Three Essays in Insider Trading

by

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To My Parents, My Wife and My Son

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1.1 Introduction

Standard option pricing models, such as the Black-Scholes model and the binomial option pricing model, assume that capital markets are perfect, underlying stock returns follow a martingale diffusion process and option payoffs can be readily replicated by using the underlying stocks and risk-free assets. Consequently, options can be treated as redundant securities. Therefore, stock options are priced by disallowing arbitrage opportunities. More specifically, standard option pricing models predict that only six factors enter into the option pricing formulas, that is, the underlying stock price, the strike price, risk-free rate, volatility, maturity and dividends paid on the underlying stock. Other factors, such as the investor's expectation about future stock returns and their preferences about higher moments of the underlying stock return distribution, do not matter for option pricing.

This paper tests the prediction of standard option pricing models that there should be no relation between past stock returns and stock option prices. The motivation for our paper is straightforward: when the perfect capital market assumption is relaxed, it may become difficult to replicate option payoffs[1] (Evnine and Rudd (1995), Figlewski (1989), Canina and Figlewski (1993)). As a result, options can become non-redundant securities (Figlewski (1989), Figlewski and Webb (1993), and Grossman (1995)).

[1] There are a number of reasons why this is the case. For example, buying and selling stocks and options in real world are subject to transaction costs; volatility of the underlying is not known but has to be estimated; borrowing rate is not equal to lending rate for typical arbitrageurs; they also have to pay taxes and meet margin requirements.

Prices of non-redundant securities are then determined both by the limited arbitrages and by demand and supply for options. This opens up the possibilities that other factors could enter into option pricing.

In this paper we focus exclusively on one candidate factor: return predictability and examines thoroughly its implications for option pricing. Using the individual stock options data, we show that puts are significantly overvalued relative to calls after large stock prices increases and calls are significantly overvalued relative to puts after large stock prices decreases. We show that such valuation effects are both economically and statistically significant. More importantly, we argue that it is the autocorrelation structure of the individual stock returns that drives this valuation effect. Overall, our results suggest that past stock returns exert an important influence on individual stock option prices.

Our paper is linked to two separate strands of literature. The first one is the literature about stock return predictability[2]. We'd like to emphasize that the major difference between the voluminous return predictability literature and our paper is that our intention here is not to answer such questions as what kind of predictors can we employ or is the return predictability real or just an artifact of data. Instead, we want to examine the implication of return predictability (or alternatively, past stock returns given return predictability) on stock option prices. In imperfect capital markets, past stock returns can affect option prices through a number of different channels. First, past stock returns can affect investor's expectation about future stock returns given return predictability. It has been documented that individual stock returns are negatively autocorrelated (Lo and MacKinlay (1988, 1990)). Hence, if past stock returns are strongly positive, negative autocorrelation suggests that future stock returns are projected to be below average. Investors can exploit this expectation by buying put options on the underlying stock, thereby creating an upward pressure on

[2] See Cochrane (2001) and the citations therein for an excellent survey about return predictability literature.

put prices. Similarly, if past returns are strongly negative, negative autocorrelation suggests that future stock returns will be above average. Investors can also exploit this expectation by buying call options on the underlying stock, thereby creating an upward pressure on call prices.

Second, past stock returns can affect option prices through investors' risk aversion and portfolio insurance considerations. Risk aversion suggests that investors' exposure to stock prices can depend on recent stock price movements, which then affects their demand and supply for calls and puts. An easy way of changing their exposure to the stock price movements is by buying call and put options on the underlying stock. If, after stock prices have risen, a greater proportion of investors demand increased exposure to equities, they can purchase call options on the underlying stock, thereby creating upward pressure on call prices, which will rise in this case to increase the supply of call writers. If on the other hand, stock prices have fallen, a greater proportion of investors demand decreased exposure to stock prices, they can purchase put options on the underlying stock, thereby creating upward pressure on put prices, which will rise in this case to increase of out writers.

Third, past stock returns can change investor's expectations about the higher moments of the underlying stock return distributions. If investors care about these higher moments[3], then their demand and supply for calls and puts will change as their expectations about these higher moments change. Once again, given return predictability, past stock returns can change investor's skewness and kurtosis expectations.

