returns are measured similarly. Finally, to obviate the need for an error model, we sample the data every 20 trading days. This reduces the auto-correlation structure of the residuals and eliminates the need for an error model. We also experimented with using daily data with higher-order error models. Results are generally similar, and we show the simpler models here.

The results in Table 7 indicate that past stock returns continue to show up with positive coefficient against the volatility spread as in Table 6. Hence, including higher moments of stock return distributions does not eliminate the positive relation between past stock returns and volatility spread. This finding suggests that investors' expectations about future returns directly affect their valuations of index options, independently of other channels of influence. Our result suggests i) that past returns do not act as a proxy variable for higher moments of stock return such as increased volatility, and ii) that the market momentum hypothesis is not rejected even when we control for other factors. When past stock returns are positive, investors' demand for call options increases, putting upward pressure on call prices. Similarly, when past stock returns are negative, investors' demand for put options increases, putting upward pressure on put prices.

Expectations about increased stock return volatility reduce the volatility spread in Table 7. This finding is consistent with a scenario where portfolio insurance considerations play an independent role separately from market momentum explanation. Our results suggest that a greater number of investors demand put options in the presence of increased market volatility, which puts an upward pressure on put prices and reduces the volatility spread. Similarly, a greater number of investors demand call options in the presence of reduced market volatility, which puts an upward pressure on call prices and increases the volatility spread.

As hypothesized before, we find a positive relation between skewness expectations and volatility spread. An expectation of increased skewness leads to increased volatility spread. This finding is consistent with a scenario where investors prefer skewness in stock returns and bid up the call prices when they expect higher skewness. Also, inclusion of the skewness variable does not drive away the effects of past stock returns or volatility.

Finally, the kurtosis measure shows up with positive, negative, and insignificant coefficients at different horizons. Statistically significant coefficients tend to be positive, although most of the coefficients are statistically insignificant. Since we could not specify an ex-ante sign for this coefficient, our results are not too surprising. However, what is interesting about the kurtosis measure is that there is no stable negative relation between kurtosis and volatility spread. This finding suggests that kurtosis expectations work in both tails and the kurtosis measure cannot be taken as a good measure of crash worries.

Given that the kurtosis measure does not measure investors' expectations about crash, it would be interesting to include an additional measure that captures investors' worries about a crash. It would also be interesting to determine whether any of our findings in Table 7 can be attributed to crash worries. Our evidence so far suggests that crash worries are not driving our main findings since the relation between boundary condition violations and past stock returns was significant during the pre-crash period (Table 2). Moreover, the relation between volatility spread and past stock return was also significantly positive during the pre-crash period (Table 6).

In Table 8 we include an additional independent variable, named crash-worry, to our regression. Crash-worry is measured as the implied volatility of the most out-of-money put option with more than 10 days to maturity on each day. When there is more than one maturity that meets this criterion, we average the implied volatilities of these put options. In general, the most out-of-money put option is about 10% out of money. Hence, this variable captures market's expectations of a greater than 10% fall in stock prices during the life of the option. We expect the crash-worry variable to be strongly negatively related to the implied volatility measure. What we would like to find out is whether crash worries also drive away the relation between volatility spread and the four moments of stock returns.

Our results are shown in Table 8. As expected, the crash-worry variable comes in with a significant negative coefficient. However, the signs and significance of the past stock returns and skewness variables are mostly unaffected. Past stock returns continue to have a positive (albeit somewhat attenuated) influence on volatility spread. Similarly, expectations about increased skewness continue to have a positive influence on volatility spread. Hence, our main finding that market momentum affects option valuations is not produced by crash worries. In contrast, the crash-worry variable kills the strong negative influence of the volatility measure. Again, this finding is not surprising. Both of these variables measure investors' worries about significant market declines. Our evidence suggests that the crash-worry variable does a better job of capturing these expectations than the auto-regressive model of realized historical volatilities.

