Deviations from Put-Call Parity and Stock Return Predictability*

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Abstract

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I. Introduction

Put-call parity is one of the simplest and best known no-arbitrage relations. It requires neither assumptions about the probability distribution of the future price of the underlying asset, nor continuous trading, nor a host of other complications often associated with option pricing models. Investigations into apparent violations of put-call parity generally find that the violations do not represent tradable arbitrage opportunities once one accounts for market features such as dividend payments, the early exercise value of American options, short-sales restrictions, simultaneity problems in trading calls, puts, stocks and bonds at once, transaction costs, lending rates that do not equal borrowing rates, margin requirements, and taxes, to name a few.[1]

Several recent papers argue that deviations from put-call parity can arise in the presence of short sales constraints on the underlying stocks, e.g., Lamont and Thaler (2003), Ofek and Richardson (2003) and Ofek, Richardson, and Whitelaw (2004). This is because if the price of a put option becomes sufficiently high relative to the price of the corresponding call and the underlying asset, then the standard arbitrage strategy involves selling the underlying stock short. Ofek, Richardson, and Whitelaw (2004) show that deviations from put-call parity are asymmetric in the direction of short sales constraints and that they are more likely to be observed in options written on stocks that are difficult or expensive to short. They also show that stocks with relatively expensive puts subsequently earn negative abnormal returns. Battalio and Schultz (2006) question these findings, arguing that short-sales constraints have little impact and that careful use of intraday options data, rather than closing quotes, resolves most of the apparent violations of put-call parity. As Cochrane (2005) points out, however, they do not address the finding of negative average returns on the underlying stocks subsequent to observing such deviations from put-call parity.

There are several possible interpretations to these somewhat conflicting results. First, apparent deviations from put-call parity may simply be the random outcome of market imperfections and data

[1] See, e.g., Brenner and Galai (1986), Kamara and Miller (1995), Klemkosky and Resnick (1979, 1980), and Nisbet (1992), among others.

related issues, i.e., mere noise. Second, deviations from put-call parity may reflect short-sales constraints. Third, they may reflect the trading activity of informed investors: if investors trade in the options market first, perhaps because of leverage, then we might expect deviations from put-call parity, e.g., along the lines of the equilibrium model of Easley, O'Hara, and Srinivas (1998). This paper provides a comprehensive analysis of these hypotheses.

In the sequential trade model of Easley, O'Hara, and Srinivas (1998), if at least some informed investors choose to trade in options before trading in the underlying stocks, then option prices can carry information that is predictive of future stock price movements. Prices are not fully efficient in the model and option prices deviate from put-call parity in the direction of the informed investors' private information. Over time, of course, deviations are expected to be arbitraged away, but this is not instantaneous given that there is private information. In practice one would also expect any tradable violations of put-call parity to be quickly arbitraged away. However, options on individual stocks are American and can be exercised before expiration, therefore put-call parity is an inequality rather than a strict equality; in addition, market imperfections and transactions costs only widen the range within which call and put prices are required to fall so as not to violate arbitrage restrictions.

We investigate whether the relative position of call and put prices within this range contains information about the future prices of the underlying stocks. We use the difference in implied volatility, or "volatility spread," between call and put options on the same underlying equity, and with the same strike price and the same expiration date, to measure deviations from put-call parity. Because single equity options are American, differences between call and put implied volatilities capture deviations from model values; we thus make no claim that volatility spreads represent arbitrage opportunities. Rather, we view them as a convenient means of identifying price pressures in the option market.

Our main results are easily summarized. First, option price deviations related to put-call parity contain economically and statistically significant information about future stock returns. For example, between January 1996 and December 2005, a portfolio that is long stocks with relatively expensive calls (stocks with both a high volatility spread and a high change in the volatility spread) and short stocks with relatively expensive puts (stocks with both a low volatility spread and a low change) earns a value-weighted, five-factor adjusted abnormal return of 50 basis points per week (*t*-statistic 3.76) in the week that follows portfolio formation, controlling for the four Fama and French (1993) and Carhart (1997) factors, and the Harvey and Siddique (2000) skewness factor. Consistent with the view that deviations from put-call parity are not driven by short sales constraints, the long side of this portfolio earns abnormal returns that are about as large as the returns on the short side: 23 basis points (*t*-statistic 2.40) for the long side versus -26 basis points (*t*-statistic -2.50) for the short side. In addition, we present direct evidence that our results are not driven by short sales constraints by using a shorter sample for which we have rebate rates, a proxy for the difficulty of short selling from the stock lending market.

A possible concern is non-synchronicity: evidence that option prices contain information not yet incorporated in the prices of the underlying securities could simply reflect the fact that option markets close two minutes after the underlying stock markets. Battalio and Schultz (2006) demonstrate that such non-synchronicity can lead empirical researchers to discover violations of put-call parity where none exist. This cannot explain the results, however, as the 50 basis point abnormal return is estimated assuming that purchases and sales of stocks take place at the opening of trading on the day after the option signal is observed, thus ignoring the first overnight return. Further, the abnormal performance persists, and there are no reversals: the hedge portfolio earns 99 basis points over the month that follows portfolio formation (*t*-statistic 2.37). Thus we present strong evidence that option prices contain information not yet incorporated in stock prices, that it takes several days until this information is fully incorporated, and that the predictability is not due to short sales constraints. This constitutes our first and main result.

Our second contribution is to show that this predictability seems to reflect informed trading, with informed investors trading first in the options market. Three sets of results suggest that this is the case. First, consistent with the Easley, O'Hara, and Srinivas (1998) model, the degree of predictability is substantially larger when option liquidity is relatively high and stock liquidity relatively low, while there is little predictability when the opposite is true. Second, using the probability of informed trading or 'PIN' from Easley, Kiefer, and O'Hara (1997) and Easley, Hvidkjaer, and O'Hara (2002), and controlling for size, we show that deviations from put-call parity are more likely to occur when the underlying stock faces a more asymmetric information environment.[2] Third, deviations from put-call parity are significantly related to the transactions volume in puts and calls initiated by option buyers to open new positions, i.e., to the open buy put-call ratios of Pan and Poteshman (2006).[3]

While the sequential trade model of Easley, O'Hara, and Srinivas (1998) is useful in interpreting the nature of the documented predictability, our results not only imply that price discovery takes place in the options market, but could potentially point to market inefficiency as well: in well-functioning markets, prices might adjust slowly to the private information possessed by informed traders, but they should adjust immediately to the public information impounded in the trading process, including the prices of other assets such as options. Why, then, would sophisticated investors not exploit the information contained in the prices of call and put options?

We find that they actually do, which leads to this paper's third main result: we show that the degree of predictability has declined over time. For example, the long/short hedge portfolio that buys stocks with high and increasing volatility spreads, and sells stocks with low and decreasing volatility spreads, earns a value-weighted abnormal return of 70 basis points per week (t-statistic 3.57) in 1996-2000, but only 33 basis points (t-statistic 1.83) in 2001-2005. We interpret this as evidence of a reduction of mispricing over time, consistent with the decrease in trading costs and growth in the amount of hedge fund capital over our sample period.

This paper contributes to the literature in several ways. First, we show that deviations from put-call parity can predict both negative and positive future abnormal returns. Using rebate rates from the

[2] PIN is a measure of the probability that each trade in a stock is information based. Within the model under which it is developed, PIN measures the fraction of informed traders, and reflects the prevalence of informed trading in the market.

[3] We know from Pan and Poteshman (2006) that open-buy option volume predicts stock returns, and consequently that informed trading takes place in the option market. Unlike deviations from put-call parity however, open-buy volume is *not* observable by *any market participant*, thus our results are quite different, and imply that the informed trade is revealed in the prices of options in the form of deviations from put-call parity.

stock short lending market, we show directly that our results are not driven by those stocks that are difficult to short. This is important, because the empirical evidence so far focuses exclusively on overpricing and subsequent negative returns when there are deviations from put-call parity because of short sale constrains, e.g., Ofek, Richardson, and Whitelaw (2004). In contrast, we show that there are significant returns on the underlying stocks on both the short side and the long side. We use the term 'deviation from put-call parity' rather than 'violation of put-call parity' to emphasize that we do not claim that volatility spreads represent unexploited arbitrage opportunities. Because individual stock options are American, differences between put and call implied volatilities do not represent pure arbitrage opportunities, rather they capture deviations from model values and we view them as proxies for price pressure. Our results imply that even though these differences do not represent arbitrage opportunities in the options market, they are not merely the random result of data peculiarities such as non-synchronicity and noisy quotes. Importantly, while we condition on lognormality in computing implied volatilities, we find strong evidence of predictability even when we control for factors that could drive a wedge between call and put implied volatilities, namely skewness and skewness risk.[4]

Second, our results are related to a recent strand of literature that shows that the demand for an option can affect its price, see Bollen and Whaley (2004) and Garleanu, Pederson, and Poteshman (2006). Our results here are largely complementary: while Garleanu, Pederson, and Poteshman (2006) show how option demand affects option prices, their model and empirical evidence imply a symmetric impact on call and put prices of either call or put demand. Specifically, they develop a model where the inability of risk-averse option market makers to perfectly hedge their option inventories causes the demand for options to impact their prices. In the model put-call parity still holds and consequently, within the model, the price impact of the demand from a call with a certain strike price and maturity will be the same as the price impact from the corresponding put. In contrast, an important

[4] Upon completion of this paper, we became aware of related independent work by Conrad, Dittmar, and Ghysels (2008), Xing, Zhang, and Zhao (2008) and Giovinazzo (2008). The first two papers focus more on whether option-implied skewness predicts returns, while the third investigates predictability based on a measure of deviations from put-call parity derived from the implied risk-free return.

element of our empirical design is that we consider jointly the information content of both put and call prices. A by-product of our approach is that we present the first evidence that the demand for options impacts their prices for reasons beyond the Garleanu, Pederson, and Poteshman (2006) model.