Our paper is also closely related to the literature about the reflections into the standard option pricing models in the case of either incomplete markets (Figlewski (1989)) or

[3] It has been established in asset pricing literature that investors do care about these higher moments. See Arditti (1967), Kraus and Litzenberger (1976), Harvey et. al. (2000) and Dittmar (2002) for references.

other market frictions (Lo and Wang (1995). Our paper falls into this category in the sense that we investigate option pricing in the situations where stock returns are predictable[4]. However, despite the huge literature about return predictability and option pricing respectively, the relation between past stock returns and option prices has not been thoroughly examined before. The only exception as far as we know, is Amin et al. (2004), where they examine the implication of stock market momentum on option prices at index option level. Using the OEX option (S&P 100 index options) data, they have shown OEX calls are significantly overvalued relative to OEX puts after large stock price increases and OEX puts are significantly overvalued relative to OEX calls after large stock price decreases. Their conclusion is that past stock market returns exert an important influence on index option prices. The novelty of our paper is that we extend their analysis from index options to individual stock options. There are at least two motivations why this extension might be interesting and important.

First, it has been established that portfolio (index) returns are strongly positively autocorrelated while individual stock returns are negatively autocorrelated. While the result of Amin et. al (2004) is thought-provoking, it leaves one important question unanswered: Does the autocorrelation structure or risk aversion drive their result? Given that index and individual stocks have the opposite autocorrelation structure, extending their analysis from index option to individual stock options can help us answer this question. If autocorrelation structure is the underlying and fundamental driving force, we would expect to see exactly the opposite results in the case of individual stock options. That's, call options will be significantly undervalued relative to put options after large stock price increases and put options will be significantly undervalued relative to call options after large stock price decreases. We confirm this projection in our empirical tests.

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[4] We want to point out that since our interest is to examine the implications of individual stock returns on option prices, we mainly focus on short-horizon return predictability in this paper. More specifically, we focus on returns over the past 5 days, though we replicate our tests using returns over the past 7 and 9 days.

Second, by extending the analysis from index options to individual stock options, we can further look at the cross sections of individual stock options. It has been established in market microstructure literature that large stock returns lead small stock returns due to more frequent trading of large stocks and more quick incorporation of new information in large stocks as opposed to small stocks. Given this cross sectional return predictability, investors can also exploit their expectations of future small stock returns by jointly taking into account past large stock returns and lead-lag relationship between large and small stock returns. This lead-lag relationship, while absent from research at index option level, may interact with the above autocorrelation structure in such a way that important implications for option pricing can be further identified and investor patterns can be better studied.

While these two motivations look different at first glance, the underlying logic remains the same. In the case of index versus individual stock options, we focus on the return predictability along the time series dimension while in the case of large versus small stocks, we focus on return predictability along the cross sectional dimension. The fundamental predictions of this return predictability hypothesis remain the same. That is, return predictability, either along the time series dimension, or along the cross sectional dimension, can have important impact on option prices. Due to space limit, we focus on the first motivation in this paper.

The rest of the paper is organized as follows: in Section 2 we provide details on data and methodology we use in this paper; Section 3 contains our non-parametric tests of the boundary conditions violations. We perform our parametric tests of volatility spread in Section 4. We conclude in Section 5.

1.2 Data and Methodology

1.2.1 Data

The option trades and quotes data we use in this study come from Berkeley Options Databases (BODB). BODB covers all the option trades and quotes that took place in Chicago Board Options Exchange (CBOE) from Dec 1979 to Dec 1995. For each trade, BODB records the option's type (call or put), the transaction price, strike price, maturity, trading volume and the contemporaneous price of the underlying stocks. The Berkeley transaction database contains a number of data entry errors, especially in its early years. These errors mainly involve the miscoding of the underlying price. We corrected these errors by checking the recorded underlying stock price with the prices from CRSP[5]. We also delete all transactions with missing or negative option prices. In addition, all transactions where option prices below their intrinsic values are also deleted. The reason is that later on we need to compute the implied volatility estimates for each option trade in our sample. The implied volatility estimates for the transactions where option prices are below their intrinsic values are simply meaningless.

Since BODB is essentially a transaction database, we cannot afford to examine all the stocks with options trading on them. Instead, we select five stocks based on the number of options trades in Dec 1995. Table 1.1 contains the detailed information for these five selected stocks. We want to emphasize that all these five selected stocks are well-established firms, which provides us the additional advantage that they are less subject to stale prices and they pay quarterly dividends regularly within our sample period. This greatly facilitates our empirical tests.

The daily stock returns come from the daily stock returns files that are available from

[5] We find that these miscoded underlying stock prices are easily to detect. So we apply the following simple price filters: for any record, if the absolute deviation of the recorded underlying price from the closing price is greater than half the closing price, we delete the record.

CRSP. When we examine the boundary conditions violations, we need to compute the present value of strike prices and dividends. We use the risk-free rates that come from the Fama-French risk-free rate files also available from CRSP. We focus on regularly quarterly dividends for these selected stocks, the information of which is also available from CRSP. Following standard practice in the literature, we assume that investors know these dividends on the underlying stocks in advance. The realized dividends are used to compute the present value of dividends during the life of each option.

