Deviations from Put-Call Parity and Stock Returns

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1. Introduction

Put-call parity figures prominently as one of the simplest and best known no-arbitrage relations in finance.[1] Based on a straightforward no-arbitrage argument, 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. Empirical investigations into apparent violations of put-call parity for the most part find that the violations do not represent tradable arbitrage opportunities once one accounts for real-world 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 (such as commissions and the bid/ask spread), lending rates that do not equal borrowing rates, margin requirements, and taxes, to name a few.[2]

Several recent papers argue that large deviations from put-call parity in options on individual stocks 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 put, buying the call, selling short the underlying asset, and lending the present value of the strike price. The profitability of this strategy obviously depends on the costs of selling the underlying security short; thus in the presence of short sales constraints puts can become expensive relative to the corresponding calls. In particular, 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, it is possible that apparent deviations from put-call parity are simply the random outcome of market imperfections and data 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

[1] Put-call parity was first formalized by Stoll in 1969 but it has a long history in financial economics, in that it was described as early as 1877 by Castelli.
[2] See, e.g., Brenner and Galai (1986), Kamara and Miller (1995), Klemkoski and Resnick (1979, 1980) and Nisbet (1992), among others.

investors, e.g., along the lines of the equilibrium model of Easley, O'Hara and Srinivas (1998). This paper provides a comprehensive analysis of this hypothesis.

Limits to arbitrage are not sufficient for put-call parity to be violated: there must also be a reason why the option prices and the stock prices diverge to begin with. In the sequential trade model of Easley, O'Hara and Srinivas (1998), if at least some informed investors choose to trade in options before they trade in the underlying stock, possibly because of the leverage that options offer, 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. In this paper we investigate whether the relative position of call and put prices within this range matters. We use the difference in implied volatility, or "volatility spread," between pairs of 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. We report several interesting results.

First, we find that deviations from put-call parity contain information about subsequent stock prices, i.e., they predict subsequent stock returns. The evidence of predictability that we report is significant, both economically and statistically. For example, between January 1996 and December 2005, a portfolio that is long stocks with relatively expensive calls (stocks with high volatility spreads) and short stocks with relatively expensive puts (stocks with low volatility spreads) earns a value-weighted, four-factor adjusted abnormal return of 50 basis points per week (with a t-statistic of 8.01) in the week that follows portfolio formation. Consistent with the hypothesis that deviations from put-call parity reflect asymmetric information rather than frictions such as short sales constraints, the long side of this portfolio earns abnormal returns that are as large as the returns on the short side: 29 basis points with a t-statistic of 6.3 for the long side versus -21 basis points (with a t-statistic of -4.47) for the short side. We corroborate that our main results are not driven by short sales constraints using a shorter sample for which we could obtain data on rebate rates, a proxy for the difficulty of short selling from the stock lending market.

Another possible concern is non-synchronicity. Specifically, evidence that option prices contain significant 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) argue that such non-synchronicity can lead empirical researchers to discover violations of put-call parity where none exist. To show that this cannot explain our results, we lag the option signal and show that the abnormal returns persist even when the conservative assumption is made that purchases and sales of stocks take place on the day after the option signal is observed. For example, the above hedge portfolio that is long stocks with high volatility spreads and short stocks with low volatility spreads earns a weekly value-weighted abnormal return of 20 basis points (with a t-statistic of 3.24) starting from the opening of trading on the day after the deviations from put-call parity are observed. Moreover, the abnormal performance persists, and there are no reversals. Excluding the first overnight return, the hedge portfolio earns 42 basis points over the month that follows portfolio formation, with a t-statistic of 2.88. Therefore, option prices contain a significant amount of information not yet incorporated into stock prices, and it takes several days until this information is fully incorporated. This delayed reaction leads to substantial predictability.

We find even stronger results economically when we form portfolios based on both changes and levels of volatility spreads. Specifically, a portfolio that buys stocks with high and increasing volatility spreads and sells stocks with low and decreasing volatility spreads earns a value-weighted and four-factor adjusted 107 basis points per week (with a t-statistic of 7.69) including the first overnight period, and 45 basis points (t-statistic of 3.53) excluding it. Again, the long side of this portfolio earns abnormal returns that are as large as the returns on the short side: 63 basis points (t-statistic of 5.34) for the long side versus -46 basis points (t-statistic of -4.38) for the short side, including the first overnight period, or 26 basis points on the long side (t-statistic of 2.29) and -22 basis points on the short side (t-statistic of -2.13) excluding the overnight period and trading on the day after the option signals are observed.

Second, we use the Easley, O’Hara and Srinivas (1998) model to guide our empirical work. Consistent with the view that deviations from put-call parity reflect asymmetric information, we show that these deviations (on either side) are on average more likely to occur when the underlying stock faces a more asymmetric information environment. Further, the extent of the predictability is greater among firms that face a more asymmetric information environment. When we sort firms into groups based on a proxy for the extent to which the information environment is asymmetric, using the probability of informed trading or ‘PIN’ from Easley, Kiefer and O’Hara (1997) and Easley, Hvidkjaer and O'Hara (2002), we find that the abnormal return to a portfolio that is long stocks with high volatility spreads (i.e., with calls that are expensive relative to the puts) and short stocks with low volatility spreads, is twice as large in the high PIN group as in the low PIN group. For example, during the period for which PIN data are available, high volatility spread stocks outperform low volatility spread stocks by 69 basis points per week (with a t-statistic of 4.65) on a value weighted basis and ignoring the first overnight return. We also find that deviations from put-call parity are generally related to the transactions volume in puts and calls initiated by option buyers to open new positions, i.e., they are related to the open buy put-call ratios of Pan and Poteshman (2006).

While the sequential trade model of Easley, O'Hara and Srinivas (1998) is useful in interpreting the nature of the predictability that we find, our main results not only imply that a significant amount of price discovery takes place in the equity derivatives market, but they could also potentially point to an important market inefficiency. 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, do 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 forces of arbitrage eventually act so as to limit the mispricing of assets. Specifically, we provide evidence on this latter issue by showing that the degree of predictability has declined significantly over time. For example, a portfolio that buys stocks with high volatility spreads and sells stocks with low volatility spreads earns an abnormal return of 63 basis points per week (t-statistic of 6.48) in 1996 - 2000, but only 39 basis points (t-statistic of 5.15) in 2000 - 2005, and 14 basis points (t-statistic of 2.08) over the last three years of 2003 - 2005. These abnormal returns include the first overnight period and thus represent an upper bound on the degree of predictability. If one takes a conservative view and excludes the first overnight period, the abnormal return drops to 2 basis points per week (t-statistic of 0.33) over the last three years of our sample, which is insignificant both statistically and economically. We interpret these results as evidence of mispricing during the earlier years of the study, with a gradual elimination of the mispricing by market participants over time.

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. 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 frictions, most notably short sale constrains, e.g., Ofek and Richardson (2003) and Ofek, Richardson and Whitelaw (2004). In contrast, we consider information-based deviations from put-call parity and show that there are significant subsequent 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 the departures from strict put-call parity that we find represent unexploited arbitrage opportunities. Rather, we view our volatility spread as a proxy for informed trading in calls or puts by investors with private positive or negative information. We show that even if these differences are too small to represent arbitrage opportunities, they are not merely the random result of data peculiarities such as non-synchronicity and noisy quotes.

Finally, using rebate rates from the stock short lending market, we show directly that our results are not driven by those stocks that are difficult to short.

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, a novel element of our empirical design is that we consider jointly the information content of both put prices and call prices. An important by-product of our approach is that we present the first evidence that the demand for options impacts their prices for information reasons in addition to the existing friction-based results in Bollen and Whaley (2004) and Garleanu, Pederson, and Poteshman (2006).

Third, our results are related to the literature on information discovery in the options market. 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 several days, not simply minutes. Our empirical design exploits the information content in both put options and call options; in other words it relies on the insight of the sequential trade model of Easley, O'Hara and Srinivas (1998) that both call and put prices will contain important information in the context of asymmetric information. We take the view that puts and calls are complements rather then substitutes in terms of information content. In contrast, Chakravarty, Gullen and Mayhew (2004), for example, include only call options in their analysis. However, it is by combining puts and calls that we are able to find significant evidence of stock return predictability.

More closely related to this study is the work of Pan and Poteshman (2006). They show that buyer-initiated option transactions volume predicts stock returns.[3] Importantly, unlike deviations

[3] 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

from put-call parity, buyer-initiated option volume is not publicly observable to any market participant. Our results both confirm their finding that informed trading takes place in the option market, and complement it by showing that the informed trade is largely revealed in the prices of options in the form of deviations from put-call parity.

The rest of this paper is organized as follows. In Section 2, we review the main implications of the Easley, O'Hara and Srinivas (1998) model as it guides our empirical work, and then describe our methodology and the characteristics of our data. Section 3 presents the main empirical results on predicting returns using deviations from put-call parity. Section 4 provides further evidence that the predictability is driven by asymmetric information. It also explores the importance of both levels and changes in volatility spreads and describes the extent to which the degree of predictability changes over the sample period. Section 5 shows that the results are robust to the use of pooled, cross-sectional regressions that include a battery of control variables. Section 6 concludes.