Third, our results are related to the literature on information discovery in options. The earlier literature found mixed results. Manaster and Rendleman (1982) find some evidence that option markets lead stock markets, and Kumar, Sarin, and Shastri (1992) find abnormal option returns in the 30 minutes preceding block trades in the underlying stock. However, Chan, Chung, and Johnson (1993) and Stephan and Whaley (1990) find no evidence that option prices lead stock prices. More recently, Chakravarty, Gullen, and Mayhew (2004) analyze equity and call option microstructure data between 1988 and 1992 and find that the contribution of the call option market to price discovery is about 17% on average. In contrast to these papers, we report evidence that option prices can lead stock prices by days -- not minutes. Our empirical design exploits the information content in both put options and call options, relying on the insight of the sequential trade model of Easley, O'Hara, and Srinivas (1998) that both call and put prices can contain important information. Chakravarty, Gullen, and Mayhew (2004) include only call options in their analysis, whereas it is by combining puts and calls that we are able to find significant evidence of stock return predictability.[5]

The remainder of this paper is organized as follows. Section II reviews the main implications of the Easley, O'Hara, and Srinivas (1998) model as it guides our empirical work, and describes our methodology and data. Section III presents the main empirical results on predicting returns using price pressures in the underlying options. Section IV provides evidence that the predictability is driven by informed trading. It also describes the extent to which the degree of predictability changes over the sample period. Section V shows that the results are robust to the use of pooled panel regressions that include a battery of control variables, including controls for reversal (Lo and MacKinlay

[5] Chan, Chung and Fong (2002) conclude that option volume does not predict future stock prices and Cao, Chen and Griffin (2005) find that higher pre-announcement call option volume predicts larger takeover premia. Other related work includes Anand and Chakravarty (2007), Bhattacharya (1987), Black (1975), Finucane (1991), Holowczak, Simaan, and Wu (2006), and Ni, Pan, and Poteshman (2007).

(1990)) and stock-specific skewness. It also considers the interaction of option and stock liquidity and provides direct evidence that our results are unrelated to short sales constraints. Section VI concludes.

II. Deviations from Put-Call Parity

A. Theoretical Background

The theoretical literature on the informational role of options includes Back (1993), Biais and Hillion (1994), Brennan and Cao (1996), Cao (1999), Easley, O'Hara, and Srinivas (1998), Grossman (1988), and John et al. (2003), among others. The sequential trade model of Easley, O'Hara, and Srinivas (1998) is of particular interest to our work. The model features uninformed liquidity traders who trade in both the equity market and the equity options market for exogenous reasons, and informed investors who must decide whether to trade in the equity market, the options market, or both. Informed traders who are privy to a positive signal can buy the stock, buy a call or sell a put; similarly, traders with negative information can sell the stock, buy a put or sell a call. Importantly, prices are not full-information efficient because of private information. Also, in this sequential trade model, put-call parity need not hold exactly at any point in time, and each of the call, the put, and the underlying stock can carry information about subsequent prices.

The Easley, O'Hara, and Srinivas (1998) model makes two important predictions that guide our empirical work. First, in the model, buying a call or selling a put are trades that both increase call prices relative to put prices and that carry positive information about future stock prices. Similarly, buying a put or selling a call are trades that increase put prices relative to call prices and that carry negative information about future stock prices. Thus, within the model, deviations from put-call parity can predict subsequent returns on the underlying stock, as long as the market is in a 'pooling equilibrium' in the sense that the informed traders trade in both the stock market and the options market.

Within the model, arbitrage across the stock and the options market will bring the prices of calls and puts in line with put-call parity over time, and as a result private information will be incorporated in the underlying stock price. Of course, real world options on individual stocks need not satisfy put-call parity exactly, because options are subject to large transactions costs, because the options are American, because borrowing rates do not equal lending rates, and there are margin requirements and taxes. Therefore, option prices can deviate from “put-call parity” without there being an arbitrage opportunity. Whether these deviations have any ability to predict subsequent returns in the underlying securities, as Easley, O’Hara, and Srinivas (1998) suggest, is an empirical question that forms the basis of our main test.

The second prediction of Easley, O’Hara, and Srinivas (1998) is the specific condition under which informed trading, and thus price discovery, will take place in the options market. This condition is satisfied when the overall fraction of informed traders is high or when the leverage and liquidity in the options is high. As a result, we investigate whether deviations from put-call parity are more likely to arise when the probability of informed trading, or PIN, is high. We also investigate whether there is greater predictability when options are more liquid relative to the underlying stocks.

B. Empirical Methodology

We follow Amin, Coval, and Seyhun (2004) and Figlewski and Webb (1993) and measure deviations from put-call parity as the average difference in implied volatility between call and put options with the same strike price and expiration date. This choice requires some justification.

The classical put-call parity relation originally derived by Stoll (1969) states that, in perfect markets, the following equality must hold for European options on non dividend paying stocks,

(1) $$C - P = S - PV(K),$$

where S is the stock price, C and P are the call and put prices on options with the same strike price K and identical expiration date, and $PV(\cdot)$ denotes present value. The Black-Scholes formula satisfies put-call parity for any assumed value of the volatility parameter σ, thus,

(2) $$\forall \sigma > 0 \quad C^{BS}(\sigma) + PV(K) = P^{BS}(\sigma) + S,$$

where $C^{BS}(\sigma)$ and $P^{BS}(\sigma)$ denote Black-Scholes call and put prices, respectively, as a function of the volatility parameter σ. Now equations (1) and (2) imply that,

(3) $$\forall \sigma > 0 \quad C^{BS}(\sigma) - C = P^{BS}(\sigma) - P .$$

By definition, the implied volatility on the call, IV^{call}, is the number that makes the following equality hold,

(4) $$C^{BS}\left(IV^{call}\right) = C ,$$

which by virtue of equation (3) implies that,

(5) $$P^{BS}\left(IV^{call}\right) = P ,$$

which in turn implies that,

(6) $$IV^{call} = IV^{put} .$$

Thus, for European options, put-call parity is equivalent to the statement that Black-Scholes implied volatilities of pairs of call and put options must be equal, even if option prices do not conform to the Black-Scholes formula. Of course, exchange traded options on individual stocks are American and can thus be exercised early. In the case of American options, put-call parity takes the form of an inequality. To identify price pressures in the equity options market, we nonetheless measure differences between Black-Scholes put and call implied volatilities (adjusted for dividends and the possibility of early exercise) in the spirit of equation (6). It should be emphasized that because we work with American options, equation (6) is no longer a no-arbitrage relation, as the value of the early exercise premium is incorporated explicitly, assuming lognormal distributions. Specifically, our approach assumes the Black-Scholes model, but only in its treatment of the early exercise premium.[6] As such, differences between call and put implied volatilities can be interpreted as deviations from model values. While these deviations do not constitute pure arbitrage opportunities, we show below that they

[6] Recent papers that follow this approach include Broadie, Chernov, and Johannes (2007, 2008). Broadie, Chernov, and Johannes (2007) use simulations to show that this procedure provides an accurate correction for the American feature in models with jumps and stochastic volatility. Ofek, Richardson, and Whitelaw (2004) also follow this approach and measure deviations from put-call parity as the ratio of the actual stock price to the synthetic stock price implied by equation (1), after subtracting the Black-Scholes value of the early exercise premium so as to treat American options as if they were European.

contain significant information about future returns.

Quite intuitively, high call implied volatilities relative to put implied volatilities suggest that calls are expensive relative to puts, and high put implied volatilities relative to call implied volatilities suggest the opposite. Following Amin, Coval, and Seyhun (2004) we refer to the difference between call and put implied volatilities as the volatility spread. More precisely, our measure of price pressure in the options market is the average difference in implied volatilities, or the volatility spread, between call options and put options (with the same strike price and maturity) across option pairs. In other words, every day *t* and for every stock *i* with put and call option data on day *t*, we compute the volatility spread as,

$$
\begin{aligned}
VS_{i,t} &= IV_{i,t}^{calls} - IV_{i,t}^{puts} \\
&= \sum_{j=1}^{N_{i,t}} w_{j,t}^{i} \left(IV_{j,t}^{i,call} - IV_{j,t}^{i,put} \right),
\end{aligned}
\tag{7}
$$

where j refers to pairs of put and call options and thus indexes both strike prices and maturities, the $w^i_{j,t}$ are weights, there are $N_{i,t}$ valid pairs of options on stock i on day t, and $IV^i_{j,t}$ denotes Black-Scholes implied volatility (adjusted for expected dividends and early exercise). We eliminate option pairs for which either the call or put has zero open interest or bid price of zero. In addition, the option quotes must not violate basic no arbitrage relations that would make it impossible to calculate implied volatilities, e.g., the call option bid-ask midpoint must not exceed the stock price less the present value of the strike price. The results that we report use average open interest in the call and put as weights.[7]

A potential concern with our approach is that differences between call and put implied volatilities may be systematically related to higher moments of the risk neutral distribution of underlying returns, especially skewness. For example, one might expect stocks with high call (put) prices to have posi-

[7] The results in this paper are robust to numerous variations on these specific calculations. For example, the results are qualitatively similar if we weight the option observations by trading volume as opposed to open interest, if we eliminate stocks with prices less than $5, options that expire in the current month, that have more than a year to expiration, or that are far from at-the-money.

tively (negatively) skewed distributions.[8] We investigate this numerically by generating American option prices for underlying assets with non-zero skewness using the procedure in Rubinstein (1998) and then computing call and put implied volatilities using standard binomial trees. The (untabulated) results confirm that differences between call and put implied volatilities can be non-zero when the underlying asset distribution is skewed, suggesting that they are noisy measures of price pressure. However, positively and negatively skewed distributions can both generate positive and negative differences between call and put implied volatilities, depending on the moneyness and maturity of the options. We also investigate the effect of changes in skewness on the difference in put and call implied volatilities and again do not find a systematic pattern, e.g., both increases and decreases in skewness move differences in implied volatilities in the same direction in large ranges of option moneyness. Consistent with Broadie, Chernov, and Johannes (2007), differences in call and put implied volatilities are noisier for deep in the money puts. Also, large positive (negative) volatility spreads are more likely to be observed in negatively (positively) skewed distributions. It is therefore important to directly control for idiosyncratic skewness and skewness risk in our empirical specifications.

C. Data

The option data originate from OptionMetrics. This comprehensive dataset covers all exchange listed call and put options on US equities, and consists of end-of-day bid and ask quotes, open interest, and volume for our sample period of January 1996 to December 2005. OptionMetrics also reports the implied volatility on each option. For options on individual stocks, which are American, implied volatilities are calculated using a binomial tree, taking into account discrete dividend payments and the possibility of early exercise, and using historical LIBOR/Eurodollar rates for interest rate inputs as well as the closing transaction price on the underlying asset.[9]

[8] We thank the referee for bringing this point to our attention.

[9] This introduces a potentially serious non-synchronicity problem (Battalio and Schultz (2006)). We address this concern in detail in our empirical tests.