1.2.2 Methodology

Similar to Amin et al. (2004), our methodology in this paper also consists of two different sets of tests. The first set of tests, which are non-parametric, are mainly about the violations for American put-call parity boundary conditions. More specifically, we examine whether the put-call parity boundary conditions for American options are systematically violated more frequently after stock price increases or decreases. These relations are completely model independent. The purpose of this non-parametric test is that, if systematic violations of these arbitrage bounds as a function of past stock returns exist, this suggests strong evidence of systematic pricing pressures on calls and puts. As we have argued in the introduction part, return predictability hypothesis would predict that given negative autocorrelation, strongly positive past stock returns lead to violations of the American put-call boundary conditions by increasing put option prices. Strongly negative past stock returns lead to violations of the American put-call boundary conditions by increasing the call option prices. Therefore, if investors significantly bid up put prices after large stock price increases, the probability of put price run-ups should be higher during periods after large stock price increases than during periods after large stock price decreases. Similarly, following large stock price declines, call prices should be relatively high, increasing the probability of call price run-ups.

Our second set of parametric tests aim at quantifying the magnitude and separate the sources of price distortions. There are a number of reasons why this set of tests is necessary. First, the non-parametric tests we perform examine only the boundary conditions. Given that these boundary conditions and their violations come in the form of inequalities, we are essentially restricting ourselves to extreme observations in our sample. We'd like to find our whether pricing pressures on option prices occur in general or only in extreme situations. Second, we'd like to know whether the return predictability hypothesis continues to hold for parametric specifications of option pricing. Most importantly, we'd like to quantify the magnitude and separate the sources of price distortions, as suggested by the non-parametric tests.

To implement this test, we measure the overpricing of calls relative to puts by the difference between their implied volatilities, or volatility spread. Implied volatility is now a widely accepted paradigm for empirical tests of option valuation (Jarrow and Wiggins (1989)). The motivation of using volatility spread as a measure for option pricing distortion is as follows: under perfect market conditions and for a given maturity date, the volatility implicit in call prices must be equal to the volatility implicit in put prices. On the other hand, higher call-implied volatilities relative to put-implied volatilities indicate that calls are overpriced relative to puts. Therefore, we can measure the relative overpricing or underpricing of call and put options by their implied volatilities[6].

Throughout our implementation of this parametric test, we adopt binomial option pricing model to estimate the implied volatilities and thus construct the volatility spread measure. By going to binomial option pricing model implied volatilities, we give up the model independency of the non-parametric tests. However, by examining implied volatilities, we can now quantify and relate the effects of price distortions to previously established biases of the standard option pricing model. More specifically,

[6] A similar procedure has been adopted by Figlewski and Webb (1993) to investigate the pricing pressures in options market as a function of short interest. Therefore, we are not the first one to advocate this measure.

we show that the volatility spread increases after stock price decreases and decreases after stock price increases. Therefore, put options are relatively overpriced immediately following large stock prices increases and call options are relatively overpriced immediately following large stock price decreases. We also show that these effects are not affected when we control for moneyness and maturity effects in the implied volatilities.

1.3 Boundary Condition Tests Based on Put-Call Parity for American Options

1.3.1 American Put-Call Parity Boundary Conditions

We first investigate whether the put-call parity boundary conditions for American options are systematically violated as a function of past stock returns. The absence of arbitrage opportunities implies the following boundary conditions must hold for American options for a strike price and maturity date:

$$B1 = Callprice - Putprice - Stockprice + PV(strikeprice) \leq 0$$
$$B2 = Putprice - Callprice + Stockprice - PV(dividends) - Strikeprice \leq 0,$$

where PV is the present value operator and dividends corresponds to the dividends paid on the underlying stock during the remaining life of the options.

Suppose the first boundary condition (B1) is violated, then a typical arbitrageur can make a riskless arbitrage profit by buying the put, settling the call, buying the underlying stock and borrowing the present value of the strike price. This strategy will yield an initial positive cash inflow equal to the amount of boundary violations. In the future, there will be no cash outflows. In contrast, suppose the second boundary condition (B2) is violated, then again a typical arbitrageur can a riskless arbitrage profit by buying the call, settling the put, shorting the underlying stock and lending the strike price and the present value of the dividends. This strategy will yield an initial positive cash flow equal to the amount of the boundary condition violation and no future cash outflows[7].