2. Deviations from put-call parity

2.1. 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. That 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, in this model prices are not full-information efficient because of private information. Therefore, 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

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work includes Anand and Chakravarty (2006), Bhattacharya (1987), Black (1975), Choi and Jayaraman (2006), Finucane (1991), Ni, Pan and Poteshman (2006) and Seyhun and Wang (2006).

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 together 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, and because borrowing rates do not equal lending rates, and there are margin requirements and taxes. Therefore, option prices can deviate from put-call parity by a significant amount without there being a riskless 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 and 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 better able to predict subsequent returns when the probability of informed trading, or PIN, is high, and when the options are more liquid and have more leverage, by breaking down the option data into moneyness and time-to-maturity categories.

2.2. 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 volatilities 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,

$$C - P = S - PV(K)\,, \tag{1}$$

where S is the stock price, K is the strike price, C and P are the call and put prices on options with the same strike price K and identical expiration dates, and $PV(K)$ is the present value of the strike price common to both the call and the put. Exchange traded options on individual stocks are American and can thus be exercised early. In the case of American options on non-dividend paying stocks, Merton (1973a, b) shows that put-call parity becomes an inequality,

$$S - K \le C - P \le S - PV(K)\,. \tag{2}$$

Finally, in the absence of arbitrage, the following put-call parity condition must hold for American options on dividend paying stocks,

$$S - PV(div) - K \leq C - P \leq S - PV(K)\,, \tag{3}$$

where *PV*(*div*) is the present value of all the dividends to be paid until the options expire (see, e.g., Jarrow and Rudd (1983) and Amin, Coval and Seyhun (2004) for similar conditions).

The advantage of writing put-call parity in the form of equation (3) is that the approach is largely model-free in that it does not make any assumptions about the process through which the stock price evolves over time.[4] The disadvantage is that the previous discussion of the theory does not require actual violations of put-call parity, but merely deviations from 'fair value'. By examining only violations of equation (3) we would be restricting our sample to extreme observations. Recall also that our objective is to identify price pressures rather than unexploited arbitrage opportunities in the options market, a hypothesis that cannot be tested using our data (because we only have closing option quotes) as Battalio and Schultz (2006) demonstrate convincingly. Thus we replace equation (3) with

$$C - P = S - PV(K) - PV(div) - EEP(P) + EEP(C)\,, \tag{4}$$

where *EEP*(*P*) and *EEP*(*C*) denote the early exercise premium on the put and the call, respectively. Of course, equation (4) is no longer a no-arbitrage relation, since the value of the possibility of early exercise is incorporated explicitly, but we nonetheless still refer to it as put-call parity. 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 (4).[5] Similarly, we measure deviations from put-call parity as differences between call and put implied volatilities. 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.[6]

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 deviations from put-call parity is the average difference in implied volatilities, or the volatility spread, between call

[4] There are still assumptions in equation (3), e.g. that future dividends are known with certainty.
[5] Ofek et al. (2004) restrict their analysis to options on stocks that do not pay dividends, such that *EEP*(*C*) = 0.
[6] Equation (4) implicitly conditions on an option pricing model to compute the early exercise premia, *EEP*(*C*) and *EEP*(*P*). We use OptionMetrics implied volatilities and consequently our measure of deviations from put-call parity conditions on the Black and Scholes (1973) model. Therefore, it is possible for put-call parity not to be violated and yet to find non-zero differences between call and put implied volatilities.

options and put options (with the same strike price and maturity) across all option pairs. In other words, every day *t* and for every stock *i* with put and call option volume on day *t*, we compute the volatility spread as

$$
\begin{aligned}
VS_{i,t} &= IV_{i,t}^{\;calls} - IV_{i,t}^{\;puts} \\
&= \sum_{j=1}^{N_{i,t}} w_{j,t}^{i} \left(IV_{j,t}^{i,call} - IV_{j,t}^{i,put} \right)
\end{aligned}
\tag{5}
$$

where *j* refers to pairs of options 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 (1973) implied volatility (adjusted for dividends and the possibility of early exercise). For an option pair to be included in our analysis, both the call and the put must have positive open interest, and 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 in this paper use average open interest in the call and put as weights.[7] We describe the data in detail next.

2.3. 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.[8]

We merge the option data set with the Center for Research in Security Prices (CRSP) daily stock data following Duarte, Lou and Sadka (2005). We use the procedure described above to 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 5,325,562 volatility spreads, for 4,987 unique firms from January 1996 to December 2005. There are approximately 1,500 stocks per day in the sample initially, and 2,300 by December 2005.

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[7] The results in this paper are robust to numerous variations on these specific calculations. For example, the results are qualitatively the same if we weigh the option observations by trading volume as opposed to open interest (even though the sample sizes decrease), if we eliminate stocks with prices less than $5, if we eliminate options that expire in the current month, or that have more than a year to expiration.

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

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 three subperiods (January 1996 – December 2000, January 2001 – December 2005, and January 2003 – 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% (unreported). 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.[9] 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 -3.89% over the last three years; for the 90th percentile the corresponding estimates are 5.79% and 1.95%.

Panel C in Table 1 shows that volatility spreads exhibit autocorrelation: the average (across firms) first-order autocorrelation in volatility spreads is 32%. The autocorrelations decline exponentially fast, though (in unreported 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 December 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 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.

3. Put-call parity and stock prices

As discussed in Section 2.1, if deviations from put-call parity arise because of informed trading in options, how quickly the information would be incorporated in stock prices is an empirical

[9] 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.

question. As a result, it might be possible for deviations from put-call parity to predict subsequent returns on the underlying stocks. To test this, we sort stocks into portfolios based on their volatility spreads and consider the subsequent returns on those portfolios. To preview the main result, stocks with high volatility spreads earn significant positive future abnormal returns, and stocks with low 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.

3.1. Preliminary analysis using monthly sorts

Beginning in January 1996, we sort stocks into five groups based on the quintiles of the volatility spread on the last trading day of the month. This portfolio formation is repeated monthly through December 2005. At the end of each month, only stocks with at least one reported valid option pair (same strike and same maturity) on the last trade date of the month are included in the analysis. Consequently, the size of the pools of securities fluctuates over time. On average, there are about 421 stocks in each quintile, or 2,105 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 (at about 60% whereas the average volatility of stocks in the middle quintile is about 46%), 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 tend to be large.

The fact that stocks with larger deviations from put-call parity tend to be smaller can be interpreted in two ways. First, 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 (2006). 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. To make sure that our volatility spread strategy is not simply a momentum strategy, we investigate the performance of portfolios formed on the basis of their volatility spreads in the month leading up to the portfolio formation date. We measure past returns as the value weighted average return during the month or during the month except that we skip the last day of the month, 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, a contrarian strategy: it buys stocks that have underperformed the market by 2.5% over the prior month. 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. Next, we show next that these large call option prices (relative to put prices) predict strong subsequent performance in the underlying asset.

3.2. Measuring abnormal performance: daily, weekly, and four-weekly

We sort stocks into quintile portfolios based on their volatility spreads and consider the returns on those portfolios over horizons of varying lengths: daily, weekly, and four-weekly. On each trading date, we sort stocks into five groups based on the quintiles of the volatility spread on that date. At the weekly frequency, we sort stocks into portfolios based on their volatility spreads every Wednesday.[10] At the four-weekly frequency, we sort stocks into portfolios based on their volatility spreads on Wednesdays 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 significant 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 4pm EST.[11] Thus 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) argue that such non-synchronicity can lead empirical researchers to discover violations of put-call parity where none exist.

[10] Like Hou and Moskowitz (2005) we compute returns between adjacent Wednesdays rather than Mondays or Fridays. This is because Friday-to-Friday returns have high autocorrelations, while Monday-to-Monday returns have low autocorrelations (e.g., Chordia and Swaminathan, 2000).

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

Ideally, one would like to compute volatility spreads as of 4pm EST to address this; however, we do not have intraday options data. To be conservative and to provide an unambiguous lower bound on the amount of predictability, we also provide results based on lagging the option signal. Specifically, for every horizon at which we form portfolios, we report both returns without a lag and returns based on lagged volatility spreads. In the latter case, we form portfolios based on the same 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).

At each frequency (daily, weekly and four-weekly) we construct five value weighted portfolios and a long/short "hedge" portfolio that buys stocks with high values of the volatility spread (in the fifth quintile) and sells stocks with low values of the volatility spread (in the first quintile). To ensure that our results are not driven by differences in risk or firm characteristics, we calculate abnormal returns using a four factor model that includes the three Fama-French (1993) factors and a momentum factor, as in Carhart (1997) and Jegadeesh and Titman (1993). The estimated abnormal return is the constant α in the regression

$$R_t = \alpha + \beta_1 \cdot MKT_t + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + \beta_4 \cdot UMD_t + \varepsilon_t , \qquad (6)$$

where R_t is the excess return over the risk free rate to a portfolio over time t, and MKT_t, SMB_t, HML_t and UMD_t are, respectively, the excess return on the market portfolio and the return on three long/short portfolios that capture size, book-to-market, and momentum effects. 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. All the portfolio returns that we report in this paper are value-weighted returns (equally-weighted returns give stronger results).