We merge the option data set with the Center for Research in Security Prices (CRSP) daily stock data following Duarte, Lou, and Sadka (2005) and compute volatility spreads at the daily frequency from all valid option pairs that have an individual stock identifiable in CRSP as their underlying asset. Our final sample has 5,118,873 volatility spreads for 4,872 unique firms from January 1996 to December 2005. There are approximately 1,400 stocks per day in the sample initially, and 2,200 in December 2005.

Table 1 contains descriptive statistics on the volatility spreads. We provide summary statistics for the full sample period (January 1996 to December 2005) and for two subperiods (January 1996 – December 2000 and January 2001 – December 2005). Panel A shows that the average volatility spread is about -1%. Volatility spreads are highly volatile and exhibit substantial cross-sectional variation: the average, across firms, of the time-series standard deviations of the volatility spreads is 6.40%, and the cross-sectional (across firms) standard deviation of the time-series averages is 3.97%. The overall, pooled standard deviation is 6.95% (untabulated). Panel B shows the deciles of the distribution of volatility spreads (both across firms and over time). Like the mean, the median volatility spread is negative (-0.77%) and Panel B confirms the finding in Ofek, Richardson, and Whitelaw (2004) that deviations from put-call parity are more likely to occur in the direction of puts being relatively more expensive than the corresponding calls.[10] Deviations from put-call parity become less pronounced, in absolute value, over our sample period: the 10th percentile of the volatility spread is -7.55% in the first half of the sample and -4.49% in the second half; for the 90th percentile the corresponding estimates are 5.79% and 2.46%.

Panel C shows that the average (across firms) first-order autocorrelation in volatility spreads is 32%. The autocorrelations decline exponentially fast, though (in untabulated results) we find that they remain significant at lags up to four weeks. Panel C also shows that the degree of autocorrelation has declined over time: the average first-order autocorrelation is 36% between January 1996 and Decem-

[10] This could be due to the presence of binding short sales constraints, as Ofek et al. (2004) argue. Alternatively, it could be due to our conditioning on the Black-Scholes model when computing volatility spreads.

ber 2000 and 28% between January 2001 and December 2005.

As another way to measure persistence, we sort firms into deciles on a daily basis based on their volatility spreads, and report for each decile the proportion of firms that remain in the decile over the next several trading days. The results in Panel D confirm the persistent nature of volatility spreads, especially in the tails. For example, 47.24% of the stocks in the lowest decile on one day remain there the next, as do 41.21% of the stocks in the highest decile. The persistence is lower for stocks with volatility spreads in the other deciles: about 17% to 24%, which is still significantly larger than 10% at conventional levels of significance. Roughly a quarter of the securities in the extreme deciles remain there for a month.

III. Put-Call Parity and Stock Returns

As discussed in Section II, if deviations from put-call parity arise because informed investors trade in options first, how quickly their information is incorporated into stock prices is an empirical question. To investigate this, we sort stocks into portfolios based on either the level of volatility spreads alone, or both the level and the change, and consider the subsequent returns on those portfolios. To preview the main result, stocks with high volatility spreads (especially stocks with high and increasing volatility spreads) earn significant positive future abnormal returns, and stocks with low volatility spreads (especially stocks with low and decreasing volatility spreads) earn significant negative subsequent abnormal returns. This section first characterizes the portfolios formed on the level of the volatility spread, and then turns to the main result.

A. Pre-Formation Portfolio Characteristics

Beginning in January 1996, we sort stocks into five groups based on the quintiles of the volatility spread every Wednesday. This portfolio formation is repeated weekly through December 2005. Each week, only stocks with at least one reported valid option pair (same strike and same maturity) on Wednesday are included in the analysis. Consequently, the size of the pools of securities fluctuates over time. On average, there are about 407 stocks in each quintile, or 2,035 stocks in the pool.

Table 2 reports the average pre-formation characteristics of these quintile portfolios. Panel A reports time series averages of equally weighted cross-sectional averages for each quintile. Stocks with larger deviations from put-call parity (on either side) tend to be smaller, more volatile, and they tend to have larger market betas. For example, stocks in the extreme volatility spread quintiles, quintiles 1 and 5, have average market capitalizations that are less than one third of the market capitalizations of stocks in the middle quintile (quintile 3). Not surprisingly, their volatilities are also higher (about 60% compared to 46% in the middle quintile), as are their betas (about 1.2 compared to 1.04 in the middle quintile). This is not to say that stocks with large deviations from put-call parity are small however, as evidenced by the high average size decile assignments: even the stocks in the extreme volatility spread quintiles have average decile assignments relative to all NYSE, AMEX and NASDAQ stocks of about 8, consistent with the fact that optionable stocks generally have large market capitalization.

The fact that stocks with larger deviations from put-call parity tend to be smaller can be interpreted in two ways: smaller stocks, and their options, tend to be less liquid, thus transactions cost in these stocks will be higher, and this might result in wider arbitrage bounds. Alternatively, smaller firms are more likely to have higher information risk, see, e.g., Aslan, Easley, Hvidkjaer, and O'Hara (2007). We investigate these alternative interpretations in detail later.

Panel B of Table 2 shows the average pre-formation performance, on a value-weighted basis, of the stocks in each quintile. This analysis is reminiscent of Amin, Coval, and Seyhuns' (2004) who show that, in S&P 100 index options, volatility spreads increase after stock market increases, and decline after the market declines. We measure past returns as the value-weighted average return during the week preceding portfolio formation, either from Thursday to Wednesday (labeled 'no lag' in Table 2) or from Wednesday to Tuesday (labeled 'one day lag'), considering both average returns and returns in excess of the market index.

It turns out that our volatility spread strategy (based on options on individual stocks) is on average contrarian: it buys stocks that have underperformed the market by 84 basis points over the prior week. This stands in sharp contrast to the result in Amin, Coval, and Seyhun (2004) that index put option prices are bid up after stock market declines. With individual options, it is call options rather than put options that become expensive after large declines in the price of the underlying asset. The next sections show that these large call option prices (relative to put prices) predict strong subsequent performance in the underlying asset. Importantly, Section V shows that the predictability is robust to controlling for the past return on the underlying stock, thus the volatility spread strategy is distinct from the reversal strategy of Lo and MacKinlay (1990).

As a first step in addressing the concern that volatility spreads may in part reflect skewness in the underlying return distributions, it is worthwhile to examine the skewness of the portfolios. Panels C and D report skewness estimates for the quintile portfolios, both pre- and post-formation, and *p*-values computed using the test in Godfrey and Orme (1991), which is robust to non-normality. Pre-formation weekly returns on the lowest and highest quintile portfolios are negatively skewed, and the skewness is statistically significant at the 5% level. None of the quintile portfolios exhibit significant skewness post-formation, whether we measure returns from the close of trading on Wednesday (denoted 'no lag' in Panel D) or from the open on Thursday (denoted 'open'). In untabulated tests, we also estimate the skewness of portfolios formed on both levels and changes in volatility spreads, and again find that none of the portfolios are significantly skewed (the *p*-values all exceed 0.20). Similarly, none of the long/short hedge portfolios exhibit significant skewness, whether measured from the Wednesday close or the Thursday open, and whether they are based on volatility spread levels alone, or both levels and changes.

B. Measuring Abnormal Performance

We sort stocks into portfolios based on their volatility spreads and consider the subsequent returns on those portfolios over horizons of one and four weeks. Our option signals are measured on Wednesdays. At the four-weekly frequency, we sort stocks into portfolios every Wednesday and measure returns over the subsequent four weeks, thus using overlapping observations.

One potential problem with our empirical design is that it may lead to spurious predictability. Any evidence that option prices contain information not yet incorporated in the prices of the underlying securities could simply be due to non-synchronicity, as option markets close at 4:02pm EST, while stock exchanges close at 4:00pm EST.[11] As a result there is, at a minimum, a 2-minute gap between the last stock transaction of the day and our option signal. Because volatility spreads are computed from closing bid and ask option quotes, this could potentially severely bias the results. Battalio and Schultz (2006) show that such non-synchronicity can lead empirical researchers to discover violations of put-call parity where none exist.

Ideally, one would like to compute volatility spreads as of 4:00pm EST to address this; however, we do not have intraday options data. We therefore report returns based on lagged volatility spreads (as in Panel D of Table 2): we form portfolios based on the 4:02pm EST volatility spreads, but the returns only start to accrue with the first trade when the stock market opens on the following day (open-to-close returns).

We investigate two separate strategies based on our option signal. The first uses both the level of, and the change in, the volatility spread. The two-way sorts construct $5 \times 5 = 25$ different portfolios. Every Wednesday, we sort firms independently into five categories based on the change in the volatility spread between Tuesday and Wednesday and into five categories based on the level of the volatility spread on Tuesday. The second strategy uses the level of the volatility spread only, sorting firms into five portfolios based on the level on Wednesday.

To ensure that our results are not driven by differences in risk or firm characteristics, and to control for skewness risk, we calculate abnormal returns using a five factor model that includes the three Fama-French (1993) factors, a momentum factor as in Carhart (1997) and Jegadeesh and Titman (1993), and a systematic coskewness factor as in Harvey and Siddique (2000). The estimated abnormal return is the constant α in the regression

$$R_t = \alpha + \beta_1 \cdot MKT_t + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + \beta_4 \cdot UMD_t + \beta_5 \cdot SKEW_t + \varepsilon_t , \tag{8}$$

[11] The closing time of the CBOE market for options on individual stocks was 4:10pm EST until June 22nd, 1997.

where R_t is the excess return over the risk free rate to a portfolio over time t, MKT_t, SMB_t, HML_t, UMD_t and $SKEW_t$ are, respectively, the excess return on the market portfolio and the return on three long/short portfolios that capture size, book-to-market, momentum, and skewness effects. In constructing the systematic coskewness factor, we follow Harvey and Siddique (2000) by ranking stocks based on their past coskewness and forming three value-weighted portfolios: the 30 percent with the most negative coskewness, the middle 40 percent, and the 30 percent with the most positive coskewness. The post-ranking returns on a portfolio that is long the most negatively skewed stocks and short the most positively skewed stocks are then used to proxy for systematic coskewness. Since the four-weekly strategy uses overlapping weekly observations, the holding period returns are autocorrelated up to the degree of the overlap, i.e., the returns are autocorrelated up to three lags. Therefore, the reported asymptotic *t*-statistics are computed using the Hansen and Hodrick (1980) and Newey and West (1987) autocorrelation correction.