VI. Discussion

Our results suggest that in the presence of market imperfections, past stock returns exert a strong influence on the pricing of index options. This finding is contrary to the specifications of the standard option pricing models, which predict no relation. Our results also suggest that option prices are affected both by past stock returns as well as the higher moments of past stock returns. We also find that previously documented biases in option pricing models, which result in volatility smiles, are also strongly influenced by past stock returns. Since our findings can only exist in markets where complete arbitrage is not possible due to market imperfections, our evidence also suggests that no-arbitrage based option pricing models leave considerable room for disagreement about equilibrium option values.

Our findings are important for several reasons. First, this is the first study to empirically document the influence of past stock returns on option prices. Second, our results are general and do not depend on any equilibrium option pricing model. Third, since our evidence suggests that the effect of past stock returns is model independent, it is not possible to account for this effect through any no-arbitrage based option pricing models. Fourth, our evidence suggests that taking past stock returns into account will result in more accurate estimates of implied volatilities from index option prices, which have been used by many authors to explore arbitrage opportunities, measure risk premia in the stock markets, or forecast future volatilities. Also, many authors use only call prices to estimate option volatility. Our evidence suggests that there is information in put-implied volatilities not contained in call-implied volatilities. Consequently, using both call and put prices and taking into account past stock returns would lead to improved estimates. Fifth, our findings suggest that tests of market efficiency in options market should take into account the differential reactions of call and put markets as a function of the past stock returns. Tests of market efficiency in the options markets include boundary condition violations. In this paper, we demonstrate that probability of boundary condition violations depend on historical stock returns. Finally, our findings can help investors to choose between alternative trading strategies. Following large stock market increases, bets on further stock market increases are more expensive to implement using call options. Hence, traders wanting to place such bets may be better off using the underlying stocks. Conversely, following large price increases, reversal strategies would be cheaper to implement using options rather than the underlying stocks.

The evidence presented in this study is not due to an isolated effect of the crash of 1987, when nonsynchronous trading problems caused mismatches between option prices and their underlying assets. When we exclude the three-month period beginning with October 19, 1987, call options continue to be overpriced following market advances, and put options continue to be overpriced following market declines. Hence, the distortions in option prices captured by our study reflect a general phenomenon.

Our findings are surprising since the OEX options market is the largest and most liquid options market in the world. It represents a trading volume equivalent to almost 50% of the trading in NYSE stocks. Moreover, options are derivative securities linked to stock prices by arbitrage relationships. Identifying systematic mispricings in the options market strengthens the case for potential price pressures in the stock market where arbitrage conditions do not significantly constrain stock prices.

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Footnotes

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[1]The possibility that expected returns and risk aversion may be priced in options is recognized [Figlewski (1989), Longstaff (1995), and Bakshi, Cao, Chen (2000)]. For instance, Figlewski (1989), on p. 1310, writes "The standard arbitrage eliminates price expectations and risk aversion from option pricing in a frictionless market. However, within the wide bounds on the option prices that are all that can be established by the standard arbitrage in an actual, imperfect options market, there is certainly room for these and many other factors to have an influence."

[2]While price pressure in options market may be considered a novel idea by many, there is a long-standing literature that examines time varying expected returns, investor psychology and whether investor psychology causes price pressure in the stock market. Examples include Shiller (1981), DeBondt and Thaler (1985, 1987), Shleifer (1986), Fama and French (1988a, 1988b), Poterba and Summers (1988), Lee, Shleifer, Thaler (1991) and Shleifer and Vishny (1997). Hirshleifer (2001) reviews this literature.

[3]We examine the pricing of Standard and Poor's 100 index options (OEX). This market is important since it represents trading volume equivalent to almost half the dollar trading volume in all New York Stock Exchange (NYSE) stocks. Canina and Figlewski (1993) argue that for OEX options, "the difficulties in doing the arbitrage trade and maintaining a hedged position over time are sufficiently daunting that it is not really feasible."

[4]For instance, Jackwerth and Rubinstein (1996) find that beliefs about a crash probability increased by about ten-fold after the crash.

[5]We have also replicated our tests by waiting for a matching for the entire day. Our results were empirically robust to the choice of waiting interval.