3.3. Performance of volatility spread portfolios

Table 3 reports the performance of the volatility spread strategy at various rebalancing frequencies (daily, weekly and four-weekly). At the daily frequency, we track the performance of the portfolios for five trading days. Several important results emerge from this analysis.

First, the next-day, four-factor adjusted return on the long/short hedge portfolio is 38 basis points with a t-statistic of 27.2. The Sharpe ratio on this value weighted, zero investment hedge portfolio is 0.53. Similarly, the next-week, four-factor adjusted return on the hedge portfolio is 50 basis points with a t-statistic of 8.01, and the next-four-weeks, four-factor adjusted return on the hedge portfolio is 73 basis points with a t-statistic of 4.82. It appears that option prices lead stock prices, though at least part of this phenomenon might be attributed to non-synchronicity, as discussed above.

Second, to eliminate any possible impact of non-synchronicity, we also report open-to-close returns. The next-day, four-factor adjusted open-to-close return on the hedge portfolio is 7 basis points with a t-statistic of 5.99. While this is obviously much smaller than the 38 basis points of the next-day, close-to-close return, when we track the performance of the portfolios over time, we find that the magnitude of the predictability declines only slowly over time. Considering the trading days individually, the hedge portfolio earns statistically significant returns on the first three days, and while all the daily returns are small economically, they are consistently positive. At the weekly frequency, Table 3 reports that the hedge portfolio earns an alpha of 20 basis points per week with a t-statistic of 3.24 (excluding the first overnight return) in the first week after the portfolios are formed. In fact, the hedge portfolio earns another 11 basis points over the subsequent week (unreported result) for a total of 42 basis points (t-stat 2.88) altogether over the four weeks following portfolio formation, again ignoring the overnight return. After four weeks the predictability tapers off and the abnormal returns are no longer significantly different from zero. 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). We show in the following section that the returns are substantially larger when conditioning on both the level of, and the change in, the volatility spread.

Third, the average next-day returns increase monotonically as one goes from the first quintile to the last quintile, both for raw returns and abnormal returns. This is important because it suggests that deviations from put-call parity are driven by asymmetric information rather than frictions: the long side of the hedge portfolio earns positive abnormal returns that are both large and statistically significant. In addition, the returns on the short side are short lived, which appears at odds with explanations based on short sales constrains, e.g., Duffie, Garleanu and Pedersen (2002). For example, at the daily frequency, Table 3 shows that the returns on the quintile portfolios continue to increase monotonically from one quintile portfolio to the next for the first four days. The hedge portfolio earns statistically significant returns on the first three days. The long side remains statistically significant for four days, while the return on the short side is not significantly different from zero beyond the first day.

Finally, two pieces of evidence suggest that the first overnight return is unlikely to be entirely spurious. First, in unreported results, we merge our data with the TAQ database, and remove from the daily portfolios any stock that did not trade within three minutes of the market close. The next-day, four-factor adjusted abnormal return is 37 basis points with a t-statistic of 26.89. Second, we will show later that the amount of predictability has decreased significantly over our sample period. Most 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.

4. Further interpretation and discussion

4.1. The role of asymmetric information

Several implications follow from the hypothesis that deviations from put-call parity might be driven by informed trading and asymmetric information. First, if deviations from put-call parity reflect asymmetric information, then these deviations should occur more frequently (in either direction) when information asymmetry is more severe. Second, as discussed in Section 2, Easley, O'Hara and Srinivas (1998) derive a condition under which informed traders in their model trade in the options market. This condition is met when the fraction of informed traders is high and when the leverage and liquidity of the options is high. In this section, we provide empirical tests of these implications. Our measure of the concentration of informed traders is the probability of informed trading, or PIN, from Easley, Kiefer and O'Hara (1997) and Easley, Hvidkjaer and O'Hara (2002). We obtain the PIN estimates from Soeren Hvidkjaer's website for all NYSE and AMEX stocks for the period 1996 through 2001.

4.1.1. 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 4 provides some summary statistics on volatility spreads grouped into PIN quintiles. 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 (both across firms and over time) in the average, 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. In particular, the relative standard deviation nearly doubles, from a value of 4.7 in quintile 1 to a value 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 (2006). 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:

$$VS_{it}^{\text{mod}} = \left| VS_{it} - \overline{VS_t} \right| , \qquad (7)$$

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.[12] The t-statistics that we report employ a robust cluster variance estimator (e.g., Andrews, 1991, Petersen, 2007, and Rogers, 1993).

The results in Panel B of Table 4 show that deviations from put-call parity are more likely to occur in stocks with high PIN's, 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.

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:

$$X_{it} = \frac{P_{it}}{P_{it} + C_{it}}, \tag{8}$$

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 5.[13]

The interesting result in Table 5 is that there is a significant relation between deviations from put-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,

[12] Using alternative liquidity measures, such as the Amivest measure or the Pastor-Stambaugh (2003) reversal measure, produces very similar results.
[13] Our open-buy transactions volume data span the period January 2004 to December 2005.

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.

4.1.2. Interaction with PIN

The previous sections provide evidence that violations of put-call parity reflect asymmetric information by showing that violations of put call parity predict future returns and are more likely to occur when information risk is high. As discussed above, the Easley, O'Hara and Srinivas (1998) model suggests that an important implication of the asymmetric information mechanism is that the predictability should be stronger for firms with a more asymmetric information environment. This section provides a test of this implication.

To test whether the ability of volatility spreads to predict future returns is greater when there is more information risk, we consider double sorts of stocks on both volatility spreads and PIN. The two-way sorts construct $5 \times 3 = 15$ different portfolios. We sort firms independently into three categories based on PIN and into five categories based on the volatility spread. The portfolios are rebalanced every week on Wednesday. As before, to alleviate concerns that our findings are driven by the fact that the options quotes are observed at least two minutes after the last transaction in the underlying stocks, we measure returns both from the close on Wednesday (Panel A in Table 6) and from the open on the following day (Panel B).

The results in Table 6 show that volatility spreads are better able to predict subsequent returns among high PIN stocks than among low PIN stocks. For example, in the low PIN group, the next-week, four-factor adjusted returns range from -19 basis points (t-statistic of -2.29) in the low volatility spread quintile to 32 basis points (t-statistic of 3.54) in the high volatility spread quintile, and the hedge portfolio earns 51 basis points per week, with a t-statistic of 4.51. In the high PIN group, however, the returns are much larger: the four-factor adjusted returns range from -39 basis points (t-statistic of -3.72) in the low volatility spread quintile to 58 basis points in the high volatility spread quintile (t-statistic of 4.34), and the hedge portfolio returns 97 basis points per week (t-statistic of 6.36). The same pattern emerges if one skips the first overnight return; thus the result cannot be attributed to non-synchronicity. Looking at open-to-close returns in the low PIN group, the low volatility spread portfolio earns a risk adjusted 3 basis points per week and the high volatility spread portfolio earns 16 basis points, neither of which is statistically significantly different from zero (t-statistics of 0.35 and 1.69, respectively). The abnormal return on the hedge portfolio is only 13 basis points per week, and it is also not significantly different from zero (t-statistic of 1.16). On the other hand, in the high PIN group, stocks with low volatility spreads underperform substantially, in both economic and statistical terms, earning an average abnormal return of -30 basis points per week (t-statistic of -2.78). Similarly, stocks with high volatility spreads earn large and statistically significant abnormal returns of 39 basis points per week (t-statistic of 2.89). Excluding the first overnight return, the hedge portfolio still earns an abnormal return of 69 basis points per week (t-statistic of 4.65).[14]

We conclude that deviations from put-call parity tend to predict returns to a much larger extent in firms that face a more asymmetric information environment, or with higher probabilities of informed trading. It should again be noted that there is no asymmetry to the abnormal performance: the long side of the hedge portfolios earns returns that are at least as large as those of the short side, pointing to information, rather than short sales constraints, as the likely driver of the predictability.

4.1.3. Interaction with liquidity and leverage

The Easley, O'Hara and Srinivas (1998) model suggests that the level of predictability might be stronger in options with higher leverage and liquidity. In this section, we test this hypothesis by sorting stocks on option-based measures that are meant to proxy for these effects.

Leverage and liquidity vary with an option's time to expiration and moneyness. Because out-of-the-money options on equities have higher leverage and tend to be more liquid, one would expect out-of-the-money options to carry more information than in-the-money options. Separating option pairs into moneyness categories is somewhat problematic however, because for a given strike price, if a call is out of the money then the corresponding put is in the money, and conversely if a call is in the money, the corresponding put is out of the money. We address this in two ways. First, we sort stocks into portfolios based on the difference in implied volatility of out-of-the money calls and out-of-the-money puts. This difference in implied volatilities is no longer based on pairs of options with the same strike price, i.e., *in this test only*, we are no longer looking at deviations from put-call parity. Out-of-the money options have strike prices that are at least two strike prices away from the current underlying stock price, and at-the-money options have strike prices that directly straddle the current price of the underlying asset. The results in Panel A of Table 7 show that the resulting long-short portfolio earns 65 basis points per week (t-statistic of 9.82). Consistent with the view that leverage should matter, this is larger than the 50 basis points per week for our baseline strategy that computes volatility spreads based on all option pairs (Table 3).