An important caveat for these boundary condition tests is that in imperfect capital markets, these boundary conditions can never be perfected tested using the transaction data due to various market frictions as we have argued in the introduction. Our goal here is not to argue that there are unexploited arbitrage opportunities. Instead, we want to identify the pricing pressures on call and put options[8]. Our return predictability hypothesis predicts that if investors significantly bid up put prices after large stock price increases, then the probability that B1 is greater than zero (a violation) should be higher during periods after large stock price increases than during periods after large stock price decreases. Similarly, the probability of B2 is greater than zero (a violation) should be higher during periods after large stock price decreases than during periods after large stock price increases.

For American put-call parity boundary condition violations, the value of the underlying stock must be identical when the call and put options trade. To identify put-call pairs with identical underlying stock price, we take each day of call and put trades and conduct a combined sort by strike price, maturity, underlying stock price and time of the day. We then select from this any put-call pair that appears consecutively within the sort. This way we would be extracting only pairs with identical contract specifications and underlying stock prices. To ensure that our first-traded price is relatively fresh, we also require that no more than 10 minutes pass when the first-option trade is observed and the second-matching-option trade is observed. Otherwise, we delete the option trade and conclude that no matching trade was acknowledged.

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[7] For brevity, we refer the readers to Jarrow and Rudd (1983) for a detailed discussion of the construction and proof of these two boundary conditions.

[8] The absence of arbitrage opportunities implies that B1 and B2 should be negative for every combination of strike price and maturity date.

1.3.2 Boundary Conditional Violation Tests

Table 1.1 shows the characteristics of the options for the five selected stocks we have included for our boundary conditions violation tests. Our overall sample periods and the total number of matched call-put pairs vary across the five selected stock options. Both call and put prices increases as maturity increases from less than 1 month to more than 3 months. We also compute the number of matched option pair trades per day. With the exception of TXN options, short-term maturity options trade most frequently, and trading volume almost falls uniformly with maturity. In addition, since long maturity options trade less frequently, it becomes more difficult to match them based on the underlying stock prices, which leads to a sharp decrease in matched volume.

Table 1.2 reports the probability of boundary condition violations and the average value of violations conditional on a violation, as a function of the past 5-day stock returns for each of the five selected stocks. The probability of boundary condition violations (that is Prob(B1>0)) is computed as the number of observations of B1 for which B1 is positive divided by the number of total observations of B1. The past 5-day stock returns are computed using the daily stock returns. Boundary conditions are evaluated on date t, while the past stock returns are computed from date t-1 to t-5. This one-day window facilitates the potential implementability of our strategy and thus makes our tests realistic[9]. In Table 1.2, we report the results for the entire sample period. Later, we replicate our tests for pre-and post crash sub-sample analysis. The reason for this pre-and post-crash period analysis is that we suspect the 1987 stock market crash would result in unreliable option prices due to liquidity problems. We'd like to find out whether the results hold for these two sub-samples. In table 1.2a, we focus on the pre-crash period whereas in Table 1.2b, we focus on the post-crash period after eliminating the 3-month period immediately following the crash. Since the main results are quantitatively the same, we will focus on Table 1.2a for brevity

[9] We also experimented with computing returns from day t-2 to t-6. Our results are not affected by the chose of stock return horizons.

reasons.

Table 1.2 shows the average values of B1 and B2, the probability of boundary condition violations and the dollar magnitude of the violations for the entire sample period. Our results suggest that the average values of B1 and B2, the probability of boundary condition violations and the dollar magnitude all depend on past stock returns. First, there is a negative relation between past stock returns and the mean value of B1 and a positive relation between past stock returns and the mean value of B2 for four out of the five stock options[10]. When past returns increase from -5% to 5%, the mean value of B1 decreases by $0.06, $0.04, $0.28 and $0.14 and the mean value of B2 increases by $0.20, $0.02, $0.03 and $0.34 for GM, HWP, MRK and TXN options respectively. In contrast, the mean value of B1 increases from -0.96 to -0.87 and the mean value of B2 -0.60 to -1.02 as past returns move from -5% to 5% for IBM options; Second, the relation between past stock returns and probability conditions violations is especially strong. An increase in past stock returns from -5% to 5% causes the probability of B1 violations to decrease by 54%, 34%, 70% and 37% and the probability of B2 violations to increase by 181%, 88%, 32% and 89% for GM, HWP, MRK and TXN options respectively. In contrast, the probability of B1 violations increases from 0.05 to 0.09 and the probability of B2 violations decreases from 0.19 to 0.06 as past returns move from -5% to 5% for IBM options. Conditional on a B1 violation, the magnitude of the arbitrage violation is about $0.4, $0.3, $0.23, $0.18 and $0.29 for GM, HWP, IBM, MRK and TXN options respectively. Given an average option price of $2.8, $3.2, $3.1 and $5.9, these mispricings represent 14%, 9%, 7%, 6% and 5% of the average option price for GM, HWP, IBM, MRK and TXN options respectively. Conditional on a B2 violation, the magnitude of the arbitrage violation is about $0.2, $0.17, $0.14, $0.22 and $0.28 for GM, HWP, IBM, MRK and TXN options respectively. Given an average option price of $2.8, $3.2, $3.8, $3.1 and

[10] IBM options stand out as an “anomaly” at first glance. However, as we’ll argue later, this is exactly evidence that autocorrelation structure drives the relation between B1 and B2 boundary condition violations and past stock returns.