C. Performance of Volatility Spread Portfolios

1. Portfolios Formed on Levels and Changes in Volatility Spreads

Table 3 reports the performance of the volatility spread strategy based on both levels and changes, at the weekly and four-weekly rebalancing frequencies. We construct 25 different portfolios, sorting firms into five groups based on the change in the volatility spread between Tuesday and Wednesday and into five groups based on the level of the volatility spread on Tuesday. We report the performance of the five diagonal portfolios (1,1), (2,2), (3,3), (4,4), (5,5), and of the long/short hedge portfolio (5,5) - (1,1) that buys stocks with both a high Tuesday volatility spread and a high Tuesday to Wednesday volatility spread change, and sells stocks with both a low Tuesday volatility spread and a low Tuesday to Wednesday volatility spread change. Several important results emerge from this analysis.

First, the value-weighted, four-weekly, five-factor adjusted return on the long/short hedge portfolio is 99 basis points with a *t*-statistic of 2.37, assuming that purchases and sales of securities take place at the opening of trading on Thursday and thus excluding the first overnight period. While we do not tabulate equally-weighted returns to save space, the results for those are even more pronounced. For example, the four-week, equally-weighted alpha is 148 basis points (*t*-statistic 5.01). We therefore find strong evidence of predictability even when we ignore the first overnight period.

Second, the average returns increase monotonically as one goes from the first portfolio (low level and low change) to the fifth portfolio (high level and high change) both for raw returns and abnormal returns. This is important because it suggests that deviations from put-call parity are not driven by short-sales restrictions: the long side of the hedge portfolio earns positive abnormal returns that are large economically and statistically significant. For example, the long side of the hedge portfolio earns a value-weighted four-weekly abnormal return of 47 basis points (*t*-statistic 2.08) while the value-weighted alpha on the short side is -52 basis points (*t*-statistic -1.54).

Inferences from weekly returns are similar. Briefly, the long/short hedge portfolio generates a weekly value-weighted abnormal return of 50 basis points with a *t*-statistic of 3.76. The hedge portfolio earns another 25 basis points over the subsequent week (untabulated result). After four weeks the predictability tapers off and the abnormal returns are no longer significantly different from zero. In untabulated robustness checks, we also compute returns starting from the close of trading on Thursday rather than the open. This reveals that the hedge portfolio earns 13 basis points when it is first established on Thursday and another 37 basis points during the rest of the week. The fact that there is no reversal is important because it suggests that the effect is driven by information rather than price pressure (in which case it could be due to option market makers' delta hedging their positions in the underlying stock market).

Our double sort avoids the potential criticism that the results are simply a function of large sample sizes that inflate the significance of the strategy relative to what arbitrageurs in practice might have earned investing in a limited number of stocks (e.g., Lesmond and Wang (2006)). This is because the long/short hedge portfolio, on average, trades only 80 stocks (40 on the short side and 40 on the long side) because of the significant negative correlation between volatility spreads and subsequent volatility spread changes.[12]

To conserve space, we do not tabulate returns that include the first overnight period. Those returns exhibit even stronger predictability, though at least part of this phenomenon might be attributed to non-synchronicity, as discussed above. For example, including the first overnight period, the value-weighted, four-weekly, five-factor adjusted return on the long/short hedge portfolio is 160 basis points with a *t*-statistic of 3.65. We should point out that two pieces of evidence suggest that the first overnight return is unlikely to be entirely spurious. First, in untabulated results, we merge our data with the TAQ database, and remove from the portfolios any stock that did not trade within three minutes of the market close. This has very little effect on the returns that include the first overnight period. Second, we will show later that the amount of predictability decreases over our sample period. About half of this decrease can be attributed to a decrease in the first overnight return, consistent with the presence of rational arbitrageurs exploiting the information in deviations from put-call parity.

2. Portfolios Formed on Levels of Volatility Spreads

Table 4 reports the performance of the volatility spread strategy based on the level of the volatility spread only. This strategy is similar to that employed in Ofek, Richardson, and Whitelaw (2004) except that we consider deviations from put-call parity in either direction. Every Wednesday, we construct five portfolios by sorting stocks on their volatility spreads, as well as a long/short hedge portfolio that buys stocks with high values of the volatility spread (fifth quintile) and shorts stocks with low values (first quintile). Again, we track the performance of the portfolios over the next four weeks and also report the performance over the first week.

The results are consistent with those of the double sort. The value-weighted, four-weekly, five-factor adjusted return on the hedge portfolio is 51 basis points (*t*-statistic 3.35) when the first overnight period is excluded. We do not tabulate equally-weighted returns and alphas but they are larger. Thus we again find evidence of predictability and the predictability cannot be attributed to the first

[12] The correlation between the lagged volatility spread level and the change in the volatility spread is -0.44.

overnight return.[13]

We also find that the average returns increase monotonically as one goes from the first quintile (low volatility spread) to the fifth quintile (high volatility spread) both for raw returns and abnormal returns. This confirms that our results are not driven by short-sales constraints: the long side of the hedge portfolio earns positive abnormal returns that are as large as those of the short side. For example, the long side of the hedge portfolio earns a value-weighted four-weekly alpha of 38 basis points (*t*-statistic 2.98) and the short side earns -14 basis points (*t*-statistic -1.24).

The weekly returns are consistent with the four-weekly results and show that about half of the abnormal performance at the four-weekly frequency is due to the first week. There is again no evidence of reversal.

Finally, untabulated robustness checks show that the results are not sensitive to using Wednesday option signals. We find similar predictability when we rebalance the portfolios once a month, sorting stocks into quintiles based on volatility spreads that are observed on the last trading day of the month, and computing monthly returns, over the next calendar month, starting from the market open on the first day of that month, thus again ignoring the first "overnight" period.

IV. Further Interpretation and Discussion

A. The Role of Informed Trading

Several implications follow from the hypothesis that price pressures in the form of deviations from put-call parity might be driven by informed trade and asymmetric information. First, as discussed in Section II, the Easley, O'Hara, and Srinivas (1998) model implies that informed traders are more likely to trade in the options market when the liquidity of the options is high. We test this implication and show that the predictability in returns is stronger when the option signal is based on op-

[13] We also compared the means and medians of the raw returns on the four long/short portfolios. The medians are quite close to the means in strategies based on volatility spread levels alone, but they are below the means in strategies based upon both levels and changes. However, histograms of the returns reveal that the results are not driven by outliers. Further, removing large observations has little impact on the results, e.g., removing the 10 observations with the lowest returns and the 10 observations with the highest returns increases the mean returns from 90 to 92 basis points for the strategy based on levels and changes.

tions with higher liquidity. Second, if deviations from put-call parity reflect informed trading, then they should occur more frequently (in either direction) when the concentration of informed traders is high, using, e.g., the probability of informed trading (PIN) as a proxy. Third, they should be correlated to the transactions volume in puts and calls initiated by option buyers to open new positions, i.e., to the open buy put-call ratios of Pan and Poteshman (2006).

1. Interaction with Option Liquidity

The Easley, O'Hara, and Srinivas (1998) model suggests that the predictability will be stronger in options with higher liquidity. In this section, we test this hypothesis by sorting stocks on option signals that are constructed from option-based measures that proxy for this effect. Thus, in this section, we seek to understand whether there are certain option pairs within a given stock's option chain (i.e., the more liquid pairs) that have higher predictive value than other pairs. A related question, which we investigate in Section V using cross-sectional regressions, is whether the returns on relatively illiquid stocks with relatively liquid options can be predicted better than the returns on relatively liquid stocks with relatively less liquid options.

Each Wednesday and for each underlying equity, we sort all option pairs into three groups based on the average liquidity of the pair, using either bid-ask spreads or volume. We then compute three volatility spreads for each option liquidity measure and investigate whether volatility spreads based upon more liquid options are more informative than volatility spreads based upon less liquid options. Table 5 shows that this is indeed the case. Ignoring the first overnight period, a portfolio that is long stocks with high volatility spreads and short stocks with low volatility spreads earns an abnormal return of 66 basis points (*t*-statistic 3.77) in the four weeks that follow portfolio formation, when the volatility spreads are based upon more liquid options (those with low bid/ask spreads) but only 20 basis points (*t*-statistic 1.34) when the option signal is based on less liquid options. The difference, 46 basis points, is statistically significantly different from zero, with a *t*-statistic of 2.44. The difference in alphas between the high volume long/short hedge portfolio and the low volume hedge portfolio is also large economically, 23 basis points, but it is not statistically significantly different from zero.

2. Information Risk and Incidence of Deviations from Put-Call Parity

As a first-pass test of whether deviations from put-call parity are more likely to occur in stocks that face more information risk, Panel A of Table 6 provides some summary statistics on volatility spreads grouped into PIN quintiles. We obtain quarterly PIN estimates from Stephen Brown's website at Emory University for the period January 1996 through June 2005.[14] Every volatility spread for which we have a PIN estimate is assigned to one of five PIN quintile groups, and for each group we report the average volatility spread, the standard deviation, and the relative standard deviation, i.e., the absolute value of the standard deviation divided by the average. The volatility spreads become more volatile as the PIN quintile assignment increases: the relative standard deviation nearly doubles, from a value of 4.7 in quintile 1 to over 8 in quintile 5.

One difficulty in interpreting this result is that PIN and size are negatively correlated, see, e.g., Aslan, Easley, Hvidkjaer, and O'Hara (2007). Since small stocks are also expected to be less liquid, and to have less liquid options, we need to control for size and liquidity. To this end, we construct a variable VS_{it}^{mod} from the daily volatility spread estimates as follows:

(9) $$VS_{it}^{\text{mod}} = \left| VS_{it} - \overline{VS_t} \right|,$$

where $\overline{VS_t}$ is the median volatility spread across all securities on day *t*. We then run pooled, cross-sectional regressions of the extent to which option prices deviate from put-call parity, as proxied by VS_{it}^{mod}, on the probability of informed trading PIN, and on several control variables including log market size, the average proportional bid-ask spread in calls, the average proportional bid-ask spread in puts, and the Amihud (2002) illiquidity ratio, which is the average ratio of absolute return to volume, and corresponds loosely to a Kyle (1985) lambda.[15] The *t*-statistics that we report employ a

[14] This is an updated version of the data used in Brown, Hillegeist, and Lo (2004).
[15] Using alternative liquidity measures, such as the Amivest measure or the Pastor-Stambaugh (2003) reversal measure, produces very similar results.

robust cluster variance estimator (e.g., Andrews (1991), Petersen (2007), and Rogers (1993)).