[14] The returns in Table 6 exceed those in Table 3. This is because the results on the PIN interaction in Table 6 limit the sample to the time period for which PIN estimates are available, namely 1996 to 2001, and there is more predictability in the earlier part of our sample, as we discuss later.

A potential drawback of this measure based on out-of-the-money options is that it is likely to incorporate much information that is both unrelated to private information and possibly correlated with future returns. Specifically, many models can generate implied volatility skews, but only asymmetric information can generate deviations from put-call parity (Easley, O'Hara and Srinivas, 1998). For example, if skewness (or downside risk) is priced in stock returns, then this could lead to evidence of predictability of the sort we document in Panel A of Table 7, but it could not drive our main results, which are based on deviations from put-call parity.

Second, and to address this issue, we again consider only pairs of options with the same strike price and the same maturity date. We sort option pairs into three moneyness groups and compute volatility spreads for each group as follows. If a call option has an implied volatility that exceeds that of the corresponding put, the moneyness assigned to the pair is the moneyness of the call, because the call option is viewed as the component of the pair driving the positive implied volatility spread. Similarly, if a call option has an implied volatility that is lower than that of the corresponding put, the moneyness assigned to the pair is the moneyness of the put because the put option would be the component of the pair driving the negative implied volatility spread. We thus compute three different types of volatility spreads, each corresponding to a moneyness group. For each type of volatility spread, we sort stocks into quintiles and report the returns on the quintile portfolios as well as a hedge portfolio that is long stocks in the quintile with the highest values of that volatility spread type and short stocks in the quintile with the lowest values. The results in Panel B of Table 7 are again consistent with the notion that leverage and liquidity matter. The hedge portfolio in the trading strategy based on volatility spreads computed from in-the-money options earns a weekly abnormal return of only 15 basis points, with a t-statistic of 2.16. In contrast, the hedge portfolio based on either at-the-money or out-of-the-money options provides an alpha of 58 basis points per week (with a t-statistic of 8.35 at the money and of 7.21 out of the money). The difference in alphas between the in-the-money long/short hedge portfolio and the at- or out-of-the-money hedge portfolio is significant: 43 basis points in both cases (with a t-statistic of, respectively, 4.87 and 3.74).

As a third test, we sort option pairs into maturity groups. At any point in time, stocks have options that expire in the current month, the next month, the following two months (based on the expiration cycle that the underlying equity belongs to) and long-term options with at least one year to expiration (LEAPS). We again compute four different types of volatility spreads, one per maturity group and sort stocks into portfolios based on these various types of volatility spreads. The results are in Panel C of Table 7. Again consistent with the idea that leverage and liquidity matter, deviations from put-call parity among short-term options are more informative than deviations among longer-term options. The hedge portfolio from the strategy that uses options that expire in the next month earns an abnormal return of 54 basis points per week (t-statistic of

8.05), while the hedge portfolio from the strategy that uses LEAPS earns an abnormal return of 26 basis points per week (t-statistic of 3.18).

4.2. Changes and levels of volatility spreads

As discussed earlier, volatility spreads exhibit a fairly large degree of persistence (Table 1). For example, 47% of the stocks in the lowest decile on one day remain there the next, as do 41% of the stocks in the highest decile. This observation suggests that changes in volatility spreads might convey relevant information beyond what is in the level of volatility spreads. This section provides a test of this hypothesis.

To test whether the ability of deviations from put-call parity to predict future returns is greater when one takes into account both levels and changes in volatility spreads, we consider double sorts of stocks on both volatility spread changes and levels. 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 portfolios are rebalanced every week. Again, to alleviate concerns that our findings are driven by the fact that the options quotes are observed at least two minutes after the last transaction in the underlying stocks, we report returns both from the close on Wednesday (Panel A in Table 8) and from the open on Thursday (Panel B). Besides the 25 individual portfolios, we also report the performance of 11 long/short portfolios. Five of these long/short portfolios buy stocks with high (Tuesday) volatility spreads and sell stocks with low (Tuesday) volatility spreads, for stocks that are in the same quintile in terms of (Tuesday to Wednesday) change in the volatility spread. Another five long/short portfolios buy stocks with high (Tuesday to Wednesday) volatility spread changes and sell stocks with low (Tuesday to Wednesday) volatility spread changes, for stocks that are in the same quintile based on Tuesday volatility spreads. Finally, we report the performance of the long/short hedge portfolio 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 interesting results emerge from the analysis in Table 8. First, deviations from put-call parity predict returns to a much greater extent when both the level and the change in the volatility spread are taken into account. The long/short hedge portfolio that buys stocks with high and increasing volatility spreads, and sells stocks with low and decreasing volatility spreads, earns an abnormal return of 1.07% per week (with a t-statistic of 7.69) including the first overnight period. Excluding the first overnight period and buying at the opening of the market on the day after the second volatility spreads are observed still generates abnormal returns of 45 basis points per week (with a t-statistic of 3.53).[15] This result is robust to a variety of robustness checks, e.g., excluding stocks priced under $5 or not in the top two NYSE/AMEX/NASDAQ market capitalization deciles also produces significant alphas. Also, the double sort avoids the potential criticism that the results are simply a function of large sample sizes that could 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.[16]

Second, the results in Table 8 reinforce our earlier conclusion that deviations from put-call parity are driven by asymmetric information rather than frictions: the long side of the hedge portfolio again earns positive abnormal returns that are both large and statistically significant. Including the overnight period, the long side earns abnormal returns of 63 basis points per week (t-statistic of 5.34) and the short side earns -46 basis points per week (t-statistic of -4.38). Similarly, excluding the overnight period, the long side earns 26 basis points per week (t-statistic of 2.29) and the short side -22 basis points (t-statistic of -2.13).

While in Table 8 we limit ourselves to strategies rebalanced once a week to preserve space, we have verified that our results also hold at other rebalancing frequencies. For example, the four-weekly value-weighted abnormal return on the long/short hedge portfolio in this double sort on both volatility spread levels and changes is 85 basis points (t-statistic of 2.48) over the four weeks starting from the opening of the market on Thursday, i.e., not including the first overnight period.

4.3. 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's to prevent rational arbitrageurs from quickly exploiting the anomaly. 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 3, but we now break the analysis into three subperiods: the first half of the sample (January 1996 – December 2000), the second half (January 2001 –

[15] In unreported results, we find that a single weekly sort based on volatility spread changes alone produces a long/short hedge portfolio with a four-factor alpha of 40 basis points per week (t-statistic of 6.10).
[16] The correlation (both cross-sectionally and over time) between the lagged volatility spread level and the change in the volatility spread is -0.44.

December 2005), and the last three years (from January 2003 to December 2005), as reported in Table 9. The main result is that extent to which volatility spreads predict returns decreases substantially over our sample period. For example, ignoring the first overnight return, the open-to-close four-factor adjusted returns on the volatility spread level hedge portfolio go from 26 basis points per week over the first half of the sample, to 15 basis points per week in the second half, and only 2 basis points over the last three years (Panel A). Similarly, and again ignoring the first overnight return, the open-to-close four-factor adjusted returns on the hedge portfolio constructed from both levels and changes in volatility spreads go from 72 basis points per week over the first half of the sample, to 24 basis points per week in the second half, and only 9 basis points over the last three years (Panel B).

These results are clearly conservative in that they skip the first overnight return entirely and only rebalance the portfolios once per week, but they do suggest that it has become significantly more difficult to profit from trading strategies based on deviations from put-call parity. At the same time, the daily results in Panel A suggest that some predictability may still persist, e.g., the next-day risk adjusted return on the hedge portfolio based on levels of volatility spreads over the last three years of the sample is 20 basis points (t-statistic of 14.49) including the overnight return and 7 basis points (t-statistic of 5.43) excluding it. Note however that there is some evidence of reversal in this latter part of the sample, indicating that price pressure (rather than information) might be the mechanism here: the weekly abnormal return on the hedge portfolio in Panel A, including the first overnight return, is only 14 basis points (t-statistic of 2.08), though there is considerable noise in the estimation of alphas over such a short sample period.

The results in the last two columns of Panel A, which decompose the next-day return into an overnight component and an open-market component, can help to 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, and 14 basis points over the last three. Surprisingly, we also find some evidence that the open-market return increases 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.

The top plot in Figure 1 shows the evolution over time in the Sharpe ratio of the daily rebalanced hedged strategy based on the volatility spread level. This Sharpe ratio is calculated from daily returns on the hedge portfolio over the preceding 90 days. Clearly, the daily Sharpe ratio decreases over time, from about 1.4 in 1996 to less than 0.2 at the end of 2005. The bottom plot shows the average 90-day return on the hedge portfolio, calculated analogously, showing the same pattern of decreasing predictability over time. The Sharpe ratios and average returns on the daily rebalanced hedged strategy based on both levels and changes in the volatility spread (not reported) are similarly consistent with decreasing predictability over time.

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

5. Robustness

This section investigates the extent to which deviations from put-call parity predict stock returns using pool-panel regressions of stock returns on volatility spreads and a battery of control variables, including proxies for liquidity and the difficulty of short-selling the stock.