$5.9, these mispricings represent 7%, 5%, 4%, 7% and 5% of the average option price respectively for GM, HWP, IBM, MRK and TXN options respectively. Therefore, our results suggest that the magnitude of these arbitrage violations is economically significant.

To get a clearer picture for the entire range rather than the specific categories of the past returns, we plot the relation between past 5-day stock returns and the probability of boundary condition violations after grouping the past stock returns into percentiles in Figure 1-1. Again, past stock returns are calculated from day -1 to -5. Visual examination of Figure 1-1 shows with an exception of IBM options, there is a strong negative relation between B1 violations and past stock returns for the entire range of past stock returns. Similarly, Figure 1.1b suggests there is a strong positive relation between past stock returns and B2 violations. In contrast, there is a strong positive relation between past returns and B1 violations and a negative relation between past returns and B2 violations. Hence, our evidence in Table 1.2 cannot be attributed to a particular grouping scheme.

An interesting question to ask is that why the observed pattern between past stock returns and probability of B1 and B2 boundary condition violations are different from IBM options as opposed to the other four options. A partial answer is provided in Table 1.3, where we compute the first-order autocorrelation for individual stock returns during our sample period for each of the five selected stocks. We also compute the first-order autocorrelation for NYSE/AMEX/NASDAQ equally-weighted index returns. As we can see from Table 1.3, similar to the index returns, IBM stock returns are positively autocorrelated over the short horizon we have examined in our tests. In contrast, the other four stock returns are negatively autocorrelated during our sample period. Combined with the fact that return predictability hypothesis predicts that given negative (positive) autocorrelation for individual stock returns, investors project future stock returns to be below (above) average if past stock returns are strongly positive, thus leading to more violations of B2 (B1) violations during periods following large stock price decreases (increases), our results in Table 1.2 is totally consistent with the prediction of this hypothesis.

Our results so far provide initial support for the return predictability hypothesis. The fact that more violations occur as a function of past stock returns is significant but informal. To formally test the relation between past stock returns and the boundary conditions violations, we further perform a two-way classification Chi-square test[11]. The purpose of this test is twofold: first, we'd like to demonstrate that results in Table 1.2 are not due to outliers when few options are trading. Second, the Chi-square test formalizes the informal information presented in Table 1.2 without imposing any structure on the relationship.

Our Chi-square tests again focus on each matched option trade. Table 1.4 provides the results for these Chi-square tests. The null hypothesis that there is no association between past stock returns and the boundary condition violations is rejected at all conventional significance level, as judged by the resulted Chi-square test statistics. Our evidence suggests that the relation between past stock returns and boundary conditions violations is statistically significant. When past stock returns are negative, violations of B1 are more likely relative to their expected number if there was no relationship between past stock returns and B1 violations. When past stock returns are positive, violations of B2 are more likely. While not shown in Table 1.4, results are also significant for both the precrash and postcrash subsamples.

We also examine whether the boundary conditions violations are meaningful after taking into account one type of transaction costs. To test this idea, we require that purchase transaction take place at the market maker's ask price, and sale transactions take place at market maker's bid price. This way, investors pay the bid-ask spreads in the options markets before they realize any arbitrage profits. Take B1 violations as an

[11] See Daniel (1978, pp163-170) for an illustration of Chi-square tests.

example. If B1 is violated, then a typical arbitrageur can execute the arbitrage portfolio strategy of buying the put option and sell the call option. Taking transaction costs into account in this case, we record the put price at the market maker's ask price and record the call price at the market maker's bid price. Essentially this approach penalizes any arbitrage strategy by the bid-ask spread. A violation is found if either B1 or B2 is positive after incorporating the bid-ask spread. As shown in Table 1.4, our results continue to hold after taking into account the bid-ask spreads. Even after paying the bid-ask spread, violations of the boundary conditions are related to past stock returns. These findings suggest that our results are not only statistically significant but also economically significant.