The results in Panel B of Table 6 show that deviations from put-call parity are more likely to occur in stocks with high PIN, confirming the results in Panel A. Importantly, PIN remains a significant determinant of deviations from put-call parity, even after controlling for size and liquidity proxies in both options and the underlying equities.

To test whether the ability of volatility spreads to predict future returns is greater when there is more information risk, we consider double sorts on volatility spreads and PIN in untabulated results. The analysis suggests that volatility spreads are better able to predict returns among high PIN stocks than among low PIN stocks but the difference in abnormal performance is not statistically significant at conventional levels. Because PIN is known to be negatively correlated with size, we further partition each portfolio into three size groups. In the top two size groups the difference in abnormal performance is small and not significantly different from zero. In the bottom size group, the difference in abnormal performance is large and statistically significant. We conclude that while deviations from put-call parity tend to predict returns to a greater extent in firms that face a more asymmetric information environment, the probability of informed trading only matters in smaller firms.

Pan and Poteshman (2006) show that signed option trading volume contains information about future stock prices. They use put-call ratios constructed from open buy transactions volume, i.e., option volume initiated by buyers to open new positions:

(10) $$X_{it} = \frac{P_{it}}{P_{it} + C_{it}},$$

where P_{it} and C_{it} are the number of put and call options purchased by non market makers to open new positions on date t for stock i. Unlike the volatility spread, the information signal X_{it} is not public. We analyze whether the volatility spread captures some of the same information as the open buy put-call ratio X_{it} in Table 7.[16]

The interesting result in Table 7 is that there is a significant relation between deviations from put-

[16] The data originate from Market Data Express and span the period January 2004 to December 2005.

call parity and the open buy put-call ratio X_{it}. This result is robust to various specifications (with and without fixed effects, and controlling for the lagged volatility spread). The result is surprising for two reasons. First, market makers do not observe the private information signal X_{it}. They observe orders but do not know if the orders are initiated to open new positions, or to close existing ones.

Second, this is not a simple case of "demand-based option pricing." While Garleanu, Pederson, and Poteshman (2006) show that option demand affects option prices, their model and empirical evidence imply a symmetric impact on calls and puts of both call and put demand. Specifically, they develop a model where risk averse option market makers' inability to perfectly hedge their option inventories causes the demand for options to impact their prices. In the model, put-call parity still holds and consequently, within the model, the price impact of the demand from a call with a certain strike and maturity will be the same as the price impact from the corresponding put. Therefore our results complement theirs by showing that the demand for an option can affect its price for reasons that fall outside of the scope of their model.

B. Predictability Over Time

At least two conditions are needed for a financial market anomaly such as return predictability of the magnitude that we find in this paper. First, there must be some mechanism that allows the anomaly to appear, and second, if the anomaly persists, some friction that prevents rational arbitrageurs from quickly exploiting it. It is thus natural to ask whether the extent to which deviations from put-call parity can predict subsequent returns decreases over the sample period, as would be expected if investors learn about, and attempt to exploit, the predictability.

To answer this question, we again investigate whether volatility spreads predict returns over horizons of various lengths, as in Section III, but we now break the analysis into two subperiods: the first half of the sample, January 1996 – December 2000, and the second, January 2001 – December 2005, as reported in Table 8. The main result is that the extent to which volatility spreads predict returns decreases over our sample period. For example, ignoring the first overnight return, the value-weighted, four-weekly, five-factor adjusted returns on the volatility spread level hedge portfolio go from 61 basis points (*t*-statistic 2.94) over the first half of the sample to 39 basis points (*t*-statistic 2.07) in the second half (Panel A). Similarly, and again ignoring the first overnight return, the weekly, five-factor adjusted returns on the hedge portfolio constructed from both levels and changes in volatility spreads go from 70 basis points (*t*-statistic 3.57) in the first half of the sample to 33 basis points (*t*-statistic 1.83) in the second half (Panel B). These results are clearly conservative in that they skip the first overnight return entirely, but they do suggest that it has become more difficult to profit from trading strategies based on deviations from put-call parity.

In the last column of Panel A, we investigate whether the magnitude of the first overnight return changes over time. This can help shed some light on the extent to which the overnight return is spurious, i.e., due to the fact that the option market closes at 4:02pm EST while the stock market closes at 4pm EST: if the overnight return were in fact spurious and driven by information that is released after the stock market closes but before the option market closes, then we would not expect to see a substantial decrease in the magnitude of the overnight return over time.[17] Yet this is precisely what we find: the overnight return is estimated at 39 basis points during the first five years of the sample, which drops to 23 basis points over the last five years. Of the 30 basis point decrease in abnormal performance of the hedge portfolio based on levels, 16 basis points are due to the first overnight period.

Overall these results present evidence of mispricing during the earlier years of the sample (although it was perhaps not arbitrageable) with a gradual reduction of the mispricing by market participants over time.

[17] Since the closing time of the CBOE market for options on individual stocks changes during our sample period, from 4:10pm EST until June 22nd, 1997 to 4:02pm EST thereafter, a decrease in the overnight return might be expected on this date, even under the assumption that the return is due to information that is released after 4:00pm EST. We checked that this is not driving our results by breaking the sample post July 1997 into subsamples and confirming that the same pattern of decreasing predictability obtains.

V. Cross-Sectional Regressions

This section first investigates the extent to which deviations from put-call parity predict returns using pool-panel regressions of stock returns on volatility spreads and a battery of control variables, including past returns (to control for short-term reversal) and both systematic and idiosyncratic skewness. Having established that the results are robust to this alternative approach and to the controls, we then provide further evidence that the predictability is due to informed trade by (i) considering the interaction of stock and option liquidity and (ii) providing direct evidence that the predictability is unrelated to the difficulty of selling the underlying stock short, by using data on rebate rates from the short lending market.

A. Robustness

Our baseline robustness check employs pooled, cross-sectional panel regressions to determine the ability of volatility spreads to predict returns. Consistent with our earlier methodology, we again sort stocks into quintile portfolios every week based on their Wednesday volatility spreads. We then construct quintile dummy variables and regress weekly excess returns on the quintile dummies and controls, or on the quintile dummies times the volatility spread (piecewise linear regressions) and controls.

The cross-sectional regression results are not directly comparable to the earlier results based on sorted portfolios because the sorted portfolio returns are value-weighted, while the cross-sectional regressions are not. To alleviate concerns that the results may be driven by the fact that the options market closes after the stock market, we continue to report regression results using Thursday-open-to-Wednesday-close returns. The *t*-statistics we report employ a robust variance estimator clustered by firm. All the returns in our regressions are expressed as percentages.

The results in Table 9 confirm our earlier results based on time-series regressions of quintile portfolio returns. Column (1) reports the regression of weekly returns, starting from the open on Thursday, on the volatility spread quintile dummies. All the coefficients are highly significant; they imply a difference in average weekly returns between high volatility spread stocks and low volatility spread stocks of 32 basis points per week. This is larger than the 20 basis points in Table 4, but the quintile portfolio returns reported in Table 4 are value-weighted returns, while the regressions in Table 9 correspond to equally-weighted returns. Column (3) shows that this basic result continues to hold when the factors of Fama and French (1993), and Carhart (1997) are included, and when the regressions include controls for skewness. Specifically, we control for both stock-specific idiosyncratic skewness and the Harvey and Siddique (2000) skewness risk factor.[18] Finally, column (5) adds lagged stock returns and lagged factors to the regressions to control for autocorrelation and short-term reversals (Lo and Mackinlay (1990)). This is important because the results in Table 2 suggest that the volatility spread strategy is a contrarian strategy. We find that, while the short-term reversal is significant in our sample, it has little impact on the extent to which volatility spreads predict returns. The even-numbered columns in Table 9 confirm that all of these conclusions are also robust to using piecewise linear regressions.

In Table 10, we use cross-sectional regressions to investigate the extent to which both levels and changes in volatility spreads matter in predicting future stock returns. In Panel A, we run pooled panel regressions of weekly stock returns on volatility-spread-level quintile dummies and volatility-spread-change quintile dummies, again measuring returns from the opening of the market on Thursday. Volatility spread levels are as of Tuesday, and volatility spread changes are from Tuesday to Wednesday. The regressions marked as including controls include the lagged stock return as well as the four Fama-French factors, lags of the four Fama-French factors, the Harvey and Siddique (2000) skewness factor, and stock-specific skewness. The results in Panel A confirm our earlier finding that both levels and changes in volatility spreads matter: stocks with high volatility spreads that became even higher perform particularly well, and stocks with low volatility spreads that became lower per-

[18] While the sorts in Tables 3 and 4 control for skewness risk, idiosyncratic skewness could be priced separately from coskewness. For example, Barberis and Huang (2007) show that idiosyncratic skewness earns a negative premium in an economy where investors hold cumulative prospect-theoretic preferences (Tversky and Kahneman (1992)). We compute idiosyncratic skewness using three months of daily returns, but using other windows (e.g., six months or four months) does not alter the results.

form particularly poorly, with or without controls.

In Panel B, we run similar regressions but now employ a piecewise linear specification, i.e., we run cross-sectional regressions of stock returns on volatility spread levels times volatility-spread-level quintiles, and volatility spread changes times volatility-spread-change quintiles. We again report results with and without controls, starting at the open on Thursday in both instances. The results are consistent and highlight the importance of both changes in, and levels of, volatility spreads.

In Panel C, we include both the change in the volatility spread and the lagged change, on top of the volatility spread level.[19] We run regressions of weekly returns on (i) the Tuesday volatility spread level, (ii) the Tuesday-to-Wednesday volatility spread change, (iii) the Monday-to-Tuesday volatility spread change, and (iv) controls (the four Fama-French factors, lagged stock returns, lagged factors, stock-specific skewness and the skewness factor). Interestingly, we find that both the change and the lagged change in volatility spreads matter for subsequent returns.