5.1. Cross-sectional regressions

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. To alleviate concerns that the results may be driven by the fact that the options market closes after the stock market, we report regression results using both Wednesday-close-to-Wednesday-close returns (denoted ‘no lag’) and Thursday-open-to-Wednesday-close returns (denoted ‘open’). The t-statistics we report employ a robust cluster variance estimator. All the returns in our regressions are expressed as percentages.

The results in Table 10 confirm our earlier results based on time-series regressions of quintile portfolio returns. Column (1) reports the regression of weekly returns starting from the close on Wednesday. All the coefficients are highly significant statistically, and the magnitudes are economically large. For example, the coefficients in column (1) imply a difference in average weekly returns between high volatility spread stocks and low volatility spread stocks of 83 basis points per week.[18] Similarly, the coefficients in column (7) imply a spread of 32 basis points per week in returns that begin to accrue at the opening of the market on the Thursday after the volatility spreads are estimated. Columns (3) and (9) show that this basic result continues to hold when the factors of Fama and French (1993) and Carhart (1997) are included. Finally, columns (5) and (11) add lagged stock returns and lagged factors to the regressions to control for autocorrelation and short-term reversals (Lo and Mackinlay, 1990). This analysis 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 10 confirm that all of these conclusions are also robust to using piecewise linear regressions.

5.2. Changes and levels of volatility spreads

In Table 11, 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. Weekly returns are measured either from the last transaction on Wednesday (denoted 'no lag') or from the opening of the market on Thursday (denoted 'open'). Volatility spread levels are as of Tuesday, and volatility spread changes are from Tuesday to Wednesday. The t-statistics again employ a robust cluster variance estimator. The regressions marked as including controls include the lagged stock return as well as the four Fama-French factors and lags of the four Fama-French factors. 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 perform 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, and starting either at the close on Wednesday or at the open on Thursday. The results are entirely 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-

[18] This is larger than the 50 basis points in Table 3, but the quintile portfolio returns reported in Table 3 are value-weighted returns, while the regressions in Table 10 correspond to equal-weighted returns.
[19] To reduce the number of variables, we do not include dummy variables in these regressions.

Tuesday volatility spread change, and (iv) controls (the four Fama-French factors, lagged stock returns and lagged factors). Weekly returns are either Wednesday close to Wednesday close or Thursday open to Wednesday close. Interestingly, we find that both the change and the lagged change in volatility spreads matter for subsequent returns.

5.3. Liquidity

This section investigates whether the degree of predictability interacts with various proxies for the liquidity of the underlying stocks. 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 liquidity as the coefficient γ in the regression

$$r_t^e = \theta + \varphi \cdot r_{t-1}^e + \gamma \cdot \operatorname{sign}\left(r_{t-1}^e\right) \cdot V_{t-1} + \varepsilon_t \,, \qquad (9)$$

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, Table 12 contains the results of pooled, cross-sectional regressions of stock returns on quintile dummies of the liquidity measure, and products of volatility spreads and the quintile dummies. Panel A of Table 12 also includes results on size as an additional control. Each regression includes on the right-hand side the lagged stock return as well as the four Fama-French factors and lags of the four Fama-French factors. The reported t-statistics employ a robust cluster variance estimator and we again report results using both Wednesday-close-to-Wednesday-close returns as well as Thursday-open-to-Wednesday-close returns.

Table 12 shows that our main result that volatility spreads predict returns survives the inclusion of all these controls and is driven neither by small stocks nor illiquid stocks. The one exception is in Panel B, which shows that the volatility spread cannot predict returns to a statistically significant extent among stocks with a low Amihud (2002) illiquidity ratio. However, the volatility spread remains significant in stocks that are very liquid based on either the Amivest liquidity ratio or the Pastor and Stambaugh (2003) reversal measure.

5.4 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 deviations from put-call parity reflect asymmetric information (rather than frictions such as short sales constraints). Empirically, this is supported by our finding that the long side of the volatility-spread long/short portfolios earns positive abnormal returns that are as large as the negative returns on the short side. In this subsection, 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 of the value of the shorted or 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 negative 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%.

As previously discussed, the predictability of stock returns by volatility spreads is greatly diminished in the last years of our sample. However, our main interest in this subsection is to investigate whether our results are driven by the subset of stocks that are on special at any one time. Therefore, we only report the weekly return regressions including the overnight return, as excluding the overnight return generates at best marginally significant results for this last part of our sample.

We report the results of three pooled panel predictive regressions using weekly stock returns in Table 13: (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 and their lags), (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 13, excluding the volatility spread, confirms previous results (e.g., Ofek et al. (2004) and Cohen, Diether and Malloy (2006)) 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 left.[20] Also, once the volatility spread dummies are included, the significance of the rebate spread disappears. 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 diminished (significant at the 10% level or lower). However, the volatility spread dummies interacted with the 'on special' dummy is not significant and typically has the wrong sign. Therefore, we can conclude that the volatility spread predictability is not at all driven by those stocks that are hard to short.

6. Conclusion

We show that deviations from 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

[20] However, both the economic and statistical significance have clearly decreased from the earlier parts of the sample.

evidence that stocks with relatively expensive calls outperform stocks with relatively expensive puts by at least 45 basis points per week. 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. Controlling for size, we find that 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 tend to predict returns to a larger extent in firms that face a more asymmetric information environment. Taken together, the evidence in this paper suggests that the demand for an option can affect its price for information- rather than friction-based reasons.

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 considerably over time. This suggests that the forces of arbitrage eventually act so as to limit the mispricing of assets.

Table 1
Volatility spreads

This table reports descriptive statistics on the volatility spreads used in the main analysis. The volatility spread is the average difference in implied volatilities between calls and puts (with the same strike price and maturity) across all option pairs for an underlying security on a given day. The full sample period is January 1996 to December 2005. We also report results for three subperiods: January 1996 – December 2000, January 2001 – December 2005, and January 2003 – 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 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	2003 - 2005
Panel A: Summary Statistics (%)				
Mean	-0.978	-0.839	-1.031	-1.042
Standard deviation TS	6.396	5.934	3.835	3.163
Standard deviation CS	3.965	5.345	3.879	3.300
Panel B: Percentiles (%)				
(10^{th})	-6.111	-7.549	-4.492	-3.894
(20^{th})	-3.514	-4.568	-2.614	-2.344
(30^{th})	-2.222	-2.963	-1.724	-1.605
(40^{th})	-1.396	-1.845	-1.151	-1.117
(50^{th})	-0.770	-0.920	-0.700	-0.722
(60^{th})	-0.191	-0.012	-0.275	-0.345
(70^{th})	0.515	1.077	0.216	0.083
(80^{th})	1.644	2.681	0.940	0.695
(90^{th})	4.074	5.791	2.463	1.945
Panel C: Persistence – Autocorrelations				
Autocorrelation (1)	0.32	0.36	0.28	0.28
Autocorrelation (2)	0.28	0.31	0.24	0.23
Autocorrelation (3)	0.24	0.27	0.21	0.20
Autocorrelation (4)	0.22	0.25	0.18	0.18
Autocorrelation (5)	0.20	0.22	0.17	0.16

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

This table shows the pre-formation characteristics of portfolios formed on volatility spreads. Every month, we sort firms into quintiles based on their volatility spread on the last day of the month. The volatility spread is the average difference in implied volatilities between calls and puts (with the same strike price and maturity) across all 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 return during the month or during the month except that we skip the last day of the month. We report both average returns and average returns in excess of the market index. Panel A reports time series averages of equally weighted cross sectional averages, and Panel B reports time series averages of value weighted cross sectional averages. Returns are expressed in percent per month, so an excess return of -1.98 means -1.98% per month.

		Volatility Spread Quintiles				
		(1)	(2)	(3)	(4)	(5)
Panel A: Pre-formation characteristics						
Size		2,241.04	6,198.03	9,455.36	7,290.74	2,878.28
Size decile		7.98	8.75	8.99	8.81	7.97
Beta		1.19	1.10	1.04	1.05	1.15
Standard deviation		0.605	0.497	0.458	0.478	0.587
Price		23.91	32.67	36.33	32.01	21.74
Panel B: Pre-formation performance						
	mean ret	1.07	1.76	1.19	0.07	-0.73
No lag	excess ret	0.23	0.57	-0.04	-1.69	-2.49
	t-stat	0.71	0.64	-0.13	-7.50	-3.63
	mean ret	0.40	1.40	1.13	0.32	-0.27
One day lag	excess ret	-0.44	0.21	0.57	-1.08	-1.98
	t-stat	-1.31	0.23	1.57	-5.07	-2.92

Table 3

Daily returns on volatility spread portfolios

Performance of quintile portfolios formed on volatility spreads. The portfolios are rebalanced daily, weekly or four-weekly. For daily results, the volatility spread is observed on each day *t*, and returns are from the close on day *t* to the close on day *t*+1 (Day 1), or from the close on day *t*+1 to the close on day *t*+2 (Day 2), etc. 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. For Day 1, the hedge portfolio return is decomposed into an overnight return (‘close’) and an open-market return (‘open’). For weekly and four-weekly results, we sort stocks every Wednesday and report either four-weekly or weekly returns starting from either the close of trading on Wednesday (‘no lag’) or from the open on Thursday (‘open’). 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 37.9 for ‘Day 1’ means 37.9 basis points per day, and an alpha of 50 for ‘1 Week (no lag)’ means 50 basis points per week.