1.4 Implied Volatility and Past Stock Returns

While the evidence presented so far are convincing, it leaves several important questions unanswered. First, the return predictability hypothesis does not require boundary violations. By investigating only the boundary violations, we are restricted to extreme observations in our sample. We'd like to find out whether the pricing pressure on option occurs in general or only in extreme situations. Second, our tests in Table 1.2 and Table 1.4 focus mainly on the probability of boundary conditions violations and ignore the magnitude of these violations. We'd like to find out whether the dollar magnitude of the B1 and B2 violations are also affected by past stock returns. Third, we'd like to find out whether the return predictability hypothesis continues to hold for parametric specification of option pricing. Most importantly, we are interested in quantifying the magnitude of the price distortions and separate the sources of these price distortions.

To answer these questions, we formulate an additional parametric approach as an important supplement to the non-parametric tests. We employ call and put-implied volatility as a measure for the pricing pressures in options markets. Similar to Harvey and Whaley (1992), we implement the binomial option pricing model numerically to compute the implied volatility estimates. We assume that dividend paid on the underlying stock is known in advance. The advantage of binomial option pricing model is that it can easily take into account the fact that these options are American options subject to early exercise.

1.4.1 Implied Volatility Estimates

Using the Newton-Raphson search procedure similar to the one suggested by Manaster and Koehler (1982), we calculate the implied volatility for every transaction in our sample. More specifically, the following algorithm is employed: given an ith estimate implied volatility, the procedure suggests the i+1th should be:

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

Where $C(\sigma_i)$ is the price of the option with an implied volatility of σ_i computed from the binomial model, $C(\sigma^*)$ is the observed option price and vega is the partial derivative of the option price with respect to volatility. We iterate on this procedure until the implied volatility has converged and the predicted price is equal to the market price[12].

As we have argued in the introduction, we use the volatility spread, defined as the call minus put-implied volatility as the measure for price distortions. The advantage of using this measure is that we can now quantify the magnitude and separate the source of the price distortions as suggested by Table 1.2 and Table 1.4. A caveat is in order, though. Previous literature has established that option pricing models systematically misprices options with respect to maturity and moneyness (Whaley (1982), Stein

[12] We divide days to maturity into 180 intervals. The convergence criterion is set to 0.001%. That is, the algorithm is considered convergent if the estimated price is within 0.001% of the observed price. Ideally, the number of intervals should be dependent on the length of the days to maturity. However, there is a tradeoff in terms of computation cost. We compare our estimates to the estimates we obtain from Black-Scholes when the underlying stock pays no dividends before expiration. They are very close to each other.

(1989) and Bakshi et al. (1997)). More specifically, short-term options are typically underpriced by Black-Scholes relative to long-term options. Similarly, deep in-the-money option and deep-out-of-the-money options are underpriced relative to at-the-money options. Hence, we need to control for option moneyness and maturity when we employ the volatility spread measure and examine the relation between implied volatilities and past stock returns.

In Table1.5 we show the implied volatilities of call and put options as a function of past 5-day stock returns separated by strike price and maturity. Panel A shows the call- implied volatilities when past 5-day stock returns are positive (greater than 0.05), and panel B shows the call-implied volatilities when past 5-day stock returns are negative (less than -0.05). A decline in stock prices increases call-implied volatilities regardless of the maturity and strike price. On average, as past stock returns move from -5% to 5%, the call-implied volatilities increase by 3.0, 1.8, 4.1, 2.6 and 5.5 percentage points for GM, HWP, IBM, MRK and TXN options respectively. Negative stock returns increase implied volatilities estimates across the board, while affecting the short-maturity options (1 month or less), deep-out-of-the-money and deep-in-the-money options the most. In contrast, long-maturity and at-the-money options are affected to a smaller extent.

Similar patterns are identified for the put options (Panel C and Panel D of Table 1.5). A shift from increasing to decreasing stock prices increases the put-implied volatilities by 1.9, 0.2, 3.6, 5.7 and 1.4 percentage points for GM, HWP, IBM, MRK and TXN options respectively. In addition, all implied volatility estimates increase with decreasing stock prices. Once again, the most pronounced volatility increases are observed in short-maturity options (1 month or less), deep-out-of-the-money and deep-in-the-money options. Declines in stock prices increase both call and put implied volatilities. However, call-implied volatilities increase more than put-implied volatilities for four out of the five selected stock options. Given a decrease in stock prices, investors bid up the relative prices of call options above those of the put options. Given an increase in stock prices, investors bid up the relative prices of put options above those of the call options. These patterns again are consistent with the return predictability hypothesis.

While the above results provides initial evidence that call and put implied volatilities respond differently to past stock returns, we focus on the overall volatility spread to precisely quantify this differential response. As discussed earlier, we need to control for moneyness and maturity since our results could be potentially biased if certain strike prices and maturities trade more on one side of the spread than the other due to maturity or term structure effect. To achieve this goal, we match options according to maturity and moneyness[13]. We then randomly throw out any excess calls and puts at each maturity and moneyness level. In this way, our implied volatility spread is computed from a set of call and put transaction identically matched in terms of maturity, moneyness and number.