B. Liquidity

A key prediction of the sequential trade model of Easley, O'Hara, and Srinivas (1998) is that there should be more informed trade in options if the options are liquid relative to the stocks, and less informed trade in options when the opposite is true. This section therefore investigates whether the degree of predictability varies across stocks with the relative cost of trading in the stocks versus trading in options written on the stocks, using various proxies for the liquidity of the stocks.[20]

We consider three liquidity measures: the Amivest liquidity ratio (see, e.g., Amihud, Mendelson, and Lauterbach (1997)), the Amihud (2002) illiquidity ratio (see also Acharya and Pedersen (2005)), and the Pastor and Stambaugh (2003) reversal measure. All three measures are described in detail in Hasbrouck (2005). Briefly, the Amivest liquidity ratio is the average ratio of volume to absolute return, taking the average over all days with non-zero returns. The Amihud (2002) illiquidity ratio is the average ratio of absolute return to volume. Pastor and Stambaugh (2003) suggest estimating

[19] To reduce the number of variables, we do not include dummy variables in these regressions.
[20] We thank the anonymous referee for suggesting this test.

liquidity as the coefficient γ in the regression

$$r_t^e = \theta + \varphi \cdot r_{t-1}^e + \gamma \cdot \operatorname{sign}\left(r_{t-1}^e\right) \cdot V_{t-1} + \varepsilon_t \,, \tag{11}$$

where r_t^e is the excess return on a security (over the CRSP value-weighted return) and V_{t-1} denotes dollar volume. Data on all three liquidity measures were downloaded from Joel Hasbrouck's website.

For each liquidity measure, we create two dummy variables that capture the potential interaction of stock and option liquidity. The variable 'hi option liquidity, low stock liquidity' equals one for stocks that are both in the top 25% of option liquidity (by bid/ask spread) and in the bottom 25% of stock liquidity (according to the various liquidity measures). Similarly, 'low option liquidity, hi stock liquidity' equals one for stocks that are both in the bottom 25% of option liquidity and in the top 25% of stock liquidity.

Table 11 contains the results of pooled, cross-sectional regressions of stock returns on volatility spreads and products of volatility spreads and the stock/option liquidity interaction dummies, for the three liquidity measures and market capitalization. Each regression includes on the right-hand side the lagged stock return as well as the four Fama-French factors, lags of the four Fama-French factors, and both systematic and idiosyncratic skewness. The reported *t*-statistics employ a robust cluster variance estimator and we again report results for Thursday-open-to-Wednesday-close returns, thus ignoring the first overnight period. Table 11 shows that there is more predictability when option liquidity is relatively high and stock liquidity relatively low, and less predictability when the opposite is true, consistent with the Easley, O'Hara, and Srinivas (1998) model. This result obtains consistently across the various liquidity measures. The *F* statistics that test the restriction of equal coefficients on the two liquidity interaction dummies strongly reject the hypothesis in all cases.[21]

[21] In a previous version of this article we also ran regressions of returns on volatility spreads interacted with stock liquidity quintile dummies and liquidity controls. Our main predictability results survive the inclusion of all these controls and are driven neither by small stocks nor illiquid stocks. While volatility spreads cannot predict returns to a statistically significant extent among stocks with a low Amihud (2002) illiquidity ratio, they remain significant in stocks that are very liquid based on either the Amivest or the Pastor and Stambaugh (2003) measures.

C. The Market for Stock Lending

Lamont and Thaler (2003), Ofek and Richardson (2003), and Ofek, Richardson, and Whitelaw (2004) argue that short sales restrictions on the underlying stocks can prevent arbitrage from bringing option and stock prices into equilibrium. Specifically, in the presence of short sales constraints, puts can become expensive relative to the corresponding calls. Ofek, Richardson, and Whitelaw (2004) show that deviations from put-call parity are asymmetric in the direction of short sales constraints and that they are more likely to be observed in options written on stocks that are difficult or expensive to short. They also show that stocks with relatively expensive puts subsequently earn negative abnormal returns.

This paper advances the alternative and potentially complementary hypothesis that option prices can deviate from model values because of informed trading. Empirically, this is supported by our finding that the long side of the volatility spread long/short portfolio earns positive abnormal returns that are as large as the negative returns on the short side. In this section, we use a sample of rebate rates from the stock short lending market to directly investigate to what extent our results are driven by stocks that are more difficult to short.

D'Avolio (2002) and Geczy, Musto, and Reed (2002) provide an overview of the lending market for stocks and evidence that short sales restrictions are not uncommon. Briefly, shorting a stock involves the placement of a cash deposit in the amount of the borrowed stock, and this deposit pays an interest rate that is called the rebate rate. If short selling is difficult, the rebate rate will be lower and can even become negative. A low rebate rate makes shorting the stock costly for the borrower of the stock, and can thus be interpreted as a signal of short sales constraints.

Our rebate rate data cover almost every stock in our options sample over the time period of October 2003 to December 2005, for a total of 2,277 stocks with options data. A large broker and data provider in the stock-lending market provided us with its proprietary rebate rate data for all its overnight transactions for the universe of stocks in that period. For each stock and each day, we aggregate the transactions data by weighting by volume and averaging lending and borrowing rates, and subtract the median rebate rate for each day to get the 'rebate spread' for each stock. In our weekly sample, we only use the rebate spread for Wednesday (or Tuesday if Wednesday is not available). Following Ofek et al. (2004), we focus on stocks with significantly negative rebate spreads (-1% or less), which we refer to as being difficult to short or 'on special'. In our sample, 11.5% of the firm-week observations are on special, which is very close to the 10.8% documented in Ofek et al. (2004) for their time period of July 1999 to November 2001. Finally, and again consistent with Ofek et al. (2004), there is a high correlation (34%) between the volatility spread and the rebate spread. This correlation is completely driven by stocks that are on special, as the correlation between the volatility spread and the rebate spread interacted with a dummy of being 'on special' (thus setting all rebate rates above -1% equal to zero) is also 34%. The correlation of the volatility spread and the 'on special' dummy itself equals -18%.

We report the results of three pooled panel predictive regressions using weekly stock returns in Table 12: (i) including only the 'on special' rebate rates (setting all other rebate rates to zero) and the full set of controls (lagged returns, the four Fama-French factors, their lags, and skewness), (ii) adding the volatility spread quintile dummies to the first regression, and finally (iii) adding the volatility spread quintile dummies interacted with the 'on special' dummy to the second regression.

The first regression of Table 12, excluding the volatility spread, confirms previous results (e.g., Ofek et al. (2004) and Cohen, Diether, and Malloy (2007)) that a more negative rebate spread for stocks on special predicts future stock returns: stocks that are more difficult to short have lower subsequent returns. In the second predictive regression, all four volatility spread quintile dummies are significant, indicating that even in these last years of our sample, there is still some statistically significant predictability. However, the returns include the first overnight period, and both the economic and the statistical significance have clearly decreased relative to the earlier parts of the sample. Once the volatility spread dummies are included, the significance of the rebate spread decreases. Finally, in the third regression, we add the volatility spread quintile dummies interacted with the 'on special' dummy. The volatility spread dummies themselves remain significant, albeit slightly less so (significant at the 10% level or lower). However, the volatility spread dummy interacted with the 'on special' dummy is not significant and typically has the wrong sign. Therefore we conclude that there is no evidence that the volatility spread predictability is driven by those stocks that are hard to short.

VI. Conclusion

We show that deviations from model values related to put-call parity contain information about future stock prices. We use volatility spreads, i.e., differences in implied volatility between pairs of call and put options with the same strike price and the same expiration date, to measure these deviations, and find that stocks with relatively expensive calls outperform stocks with relatively expensive puts. We find that both levels and changes in volatility spreads matter for future stock returns and present evidence that stocks with relatively expensive calls outperform stocks with relatively expensive puts by 50 basis points per week on a value-weighted and risk-adjusted basis.

Because we find both positive and negative abnormal performance our results cannot be explained by short sales constraints alone, as corroborated by a shorter sample of rebate rates from the stock lending market. The degree of predictability is substantially larger when option liquidity is high and stock liquidity low, while there is little predictability when the opposite is true. Controlling for size, deviations from put-call parity are more likely to occur in options with underlying stocks that face more information risk. Further, deviations from put-call parity are significantly related to the transactions volume in puts and calls initiated by option buyers to open new positions.

While our results suggest a degree a mispricing across the stock and the option markets, financial economists should find it reassuring that the degree of predictability that we document decreases over time. This suggests that the forces of arbitrage eventually act so as to limit the mispricing of assets.

TABLE 1
Volatility Spreads

Descriptive statistics on volatility spreads. The volatility spread is the average difference in implied volatilities between calls and puts (with the same strike price and maturity) across option pairs for an underlying stock on a given day. The full sample period is January 1996 to December 2005. We also report results for two subperiods: January 1996 – December 2000 and January 2001 – December 2005. Panel A reports the mean volatility spread (computed as the average across firms of time-series averages), the average (across firms) time-series standard deviation ('Standard deviation TS'), and the cross-sectional standard deviation (across firms) in the time-series averages ('Standard deviation CS'). Estimates are reported in percent, so an average volatility spread of -0.978 means -0.978%. Panel B reports decile breakpoints (in percent). Panel C reports the average (across firms) autocorrelation in volatility spreads. Panel D sorts firms into deciles based on their volatility spreads and reports for each decile the proportion (in percent) of firms that remain in the decile over the next several days.

	Sample		
	Full	1996 - 2000	2001 - 2005
Panel A: Summary Statistics (%)			
Mean	-0.978	-0.839	-1.031
Standard deviation TS	6.396	5.934	3.835
Standard deviation CS	3.965	5.345	3.879
Panel B: Percentiles (%)			
(10^{th})	-6.111	-7.549	-4.492
(20^{th})	-3.514	-4.568	-2.614
(30^{th})	-2.222	-2.963	-1.724
(40^{th})	-1.396	-1.845	-1.151
(50^{th})	-0.770	-0.920	-0.700
(60^{th})	-0.191	-0.012	-0.275
(70^{th})	0.515	1.077	0.216
(80^{th})	1.644	2.681	0.940
(90^{th})	4.074	5.791	2.463
Panel C: Persistence – Autocorrelations			
Autocorrelation (1)	0.32	0.36	0.28
Autocorrelation (2)	0.28	0.31	0.24
Autocorrelation (3)	0.24	0.27	0.21
Autocorrelation (4)	0.22	0.25	0.18
Autocorrelation (5)	0.20	0.22	0.17

Panel D: Persistence – Portfolio Allocations (%)				
	Day 1	Day 5	Day 10	Day 22
Decile 1	47.24	39.97	32.92	27.26
Decile 2	23.92	19.59	16.18	13.92
Decile 3	18.58	15.67	13.54	12.14
Decile 4	17.22	14.84	13.31	12.29
Decile 5	17.27	15.16	13.87	12.97
Decile 6	17.63	15.67	14.37	13.46
Decile 7	17.52	15.45	13.99	12.96
Decile 8	17.86	15.27	13.40	12.25
Decile 9	21.28	17.61	14.87	12.93
Decile 10	41.21	33.82	27.22	22.29

TABLE 2
Volatility Spread Quintile Portfolios

Characteristics of portfolios formed on volatility spreads. Every Wednesday we sort firms into quintiles based on volatility spreads (the weighted average difference in implied volatilities between calls and puts with the same strike price and maturity across option pairs). Panel A shows the pre-formation average size (in $ millions), size decile relative to all NYSE/AMEX/NASDAQ securities, beta and standard deviation (both estimated over the year preceding portfolio formation), and price. Panel B shows the pre-formation returns on the stocks in each quintile. We measure past returns as the value weighted average returns either from the previous Thursday to the current Wednesday ('no lag') or from the previous Wednesday to the current Tuesday ('one day lag'). We report both average returns and average returns in excess of the market index, in basis points per week. Panels C and D report pre- and post-formation skewness of weekly returns on the quintile portfolios and associated *p*-values estimated using the Godfrey and Orme (1991) robust statistic. Post-formation returns are computed weekly starting either from the close of trading on Wednesday ('no lag') or from the open on Thursday ('open').