		A: Volatility Spread Quintiles					B: Hedge Portfolio			
		(1)	(2)	(3)	(4)	(5)	return		alpha	
Day 1	mean ret	-14	-4	3	12	25	38.7		37.9	
	alpha	-17	-8	-1	7	21	(26.70)		(27.16)	
	t-stat	-17.09	-12.35	-2.07	12.40	21.70	close	open	close	open
							31.3	7.5	31.0	7.0
							(39.43)	(6.25)	(39.44)	(5.99)
Day 2	mean ret	2	3	4	7	7				
	alpha	-1	-1	0	3	3	5.0		4.3	
	t-stat	-1.43	-2.36	-0.26	4.91	2.96	(3.66)		(3.20)	
Day 3	mean ret	4	4	5	5	7				
	alpha	0	0	0	1	3	2.8		2.5	
	t-stat	0.05	0.04	0.91	1.11	2.70	(2.10)		(1.91)	

Day 4	mean ret	4	4	5	5	6	2.7	2.2
	alpha	0	0	1	1	2	(2.05)	(1.68)
	t-stat	-0.13	-0.81	1.35	0.96	2.24		
Day 5	mean ret	4	5	3	6	5	1.6	1.1
	alpha	0	1	-1	2	1	(1.25)	(0.86)
	t-stat	-0.23	1.62	-1.92	3.62	0.98		
1 Week (no lag)	mean ret	-1	11	17	34	49	50	50
	alpha	-21	-10	-3	13	29	(7.69)	(8.01)
	t-stat	-4.47	-3.35	-1.54	4.95	6.30		
1 Week (open)	mean ret	11	16	18	27	29	18	20
	alpha	-9	-4	-2	7	10	(2.93)	(3.24)
	t-stat	-1.61	-0.92	-0.66	1.94	1.98		
4 Weeks (no lag)	mean ret	58	72	72	97	122	64	73
	alpha	-21	-8	-10	21	52	(5.20)	(4.82)
	t-stat	-1.85	-1.02	-1.69	3.46	4.62		
4 Weeks (open)	mean ret	70	77	72	91	102	33	42
	alpha	-9	-1	-7	15	34	(2.97)	(2.88)
	t-stat	-0.77	-0.11	-1.12	1.95	2.75		

Table 4

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 coefficient of variation, i.e., 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 $VS_{it}^{\text{mod}} = \left| VS_{it} - \overline{VS_t} \right|$, 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. The t-statistics in parentheses employ a robust cluster variance estimator.

Panel A

	Mean	Standard deviation	Rel. stand. dev.
PIN (1)	-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 (5)	-0.012	0.096	8.023

Panel B

Independent Variables	(1)	(2)
Intercept	0.22	0.033
	(41.98)	(9.65)
PIN		0.001
		(7.34)
Call Spread	0.068	0.046
	(23.44)	(18.14)
Put Spread	0.0147	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 5
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 6

Portfolios sorted on volatility spread and PIN

Panel A: Performance of portfolios formed on volatility spread and PIN. Returns are expressed in percent per week, so an alpha of 0.51 means 51 basis points per week. The volatility spread is observed each Wednesday, and we report weekly returns starting from the close on Wednesday.

		Volatility Spread					
	PIN	(1)	(2)	(3)	(4)	(5)	(5) – (1)
Mean Return	(1)	0.09	0.17	0.24	0.43	0.56	0.47
	(2)	0.05	0.30	0.26	0.50	0.75	0.71
	(3)	-0.07	0.22	0.44	0.52	0.91	0.98
Alpha	(1)	-0.19	-0.12	-0.01	0.16	0.32	0.51
	(2)	-0.23	0.01	-0.05	0.19	0.43	0.66
	(3)	-0.39	-0.11	0.09	0.19	0.58	0.97
t-stat	(1)	-2.29	-2.10	-0.24	2.74	3.54	4.51
	(2)	-2.33	0.17	-0.67	2.58	4.22	5.32
	(3)	-3.72	-1.03	0.85	1.75	4.34	6.36

Panel B: Performance of portfolios formed on volatility spread and PIN. Returns are expressed in percent per week, so an alpha of 0.13 means 13 basis points per week. The volatility spread is observed on Wednesday each week, and returns are from the open on Thursday to the close on the following Wednesday.

		Volatility Spread					
	PIN	(1)	(2)	(3)	(4)	(5)	(5) – (1)
Mean Return	(1)	0.30	0.29	0.31	0.42	0.39	0.09
	(2)	0.22	0.34	0.31	0.48	0.60	0.37
	(3)	0.01	0.24	0.48	0.47	0.70	0.69
Alpha	(1)	0.03	0.02	0.07	0.16	0.16	0.13
	(2)	-0.05	0.06	0.03	0.17	0.28	0.33
	(3)	-0.30	-0.07	0.14	0.17	0.39	0.69
t-stat	(1)	0.35	0.32	1.10	2.46	1.69	1.16
	(2)	-0.45	0.83	0.40	2.18	2.73	2.79
	(3)	-2.78	-0.64	1.31	1.52	2.89	4.65

Table 7

Portfolios sorted on volatility spread:

Leverage and time to maturity effects

This table shows the performance of quintile portfolios formed on volatility spreads calculated using options from different moneyness and maturity groups. At the money (ATM) options have strike prices that straddle the current underlying stock price. In Panel A, the option variable used to create portfolios is the difference in implied volatilities between OTM calls and OTM puts. In Panel B we again consider deviations from put-call parity. If a call option has a higher implied volatility than the corresponding put, the moneyness of the call is assigned to the pair. Conversely, if a put option has a higher implied volatility than the corresponding call, the moneyness of the put is assigned to the pair. In Panel C, short term options expire in the following month, near term and long term options expire in the following two months based on the option expiration cycle that the underlying stock belongs to, and LEAPS have at least one year to expiration. The portfolios are rebalanced every week. We sort stocks every Wednesday and report weekly returns starting at the close on Wednesday. Returns are not annualized; they are reported in percent per week. Thus an alpha of 0.65 means 65 basis points per week.

Panel A: Out-of-the-money options

		Volatility Spread Quintiles					Hedge
		(1)	(2)	(3)	(4)	(5)	(5) – (1)
	mean ret	-0.06	0.17	0.21	0.28	0.53	0.59
OTM call - OTM put	alpha	-0.28	-0.04	0.00	0.09	0.37	0.65
	t-stat	-6.56	-1.11	-0.02	3.08	7.11	9.82

Panel B: Moneyness groups

		Volatility Spread Quintiles					Hedge
		(1)	(2)	(3)	(4)	(5)	(5) – (1)
	mean ret	0.12	0.14	0.23	0.27	0.37	0.25
ITM	alpha	-0.03	-0.03	0.04	0.06	0.12	0.15
	t-stat	-0.55	-0.69	1.24	1.83	3.26	2.16
	mean ret	0.00	0.12	0.17	0.34	0.52	0.52
ATM	alpha	-0.21	-0.10	-0.03	0.15	0.37	0.58
	t-stat	-5.10	-3.10	-1.15	4.86	6.74	8.35
	mean ret	0.05	0.12	0.24	0.42	0.51	0.46
OTM	alpha	-0.20	-0.11	0.04	0.26	0.38	0.58
	t-stat	-5.10	-3.62	1.46	6.32	5.86	7.21

Panel C: Time-to-maturity groups

		Volatility Spread Quintiles					Hedge
		(1)	(2)	(3)	(4)	(5)	(5) – (1)
Short term	mean ret	-0.03	0.04	0.23	0.32	0.47	0.49
	alpha	-0.25	-0.18	0.02	0.13	0.28	0.54
	t-stat	-5.30	-6.23	0.92	4.75	5.23	8.05
Near term	mean ret	-0.01	0.14	0.17	0.31	0.45	0.46
	alpha	-0.22	-0.06	-0.04	0.12	0.27	0.49
	t-stat	-4.73	-1.99	-1.95	4.29	5.56	7.25
Long term	mean ret	0.01	0.18	0.19	0.28	0.46	0.46
	alpha	-0.23	-0.04	-0.01	0.10	0.29	0.51
	t-stat	-4.53	-1.26	-0.65	3.42	5.37	7.07
LEAPS	mean ret	0.07	0.14	0.21	0.34	0.34	0.27
	alpha	-0.09	-0.07	0.01	0.18	0.17	0.26
	t-stat	-1.42	-1.78	0.20	4.29	3.36	3.18

Table 8

Weekly returns on portfolios formed on levels and changes in volatility spreads

This table shows the performance of quintile portfolios formed on both levels and changes in volatility spreads. The portfolios are rebalanced every week. We sort stocks every Wednesday and report weekly returns starting either from the close of trading on Wednesday (Panel A) or from the open on Thursday (Panel B). We sort stocks into 5 × 5 = 25 different portfolios: every Wednesday we sort stocks into five groups based on the change in the volatility spread between Tuesday and Wednesday, and then into five groups based on the level of the volatility spread on Tuesday. These double sorts are independent sorts. We report the weekly raw return (in %), abnormal return (in %) and its t-statistic for the 25 portfolios as well as 11 long/short portfolios. The indices (1), (2), (3), (4), and (5) refer to the sorted portfolios, with higher values of the indices designating portfolios of stocks with higher values of changes or levels of the volatility spread variable. The long/short portfolio that buys stocks with calls that were relatively expensive and became more expensive, and sells stocks with puts that were expensive and became more expensive is denoted ‘(5,5) - (1,1)’.