1.4.2 Four Weighting-Schemes for Implied Volatility Spreads

Each day, for the given set of calls and puts, we compute the implied volatility spread in four different ways. The purpose of this exercise is to examine the sensitivity of various options to the return predictability hypothesis and ensure that our results are general. We first weight each option-implied volatility equally, averaging across all call and put volatilities and taking the difference, resulting in an equally weighted estimate of the volatility spread. Second, we compute vega-weighted volatility spread. This weighting scheme takes a weighted average of all call and put volatilities based on the partial derivative of each option's price with respect to the volatility. This scheme weights at-the-money options more than out-of-the-money options. If at-the-money options are not affected by past stock returns, then there should be little or no

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

relation between past stock returns and vega-weighted average spreads. The third measure is the elasticity-weighted volatility spread, which weights by the elasticity of each option with respect to the value of the underlying stock price level. This weighting scheme is similar to Chiras and Manaster (1978) and Franks and Schwartz (1991) and incorporates leverage constraint. Since elasticity is a decreasing function of how much the option is in the money, this procedure weights out-of-the-money options more than in-the-money options. Our final weighting scheme uses only at-the-money options only. This scheme is used by Harvey and Whaley (1991) and Figlewski and Webb (1993). At-the-money options are defined as the call-put pairs with strike price immediately bracketing the underlying stock prices prior to option trade. Available options are weighted equally within strike price then interpolated based on their distance from the opening underlying stock price level. The difference between call and put measures is referred to as the at-the-money implied volatility spread. This scheme usually throws away a lot of option data.

Table 1.6 presents summary statistics for the volatility spreads averaged for each trading day for each of the four weighting schemes. Several observations are in order. First, typically, the mean and median weighted-average volatility spread is small and negative, on the order of 4%. Negative estimates indicate that put-implied volatilities exceed call-implied volatilities. Second, standard deviations of the volatility spreads tend to be between 4% and 9% for each of the five selected stock options. Also, 80% of the volatility spreads fall between -1% and 1%.

Table 1.6 also presents the partial autocorrelation coefficients for average daily volatility spreads. All four series exhibit significantly positive partial autocorrelations. Most of the first-order partial autocorrelations for all weighting schemes are above 0.5. Some are even as high as 0.9. The large positive first-order autocorrelation suggests that implied volatility spreads follow a slow-moving diffusion process. This finding is again consistent with a situation where the innovations in volatility spread (and hence relative valuation of call and put options) arise from sustained price pressures on either call or put options. The positive serial autocorrelation makes it less likely that the volatility spread arises from either temporary measurement errors or asynchronous trading between options market and the underlying stock market. The slow-moving nature of the volatility spreads is well taken into account in our subsequent time-series regressions.

Table 1.7 provides the cross-correlations of the volatility spread by weighting type for the five selected stock options. Our four weighting schemes produce estimates that are highly correlated. Given the high degree of correlation among our four measure of volatility spread, we are not likely to get vastly different estimates using each of these measures. In our subsequent analysis, we focus on the volatility spread calculated using elasticity weighting. The main advantage for using this measure is that it utilizes all options and incorporates the leverage constraints.

1.4.3 Volatility Spread Tests

The relation between past stock returns and volatility spread is examined in Table 1.8. The return predictability hypothesis predicts a negative relation between past stock returns and volatility spreads in the presence of negative autocorrelation of stock returns and a positive relation between past stock returns and volatility spread in the presence of positive autocorrelation of stock returns. Past stock returns are computed using the returns over the past 5 days. Once again, we leave a 1-day separation between the ending day for computing stock returns and the calculation of the volatility spread. This 1-day window ensures that potential investors can have the necessary information at hand to actually implement our tests.

The slow-moving nature of the volatility spread series suggest that if daily average spreads are used as the dependent variables in ordinary least squares (OLS) regressions, the regression residuals will exhibit strong autocorrelations, leading to potential biases in the regression coefficient estimates. We found that an AR(5) autoregressive error model eliminates the correlation structure of the residuals, as judged by the Box-Pierce statistics.

1.4.4 Alternative Hypothesis Tests

So far we have established that past stock returns affect option prices. Given a negative autocorrelation, positive past stock returns increase the prices of put options whereas negative past stock returns increase the prices of call options. Both price changes lead to boundary condition violations that are inconsistent with frictionless and no-arbitrage market. There are a number of potential interpretations of our findings. In this section, we attempt to distinguish among them.