		Volatility Spread Quintiles				
		(1)	(2)	(3)	(4)	(5)
Panel A: Pre-formation characteristics						
Size		2,264.00	6,292.30	9,574.99	7,380.29	2,901.85
Size decile		8.00	8.78	9.02	8.83	7.98
Beta		1.19	1.10	1.05	1.05	1.15
Standard deviation		0.612	0.502	0.462	0.482	0.591
Price		23.12	32.04	35.90	31.54	21.33
Panel B: Pre-formation performance						
No lag	mean ret	57	64	34	-20	-63
	excess ret	37	44	14	-40	-84
	t-stat	5.3	15.5	5.1	-14.8	-14.8
One day lag	mean ret	27	47	30	-2	-25
	excess ret	6	26	9	-22	-45
	t-stat	0.9	8.8	3.6	-7.9	-8.1
Panel C: Pre-formation skewness						
No lag	skewness	-0.804	-0.016	0.190	-0.119	-0.664
	p-value	0.03	0.93	0.27	0.56	0.05
One day lag	skewness	-0.794	-0.148	0.060	-0.002	-0.502
	p-value	0.03	0.59	0.83	0.99	0.05
Panel D: Post-formation skewness						
No lag	skewness	-0.015	-0.022	-0.123	0.038	0.176
	p-value	0.95	0.90	0.58	0.87	0.45
Open	skewness	0.092	-0.038	-0.059	0.184	0.076
	p-value	0.72	0.81	0.78	0.41	0.71

TABLE 3
Returns on Portfolios Formed on Levels and Changes in Volatility Spreads

Performance of quintile portfolios formed on levels and changes in volatility spreads. Every Wednesday we sort stocks into 5 × 5 = 25 different portfolios: five groups based on the change in the volatility spread between Tuesday and Wednesday and five groups based on the level of the volatility spread on Tuesday. These double sorts are independent sorts. We report four-weekly and weekly returns starting from the open on Thursday for the five diagonal portfolios (1,1), (2,2), (3,3), (4,4), (5,5), and for the long/short hedge portfolio (5,5) – (1,1) that buys stocks with calls that were relatively expensive and became more expensive, and sells stocks with puts that were relatively expensive and became more expensive. Since the four-weekly strategy uses overlapping weekly observations, the holding period returns are autocorrelated up to three lags. Therefore the reported asymptotic *t*-statistics are computed using the Hansen and Hodrick (1980) and Newey and West (1987) autocorrelation correction. Returns are expressed in basis points and are not annualized, so an alpha of 99 for '4 Weeks' means that the volatility spread hedge portfolio earns 99 basis points per four weeks, ignoring the first overnight return. The returns are value-weighted. Alphas are with respect to the four Fama-French (1993) and Carhart (1997) factors and the Harvey and Siddique (2000) skewness factor.

		Volatility Spread Change/Level Quintiles					Hedge Portfolio	
		(1,1)	(2,2)	(3,3)	(4,4)	(5,5)	return	alpha
4 Weeks	mean ret	49	70	80	84	138	90	99
	alpha	-52	-8	3	19	47	(2.54)	(2.37)
	t-stat	-1.54	-0.47	0.32	1.16	2.08		
1 Week	mean ret	-5	17	21	27	44	50	50
	alpha	-26	-4	1	6	23	(3.74)	(3.76)
	t-stat	-2.50	-0.65	0.30	0.82	2.40		

TABLE 4
Returns on Portfolios Formed on Levels of Volatility Spreads

Performance of quintile portfolios formed on volatility spreads. We sort stocks every Wednesday and report four-weekly returns starting from the open on Thursday. Also shown is the performance of the corresponding volatility spread hedge portfolio, which is long high volatility spread stocks and short low volatility spread stocks. Since the four-weekly strategy uses overlapping weekly observations, the holding period returns are autocorrelated up to the degree of the overlap, i.e., the returns are autocorrelated up to three lags. Therefore, the reported asymptotic *t*-statistics are computed using the Hansen and Hodrick (1980) and Newey and West (1987) autocorrelation correction. Returns are expressed in basis points and are not annualized, so an alpha of 51 for ‘4 Weeks’ means that the volatility spread hedge portfolio earns 51 basis points per four weeks, ignoring the first overnight return. The returns are value-weighted. Alphas are with respect to the four Fama-French (1993) and Carhart (1997) factors and the Harvey and Siddique (2000) skewness factor.

		Volatility Spread Level Quintiles					Hedge Portfolio	
		(1)	(2)	(3)	(4)	(5)	return	alpha
4 Weeks	mean ret	65	76	72	91	105	40	51
	alpha	-14	-2	-7	16	38	(3.12)	(3.35)
	t-stat	-1.24	-0.27	-1.12	1.95	2.98		
1 Week	mean ret	10	16	18	27	30	20	21
	alpha	-10	-4	-2	7	11	(3.05)	(3.33)
	t-stat	-1.67	-0.90	-0.66	1.81	1.98		

TABLE 5
Portfolios Sorted on Volatility Spreads:
Option Liquidity Effects

This table shows the performance of quintile portfolios formed on volatility spreads calculated using options with different liquidity characteristics. Each Wednesday and for each underlying equity, we sort all option pairs into three groups based on the average liquidity of the pair, using either bid-ask spreads (Panel A) or volumes (Panel B), and then compute separate volatility spreads for each option liquidity measure. We form portfolios every Wednesday and report four-weekly returns starting from the open on Thursday. Also shown is the performance of the volatility spread hedge portfolio, which is long high volatility spread stocks and short low volatility spread stocks. The reported asymptotic *t*-statistics are computed using the Hansen and Hodrick (1980) and Newey and West (1987) autocorrelation correction. Returns are expressed in basis points and are not annualized, thus an alpha of 66 means 66 basis points per four weeks. Alphas are with respect to the four Fama-French (1993) and Carhart (1997) factors and the Harvey and Siddique (2000) skewness factor.

Panel A: Option bid/ask spread groups

		Volatility Spread Quintiles					Hedge
		(1)	(2)	(3)	(4)	(5)	(5) – (1)
Low	mean ret	55	71	78	85	96	42
	alpha	-38	-10	4	13	28	66
	t-stat	-3.64	-1.16	0.58	1.62	2.03	3.77
High	mean ret	69	75	76	81	92	23
	alpha	0	-2	-4	6	21	20
	t-stat	0.03	-0.21	-0.62	0.75	1.99	1.34

Panel B: Option volume groups

		Volatility Spread Quintiles					Hedge
		(1)	(2)	(3)	(4)	(5)	(5) – (1)
Low	mean ret	56	73	76	92	93	37
	alpha	-9	-7	-2	15	22	31
	t-stat	-0.58	-0.80	-0.32	1.89	1.96	1.63
High	mean ret	56	72	84	84	86	30
	alpha	-29	-4	4	13	25	54
	t-stat	-2.82	-0.57	0.57	1.44	1.68	3.09

TABLE 6
Information Asymmetry and Deviations from Put-Call Parity

Panel A shows summary statistics of volatility spreads by PIN quintile (the relative standard deviation is the absolute value of the standard deviation divided by the mean). In Panel B, we construct a variable VS_{it}^{mod} from the daily volatility spread estimates as $VS_{it}^{\mathrm{mod}} = \left| VS_{it} - \overline{VS_t} \right|$, where $\overline{VS_t}$ is the median volatility spread across all securities on day *t*. We then run pooled, cross-sectional regressions of the extent to which option prices deviate from put-call parity, as proxied by VS_{it}^{mod}, on the probability of informed trading PIN and on several control variables including log market size, the average proportional bid-ask spread in calls, the average proportional bid-ask spread in puts, and the Amihud (2002) illiquidity ratio. The *t*-statistics in parentheses employ a robust cluster variance estimator.

Panel A

	Mean	Standard deviation	Rel. stand. dev.
PIN (low)	-0.008	0.039	4.684
PIN (2)	-0.009	0.041	4.460
PIN (3)	-0.010	0.057	5.462
PIN (4)	-0.012	0.067	5.742
PIN (high)	-0.012	0.096	8.023

Panel B

Independent Variables	(1)	(2)
Intercept	0.220	0.033
	(41.98)	(9.65)
PIN		0.001
		(7.34)
Call Spread	0.068	0.046
	(23.44)	(18.14)
Put Spread	0.015	0.018
	(5.42)	(7.96)
Size		-0.005
		(-8.72)
Illiquidity ratio *I*		0.001
		(2.37)
R^2	0.024	0.078

TABLE 7
Open Buy Option Volume and Deviations from Put-Call Parity

Daily regressions of volatility spreads on open buy put-call ratios X_{it} and lagged volatility spreads. The open buy put call ratio is constructed from open buy transactions volume, as

$$X_{it} = \frac{P_{it}}{P_{it} + C_{it}},$$

where P_{it} and C_{it} are the number of put and call options purchased by non market makers to open new positions on date t for stock i. The t-statistics in parentheses employ a robust cluster variance estimator.