Panel A: No lag

		VS Level						Hedge
	VS Change	(1)	(2)	(3)	(4)	(5)	(5) - (1)	(5,5) - (1,1)
Mean Return	(1)	-0.25	-0.13	-0.01	-0.07	0.19	0.44	1.08
	(2)	0.06	0.04	-0.03	0.18	0.22	0.16	
	(3)	0.12	0.11	0.15	0.29	0.37	0.25	
	(4)	0.08	0.21	0.24	0.36	0.56	0.48	
	(5)	0.27	0.36	0.49	0.50	0.77	0.50	
	(5) – (1)	0.59	0.55	0.56	0.64	0.65		
Alpha	(1)	-0.46	-0.31	-0.19	-0.26	-0.01	0.44	1.07
	(2)	-0.08	-0.11	-0.16	0.06	0.08	0.15	
	(3)	-0.01	-0.03	0.02	0.15	0.24	0.25	
	(4)	-0.07	0.07	0.11	0.23	0.39	0.46	
	(5)	0.15	0.24	0.38	0.37	0.61	0.46	
	(5) – (1)	0.61	0.55	0.57	0.62	0.63		
t-stat	(1)	-4.38	-2.88	-2.11	-3.34	-0.19	3.96	7.69
	(2)	-0.83	-1.69	-3.07	1.43	1.06	1.32	
	(3)	-0.09	-0.60	0.40	2.99	2.80	2.36	
	(4)	-0.97	1.42	1.99	3.37	3.96	4.16	
	(5)	2.14	3.16	4.05	2.82	6.37	4.12	
	(5) – (1)	5.41	4.51	4.55	4.44	5.34		

Panel B: Next day open

	VS Change	VS Level (1)	(2)	(3)	(4)	(5)	(5) - (1)	Hedge (5,5) - (1,1)
Mean Return	(1)	-0.01	0.09	0.14	0.04	0.18	0.19	0.45
	(2)	0.10	0.10	0.03	0.17	0.18	0.07	
	(3)	0.14	0.15	0.16	0.23	0.28	0.15	
	(4)	0.07	0.17	0.19	0.22	0.36	0.29	
	(5)	0.13	0.17	0.28	0.19	0.37	0.24	
	(5) – (1)	0.21	0.15	0.21	0.21	0.27		
Alpha	(1)	-0.22	-0.08	-0.05	-0.14	-0.03	0.20	0.45
	(2)	-0.04	-0.04	-0.09	0.06	0.04	0.08	
	(3)	0.01	0.01	0.03	0.09	0.17	0.16	
	(4)	-0.08	0.03	0.07	0.08	0.19	0.26	
	(5)	0.02	0.06	0.19	0.06	0.23	0.21	
	(5) – (1)	0.24	0.14	0.24	0.20	0.26		
t-stat	(1)	-2.13	-0.79	-0.50	-1.70	-0.36	1.78	3.53
	(2)	-0.45	-0.64	-1.57	1.15	0.46	0.68	
	(3)	0.09	0.25	0.80	1.67	1.90	1.57	
	(4)	-1.05	0.70	1.13	1.05	1.95	2.53	
	(5)	0.22	0.72	1.99	0.50	2.41	2.07	
	(5) – (1)	2.23	1.23	1.94	1.56	2.29		

Table 9

Returns on volatility spread portfolios over time

This table shows how the performance of quintile 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'), weekly returns (denoted 'W'), and daily (denoted 'D') returns 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 percentages, so an alpha of 0.81 in Panel A, column '4W' means 81 basis points per four weeks, and an alpha of 1.46 in Panel B, column 'W' means 146 basis points per week.

		A: Sorts on volatility spread levels							B: Sorts on levels and changes	
		4W	4W-O	W	W-O	D	D-O	night	W	W-O
Jan 1996 - Dec 2000	mean ret	0.68	0.29	0.61	0.22	0.44	0.05	0.39	1.39	0.64
	alpha	0.81	0.44	0.63	0.26	0.44	0.05	0.39	1.46	0.72
	t-stat	3.97	2.13	6.48	2.60	21.94	2.75	35.74	7.03	3.75
Jan 2001 - Dec 2005	mean ret	0.59	0.36	0.38	0.15	0.33	0.10	0.24	0.77	0.27
	alpha	0.62	0.37	0.39	0.15	0.33	0.10	0.23	0.75	0.24
	t-stat	3.21	2.10	5.15	2.21	17.23	6.43	21.42	4.16	1.40
Jan 2003 - Dec 2005	mean ret	0.11	-0.01	0.17	0.04	0.21	0.07	0.14	0.32	0.06
	alpha	0.00	-0.12	0.14	0.02	0.20	0.07	0.14	0.32	0.09
	t-stat	-0.01	-0.88	2.08	0.33	14.49	5.43	17.12	1.83	0.49

Table 10
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 the volatility spreads (even-numbered regressions). Returns in regressions (1) through (6) include the first overnight period, while returns in regressions (7) through (12) begin to accrue at the open on the day after the volatility spreads are observed. The t-statistics in parentheses employ a robust cluster variance estimator. Returns are converted to percentages.

Independent	No lag	No lag	No lag	No lag	No lag	No lag	Open	Open	Open	Open	Open	Open
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.117	0.235	-0.012	0.084	-0.014	0.082	0.179	0.254	0.045	0.096	0.045	0.096
	(8.63)	(13.12)	(-0.95)	(4.96)	(-1.08)	(4.89)	(3.04)	(4.26)	(0.77)	(1.61)	(0.75)	(1.61)
dummy Q1	-0.311		-0.325		-0.320		-0.121		-0.140		-0.136	
	(-12.0)		(-13.4)		(-13.2)		(-2.92)		(-3.47)		(-3.24)	
dummy Q2	-0.093		-0.094		-0.093		-0.072		-0.073		-0.072	
	(-4.28)		(-4.70)		(-4.63)		(-2.15)		(-2.26)		(-2.23)	
dummy Q4	0.140		0.119		0.119		0.076		0.058		0.059	
	(6.65)		(6.19)		(6.18)		(2.40)		(1.88)		(1.91)	
dummy Q5	0.520		0.447		0.441		0.203		0.132		0.128	
	(20.30)		(18.78)		(18.51)		(5.61)		(3.78)		(3.65)	
VS × dummy Q1		3.584		3.600		3.560		1.798		1.817		1.784
		(11.11)		(11.57)		(11.47)		(5.08)		(5.25)		(5.16)
VS × dummy Q2		8.934		8.085		8.010		6.262		5.333		5.325
		(8.78)		(8.51)		(8.45)		(5.24)		(4.67)		(4.63)
VS × dummy Q3		12.979		10.983		10.976		7.376		5.172		5.273
		(5.11)		(4.67)		(4.68)		(2.32)		(1.69)		(1.72)
VS × dummy Q4		4.069		3.824		3.755		-1.077		-0.838		-0.797
		(1.45)		(1.47)		(1.44)		(-0.40)		(-0.34)		(-0.32)
VS × dummy Q5		4.268		3.695		3.626		1.173		0.663		0.604
		(9.46)		(8.87)		(8.78)		(3.32)		(1.99)		(1.82)
Lagged return					-0.015	-0.016					-0.013	-0.013
					(-4.19)	(-4.44)					(-3.57)	(-3.70)
FF4 factors?	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Lagged FF4?	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes
R^2	0.001	0.001	0.149	0.149	0.150	0.150	0.000	0.000	0.108	0.108	0.108	0.108

Table 11
Cross-sectional regressions – Changes and levels

Pool-panel regressions of weekly stock returns (in percent) on volatility spread levels and changes. Returns denoted 'no lag' include the first overnight period and returns denoted 'open' start at the open on the day 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'). 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, the lagged stock return and lagged factors.