[6]Following the standard practice in finance, we have assumed that the dividends are nonstochastic and known.

If the dividends are stochastic, typical discussion of the American put-call parity replaces the actual dividend with the maximum dividend that is known with certainty [see Jarrow and Rudd (1983), p.69]. The arbitrage arguments are otherwise identical. This caveat only applies to the second boundary condition. Given the short maturity of the options, this is a reasonable assumption. Moreover, since the index contains 100 stocks, the dividend stream on the index will be more easily forecastable than the dividends on any of the individual stocks comprising the index. Finally, the dividends on the index will typically approximate a continuous dividend stream. When the exercise price is close to the value of the index, American calls will not be exercised early since the dividend yield on the index is almost always less than the interest rate. Boundary conditions specified above already allow for stochastic interest rates. For *B1* violations, if the short call is ever exercised against us early, we lend our receipt of exercise price at the overnight interest rates and will always be able to pay the exercise price against our original debt at maturity. For *B2* violations, we need to lend the entire exercise price at the overnight interest rate instead of lending the present value of the exercise price. This guarantees that if the short put is ever exercised against us early, we can always come up with the exercise price regardless of what happens with the interest rates.

[7]While our evidence during the crash are consistent with the overall results, both the probability and the magnitude of the boundary violations during the crash are substantially higher. During the crash period, the average magnitude of *B2* boundary was positive $0.05. Hence, on average, *B2* boundary is violated. To get both positive and negative returns, we also classify the past stock returns using the last 20 trading days during the crash (instead of 60 days). When the past stock returns are greater than +5%, probability of B1 violations is 57.5% while the probability of B2 violations is 22.7%. When the past stock returns are less than -5%, probability of B1 violations is 10.0% while the probability of *B2* violations jumps to 69%. Since we did not want our results to be overly influenced by the crash period, we excluded the three months immediately following the crash.

[8]See Daniel (1978), pages 163-170, for a description of Chi-square tests.

[9]The OEX contract is traded on CBOE in an open outcry market. The participants in the auction also include the market-makers that continually update bid and ask prices. It is these continually updated bid and ask prices that are recorded in the Berkeley tapes that we used. The official web site of CBOE (www.cboe.com) states the following with respect to trading of options. "All equity options have assigned market-makers as well as a designated primary market maker (DPM) and that under obligation, market-makers continually make bids and offers good on at least 20, in many cases 50, contracts for all options in their assigned trading classes."

[10]For instance, consider the case when the past stock returns are measured over the past 60 days. These regressions

produce coefficient estimates of 0.84 and -0.35 with t-statistics of 6.31 and -4.31 for *B1* and *B2*, respectively. Both coefficient estimates have p-values less than 0.0001.

[11]We use a binomial model with a minimum of 90 periods and integer number of periods per maturity-day to estimate the implied volatilities. Hence, the the number periods vary between 90 (minimum) and 281 (for 281 days to maturity). The convergence criterion is set at 0.001%. Hence, we consider the procedure converged if the estimated price is within 0.001% of the observed price. Most options converged in 3 or 4 iterations. A small number of options (less than 1%) that did not converge after 10 iterations were removed from the sample. The convergence program runs about 25 hours on a Pentium III machine.

[12]When stock returns are positive, volatility smile averages 4.6 percentage points for deep out-of-the-money puts (20% minus 15.6%) and 3.7 percentage points for deep in-the-money puts (19.3% minus 15.6%), therefore averaging 4.1 percentage points. When stock returns are negative, volatility smile averages 13.6 percentage points for deep out-of-the-money puts (32.6% minus 19%) and 13.7 percentage points for deep in-the-money puts (32.7% minus 19%), therefore averaging 13.7 percentage points.

[13]To match on moneyness, we create a variable indicating how far in- or out-of-the-money the option's strike price is at the beginning of the day. Options between 0 and 5% in-the-money receive a moneyness indicator of 1, those 0 to 5% out-of-the-money receive an indicator of -1, those 5 to 10% in-the-money receive an indicator of 2, and so on.