	(1)	(2)	(3)	(4)
Const	-0.0108	-0.0115	-0.0029	-0.0055
	(-15.99)	(-119.53)	(-9.97)	(-13.50)
X_{it}	-0.0049	-0.0025	-0.0023	-0.0019
	(-5.30)	(-7.96)	(-9.20)	(-9.73)
Lag *VS*			0.7190	0.5230
			(21.48)	(17.10)
Lag X_{it}			0.0000	0.0010
			(0.19)	(0.51)
F effects?	N	Y	N	Y
R^2	0.0014	0.0014	0.5182	0.5182
Within		0.0005		0.2760
Between		0.0108		0.9203

TABLE 8
Returns on Volatility Spread Portfolios over Time

This table shows how the performance of portfolios formed on volatility spreads changes over time. In Panel A, we sort stocks into quintile portfolios based on the level of the volatility spread every Wednesday and report four-weekly returns (denoted ‘4W’) and weekly returns (denoted ‘W’) on the long/short hedge portfolio that is long stocks in the high volatility spread quintile and short stocks in the low volatility spread quintile. The returns begin to accrue either at the close on Wednesday or at the open on Thursday (denoted ‘-O’). We also report the return over the Wednesday-to-Thursday overnight period (denoted ‘night’). In Panel B, we sort stocks weekly based on both the level of the volatility spread on Tuesday and the change in the volatility spread from Tuesday to Wednesday, and we report returns on the hedge portfolio that is long stocks with high volatility spreads that became higher, and short stocks with low volatility spreads that became lower. Returns are not annualized and they are expressed in basis points, so an alpha of 98 in Panel A, column ‘4W’ means 98 basis points per four weeks. Alphas are with respect to the four Fama-French (1993) and Carhart (1997) factors and the Harvey and Siddique (2000) skewness factor.

		Panel A Sorts on volatility spread levels					Panel B Sorts on levels and changes			
		4W	4W-O	W	W-O	night	4W	4W-O	W	W-O
Jan 1996 - Dec 2000	mean ret	79	39	63	23	39	184	106	143	64
	alpha	98	61	68	29	39	238	163	147	70
	t-stat	4.62	2.94	6.77	2.92	35.78	3.92	2.78	6.95	3.57
Jan 2001 - Dec 2005	mean ret	64	38	39	15	24	122	72	85	35
	alpha	65	39	39	15	23	103	53	83	33
	t-stat	3.17	2.07	5.07	2.14	21.41	1.76	0.95	4.45	1.83

TABLE 9
Cross-Sectional Regressions

We sort stocks into quintile portfolios based on the level of the volatility spread every Wednesday and report results of pool-panel regressions of weekly stock returns on the quintile dummies (odd-numbered regressions) or products of the quintile dummies and volatility spreads (even-numbered regressions). 'Q1' denotes low volatility spreads and 'Q5' high volatility spreads. The returns begin to accrue at the open on the day after the volatility spreads are observed. The *t*-statistics in parentheses employ a robust variance estimator clustered by firm. Returns are converted to percentages.

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.179	0.254	-0.015	0.023	-0.014	0.025
	(3.04)	(4.26)	(-0.25)	(0.37)	(-0.24)	(0.40)
dummy Q1	-0.121		-0.182		-0.175	
	(-2.92)		(-4.67)		(-4.49)	
dummy Q2	-0.072		-0.093		-0.092	
	(-2.15)		(-2.93)		(-2.87)	
dummy Q4	0.076		0.058		0.060	
	(2.40)		(1.91)		(1.96)	
dummy Q5	0.203		0.137		0.132	
	(5.61)		(3.73)		(3.56)	
VS × dummy Q1		1.798		2.063		2.018
		(5.08)		(5.75)		(5.62)
VS × dummy Q2		6.262		5.704		5.665
		(5.24)		(4.96)		(4.89)
VS × dummy Q3		7.376		3.805		3.907
		(2.32)		(1.29)		(1.33)
VS × dummy Q4		-1.077		0.389		0.388
		(-0.40)		(0.15)		(0.15)
VS × dummy Q5		1.173		0.705		0.622
		(3.32)		(2.05)		(1.92)
Lagged return					-0.018	-0.019
					(-4.96)	(-5.15)
FF4 & skew?	No	No	Yes	Yes	Yes	Yes
Lagged FF4 & skew?	No	No	No	No	Yes	Yes
R^2	0.000	0.000	0.107	0.107	0.107	0.107

TABLE 10
Cross-Sectional Regressions – Changes and Levels

Pool-panel regressions of weekly stock returns (in percent) on volatility spread levels and changes. The returns start to accrue at the open on Thursday, after the volatility spreads are observed. In Panel A, returns are regressed on Tuesday volatility-spread-level quintile dummies (denoted 'Level') and Tuesday-to-Wednesday volatility-spread-change quintile dummies (denoted 'Change'). 'Q1' denotes the low quintile and 'Q5' the high quintile. Panel B reports results of piecewise linear regressions. Panel C adds lagged changes. The *t*-statistics in parentheses employ a robust cluster variance estimator. The controls, if included, are the four Fama-French factors, skewness, lagged returns and lagged factors.

Panel A: Quintile dummies

Intercept	Level Q1	Level Q2	Level Q4	Level Q5	Change Q1	Change Q2	Change Q4	Change Q5	Controls	R^2
0.239	-0.210	-0.031	0.059	0.105	-0.207	-0.070	0.055	0.072	No	0.000
(2.79)	(-3.74)	(-1.12)	(2.22)	(3.22)	(-3.71)	(-2.73)	(2.32)	(1.64)		
0.049	-0.209	-0.065	0.050	0.164	-0.199	-0.092	0.041	0.084	Yes	0.109
(0.56)	(-4.83)	(-2.39)	(2.08)	(3.66)	(-4.19)	(-3.84)	(1.79)	(1.73)		

Panel B: Piecewise linear

Intercept	Level Q1	Level Q2	Level Q3	Level Q4	Level Q5	Change Q1	Change Q2	Change Q3	Change Q4	Change Q5	Controls	R^2
0.146	1.605	-1.575	-0.851	13.915	1.606	1.591	-1.004	1.992	9.534	0.108	No	0.000
(3.21)	(5.13)	(-1.24)	(-0.39)	(5.33)	(4.57)	(4.16)	(-0.61)	(0.50)	(5.32)	(3.24)		
-0.041	1.894	0.025	-2.343	6.350	1.242	1.346	0.119	4.061	6.858	0.085	Yes	0.109
(-0.85)	(6.47)	(0.02)	(-1.11)	(2.37)	(3.40)	(3.63)	(0.08)	(1.06)	(3.65)	(2.55)		

Panel C: Changes and lagged changes

Intercept	VS level	VS change	Lag VS change	Controls	R^2
-0.015	1.825	1.474	0.452	Yes	0.107
(-0.27)	(7.43)	(7.06)	(2.40)		

TABLE 11
The Role of Liquidity

Pooled panel regressions of weekly stock returns on volatility spreads and the interaction of stock and option liquidity. We consider three liquidity proxies: the Amivest liquidity ratio, the Amihud (2002) illiquidity ratio, and the Pastor-Stambaugh (2003) reversal measure. The returns start to accrue at the open on Thursday, after the volatility spreads are observed. For each liquidity measure, the table reports the results of pooled, cross-sectional regressions of stock returns on volatility spreads and products of volatility spreads and two liquidity dummy variables. 'Hi option liquidity, low stock liquidity' equals one for stocks that are both in the top 25% of option liquidity (by bid/ask spread) and in the bottom 25% of stock liquidity (according to the various liquidity measures). Similarly, 'low option liquidity, hi stock liquidity' equals one for stocks that are both in the bottom 25% of option liquidity and in the top 25% of stock liquidity. The last line in the table reports *p*-values for the *F* test that the coefficients on the two liquidity interactions are equal. All the regressions control for the four Fama-French (1993) and Carhart (1997) factors, lagged factors, lagged stock returns and both systematic (Harvey and Siddique (2000)) and idiosyncratic skewness. The *t*-statistics in parentheses employ a robust variance estimator clustered by firm. Returns are converted to percentages.

	Amivest liquidity ratio	Amihud illiquidity ratio	Pastor-Stambaugh γ	Size
Independent Variables	(1)	(2)	(3)	(4)
Intercept	-0.143	-0.144	-0.143	-0.143
	(-2.65)	(-2.67)	(-2.64)	(-2.64)
VS	1.813	1.608	1.899	1.918
	(8.37)	(7.65)	(8.14)	(8.20)
Hi option liquidity	1.707	1.705	2.216	2.040
Low stock liquidity	(2.09)	(2.08)	(2.95)	(2.83)
Low option liquidity	-1.792	-4.078	-1.527	-1.586
Hi stock liquidity	(-4.43)	(-3.85)	(-4.22)	(-4.43)
Controls?	Yes	Yes	Yes	Yes
R^2	0.114	0.114	0.114	0.114
Restriction				
(p-value)	0.000	0.000	0.000	0.000

TABLE 12
Cross-Sectional Regressions – Short-Sales Constraints

We sort stocks into quintile portfolios based on the level of the volatility spread every Wednesday and report results of pool-panel regressions of weekly stock returns on (1) the rebate rate spread conditional on the stock being on special (i.e., conditional on the spread being less than -1%), (2) the rebate rate spread conditional on the stock being on special and volatility spread quintile dummies ('Q1' denotes low volatility spreads and 'Q5' high volatility spreads), and (3) the variables in (2) plus products of the quintile dummies and the on-special dummy. Returns include the first overnight period and are expressed as percentages. The regressions control for the four Fama-French (1993) and Carhart (1997) factors, lagged factors, lagged stock returns and both systematic (Harvey and Siddique (2000)) and idiosyncratic skewness. The *t*-statistics in parentheses employ a robust variance estimator clustered by firm.

Independent Variables	(1)	(2)	(3)
Intercept	0.015	-0.001	0.001
	(0.61)	(-0.01)	(0.03)
dummy Q1		-0.094	-0.097
		(-1.66)	(-1.65)
dummy Q2		-0.101	-0.102
		(-2.00)	(-2.05)
dummy Q4		0.112	0.108
		(2.29)	(2.18)
dummy Q5		0.136	0.105
		(2.44)	(1.89)
spread × on special	0.034	0.027	0.036
dummy	(2.09)	(1.65)	(1.61)
on special dummy ×			0.054
dummy Q1			(0.34)
on special dummy ×			0.018
dummy Q2			(0.10)
on special dummy ×			0.055
dummy Q4			(0.32)
on special dummy ×			0.289
dummy Q5			(1.67)
Controls?	Yes	Yes	Yes
R^2	0.173	0.174	0.174

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