Panel A: Quintile dummies

Returns	Interc.	Level Q1	Level Q2	Level Q4	Level Q5	Change Q1	Change Q2	Change Q4	Change Q5	Controls	R^2
No lag	0.129	-0.267	-0.061	0.135	0.309	-0.386	-0.105	0.149	0.422	No	0.001
	(6.84)	(-9.76)	(-2.60)	(6.02)	(11.57)	(-13.82)	(-4.77)	(6.72)	(15.78)		
No lag	0.005	-0.284	-0.079	0.115	0.292	-0.392	-0.120	0.127	0.394	Yes	0.149
	(0.30)	(-11.13)	(-3.65)	(5.58)	(11.78)	(-15.46)	(-5.86)	(6.27)	(15.81)		
Open	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)		
Open	0.114	-0.231	-0.048	0.041	0.088	-0.215	-0.088	0.032	0.044	Yes	0.108
	(1.32)	(-4.16)	(-1.81)	(1.61)	(2.81)	(-3.94)	(-3.62)	(1.45)	(2.02)		

Panel B: Piecewise linear

Returns	Interc.	Level Q1	Level Q2	Level Q3	Level Q4	Level Q5	Change Q1	Change Q2	Change Q3	Change Q4	Change Q5	Controls	R^2
No lag	0.106	2.359	1.832	4.541	16.708	3.723	4.448	3.242	7.519	13.480	0.423	No	0.001
	(7.68)	(8.43)	(2.08)	(2.43)	(9.91)	(8.44)	(11.43)	(2.53)	(2.64)	(10.10)	(17.03)		
No lag	-0.0233	2.577	2.482	2.026	9.614	3.130	4.112	3.251	8.201	10.64	0.404	Yes	0.150
	(-1.78)	(9.50)	(3.04)	(1.15)	(6.15)	(7.94)	(11.51)	(2.71)	(3.07)	(8.63)	(17.35)		
Open	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)		
Open	0.012	1.862	-1.019	-3.169	7.484	1.098	1.232	-0.817	2.709	6.859	0.090	Yes	0.108
	(0.25)	(6.09)	(-0.83)	(-1.49)	(3.00)	(3.49)	(3.40)	(-0.53)	(0.72)	(3.99)	(2.74)		

Panel C: Changes and lagged changes

Returns	Interc.	VS level	VS change	Lag VS change	Controls	R^2	Returns	Interc.	VS level	VS change	Lag VS change	Controls	R^2
No lag	0.051	3.267	4.633	0.657	Yes	0.150	Open	0.058	1.621	1.221	0.606	Yes	0.108
	(6.41)	(14.26)	(19.58)	(2.86)				(1.12)	(6.92)	(6.03)	(3.21)		

Table 12
Cross-sectional regressions – Controlling for liquidity

Pooled panel regressions of weekly stock returns on volatility spreads, controlling for size and liquidity. We consider three liquidity proxies: the Amihud (2002) illiquidity ratio, the Amivest liquidity ratio, and the Pastor-Stambaugh (2003) reversal measure. Returns denoted 'no lag' are weekly returns starting from the close on Wednesday and returns denoted 'open' begin to accrue at the open on the 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 quintile dummies of the liquidity measure, and products of volatility spreads and the quintile dummies. All the regressions control for the four Fama-French (1993) and Carhart (1997) factors, lagged factors and lagged stock returns. The t-statistics in parentheses employ a robust cluster variance estimator. Returns are converted to percentages.

Panel A: Size												
Returns	Interc.	VS × Size Q1	VS × Size Q2	VS × Size Q3	VS × Size Q4	VS × Size Q5	Size Q1	Size Q2	Size Q4	Size Q5	Controls	R^2
No lag	0.089	4.112	4.236	3.291	2.596	2.520	-0.110	-0.000	0.015	0.009	Yes	0.151
	(6.60)	(10.78)	(11.27)	(8.55)	(5.26)	(4.19)	(-4.82)	(-0.03)	(0.86)	(0.53)		
Open	0.0132	1.061	1.730	1.509	1.390	2.604	-0.151	-0.010	0.061	0.322	Yes	0.109
	(0.96)	(4.29)	(4.91)	(4.48)	(3.40)	(1.65)	(-6.24)	(-0.48)	(1.35)	(1.25)		
Panel B: Amihud (2002) illiquidity ratio, *I*												
Returns	Interc.	VS × *I* Q1	VS × *I* Q2	VS × *I* Q3	VS × *I* Q4	VS × *I* Q5	*I* Q1	*I* Q2	*I* Q4	*I* Q5	Controls	R^2
No lag	0.133	1.352	2.789	3.411	4.642	3.780	0.016	0.012	-0.071	-0.158	Yes	0.151
	(8.39)	(1.82)	(3.23)	(6.93)	(10.02)	(12.70)	(0.76)	(0.51)	(-2.87)	(-7.38)		
Open	0.081	0.101	1.817	1.438	1.618	1.280	0.142	0.253	-0.112	-0.218	Yes	0.109
	(3.55)	(0.12)	(1.39)	(3.35)	(4.17)	(5.98)	(1.37)	(1.17)	(-3.70)	(-7.97)		
Panel C: Amivest liquidity ratio, *L*												
Returns	Interc.	VS × *L* Q1	VS × *L* Q2	VS × *L* Q3	VS × *L* Q4	VS × *L* Q5	*L* Q1	*L* Q2	*L* Q4	*L* Q5	Controls	R^2
No lag	0.153	4.796	5.641	3.653	1.759	2.244	-0.468	-0.112	-0.007	0.044	Yes	0.152
	(9.01)	(14.28)	(11.36)	(7.43)	(2.53)	(5.80)	(-18.30)	(-4.27)	(-0.31)	(2.17)		
Open	0.112	1.204	2.660	1.702	1.347	1.046	-0.523	-0.144	0.279	0.024	Yes	0.109
	(2.72)	(4.95)	(6.66)	(3.52)	(1.02)	(3.26)	(-11.29)	(-4.18)	(0.91)	(0.51)		

Panel D: Pastor-Stambaugh gamma, γ												
Returns	Interc.	VS × γQ1	VS × γQ2	VS × γQ3	VS × γQ4	VS × γQ5	γQ1	γQ2	γQ4	γQ5	Controls	R^2
No lag	0.149	4.157	4.275	2.812	3.736	3.557	-0.218	-0.008	-0.034	-0.090	Yes	0.151
	(9.97)	(11.04)	(7.13)	(4.03)	(5.92)	(10.38)	(-8.95)	(-0.35)	(-1.42)	(-4.44)		
Open	0.335	1.244	1.584	1.631	1.915	1.210	-0.484	-0.291	-0.162	-0.369	Yes	0.109
	(1.83)	(4.02)	(2.91)	(1.82)	(2.94)	(5.16)	(-2.66)	(-1.58)	(-2.12)	(-2.01)		

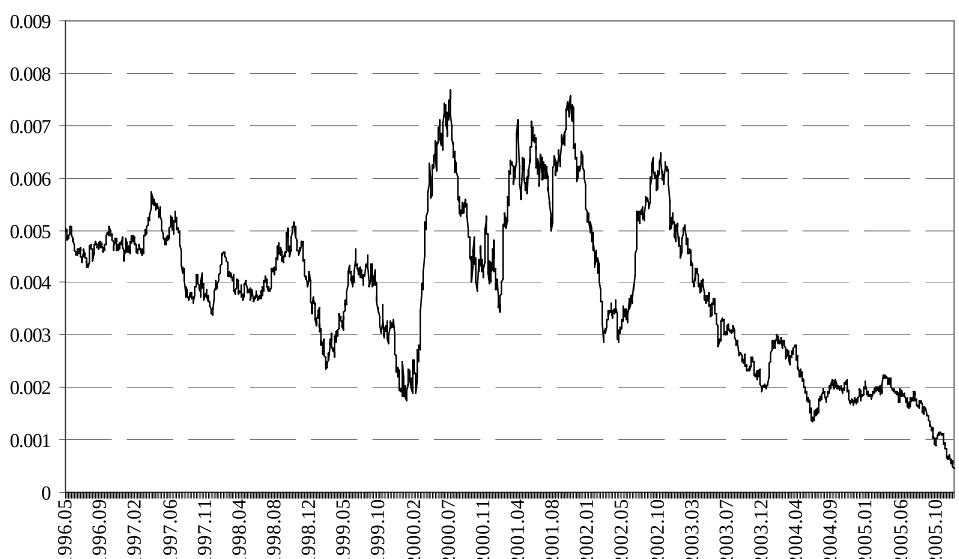
Table 13
Cross-sectional regressions – Short-sales constraints

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, 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. All the regressions control for the four Fama-French (1993) and Carhart (1997) factors, lagged factors and lagged stock returns. The t-statistics in parentheses employ a robust cluster variance estimator.

Independent Variables	(1)	(2)	(3)
Intercept	-0.045	-0.056	-0.056
	(-2.51)	(-1.75)	(-1.74)
dummy Q1		-0.084	-0.082
		(-1.77)	(-1.67)
dummy Q2		-0.079	-0.081
		(-1.92)	(-1.98)
dummy Q4		0.111	0.114
		(2.75)	(2.80)
dummy Q5		0.096	0.074
		(2.16)	(1.65)
spread × on special	0.027	0.021	0.024
dummy	(2.19)	(1.67)	(1.47)
on special dummy ×			0.005
dummy Q1			(0.03)
on special dummy ×			0.020
dummy Q2			(0.16)
on special dummy ×			-0.040
dummy Q4			(-0.27)
on special dummy ×			0.201
dummy Q5			(1.53)
Controls?	Yes	Yes	Yes
R^2	0.167	0.167	0.167

Figure 1
Sharpe ratio and average return over time

The top figure shows the Sharpe ratio, calculated from daily returns on the hedge portfolio over the preceding 90 days. The bottom figure shows the average return on the hedge portfolio, calculated analogously. The hedge portfolio is long stocks with high volatility spreads and short stocks with low volatility spreads.



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