The first possible explanation for the results documented so far is the return predictability hypothesis we've been testing. Return predictability hypothesis predicts that in the presence of negative autocorrelation for individual stock returns, if past stock returns are negative, investors will expect the future stock returns to be above average. Consequently, they will significantly bid up the prices of call options; if past stock returns are positive, investors will expect the future stock returns to be below average. Consequently, they will significantly bid up the prices of put options. On the other hand, if stock returns are positively autocorrelated, the above arguments would be reversed and we will expect prices of puts to increase following strongly negative past stock returns and prices of calls to increase following strongly positive past stock returns. In any case, the return predictability hypothesis predicts that past stock returns exert an independent influence on the volatility spread. As we have argued, the results in Table 1.8 is consistent with this return predictability hypothesis.

A second explanation for our findings can be that past stock returns are just proxies for an omitted variable that affects call and put prices differently. Literature suggests an ideal candidate for such an omitted variable is volatility (Schewert (1989)), where it is shown when stock prices fall, volatility increases; when stock prices increases, volatility falls. This idea predicts that if a separate estimate of volatility is included as a regressor in Table 1.8, it would show up with a negative coefficient and drive away the significance of the past stock returns.

Another possibility is that investors' demand and supply for options depend not only on their expectations of future stock returns but also on their portfolio insurance and risk aversion considerations, and both effects are present. The risk aversion hypothesis predicts that when the volatility of stock returns increases, an increased number of investors demand less exposure to the stock market and bid up the prices of put options; when the volatility of stock returns decreases, an increased number of investors demand greater exposure to the stock market and bid up the prices of call options. This idea suggests that if a separate estimate of the volatility is included as a regressor in Table 1.8, it would show up with a negative coefficient but would not necessarily drive away the significance of the past stock returns. Both past stock returns and volatility can show up with significance influences.

Furthermore, we can extend the above idea into higher moments of the stock return distributions in a similar fashion. If investors care about these higher moments and their expectations of higher moments are based on changes in past stock returns, then option prices can be affected. Past literature suggests that both stock returns are right skewed and investors have a preference for right skewness. Holding all else constant, if investors expect an increase in right skewness, they will bid up prices of call options relative to put options. This idea suggests a positive relation between changes in skewness and volatility spread.

Finally, the kurtosis measure captures the probability of extreme events from the volatility measure when stock returns are not normally distributed. However, since the kurtosis measure affects both the left and right tails of stock returns distributions there is no ex ante prediction of a sign of the relation between kurtosis and the volatility spread. We therefore leave the sign of this potential relation to be determined by our estimation procedure.

We test these ideas with a regression analysis using past stock returns, expectation about volatility, skewness and kurtosis as independent variables. We estimated a four-equation joint system using Generalize Methods of Moments (GMM) to take into account potential heteroscedasticity issues. To estimate the future expectations about volatility, skewness and kurtosis, we fit an AR(5) model for each of these variables. We use the elasticity-weighted volatility spread as of Table 1.8. The historical stock return volatility is estimated as the standard deviation of realized returns. Skewness and kurtosis measures are estimated similarly.

The results in Table 1.9 indicate that for 4 out of the 5 selected stock options, past stock returns continue to show up with predicted signs as in Table 1.7. Including higher moments of stock return distributions does not eliminate the predicted relation between past stock returns and volatility spread. This finding suggests that investor's expectation of future stock returns directly affect their valuation of stock options independent of other channels of influence.

Table 1.9 also suggests that past returns do not act as a proxy variable for higher moments of stock returns such as volatility. More importantly, the return predictability hypothesis is not rejected even when we control for other factors. When past stock returns are positive, investors' demand for put options increases, exerting upward pressures on put prices. Similarly, when past stock returns are negative, investors' demand for call options increases, exerting upward pressure on call prices.

1.5 Conclusions

Our results suggest that in the presence of market frictions, past stock returns exert a strong influence on the pricing of individual stock options. Autocorrelation structure for individual stock returns is the underlying and fundamental driving force for this valuation effect. This finding is contrary to the prediction of standard option pricing models. We also find that previously documented biases in option pricing models, which result in volatility smiles, are also strongly influenced by past stock returns. Since our findings can exist in markets where perfect arbitrage is not possible due to market frictions, our evidence suggests that no-arbitrage based option pricing models leave considerable room for disagreement about equilibrium option values.

Our findings are important for several reasons. First, this is the first study to empirically document the influence of past returns on option prices at the individual stock level. Second, our results are general and do not depend on any particular option pricing models. Third, given that the effect of past stock returns on option prices is model independent, it is impossible to account for this effect through any no-arbitrage based option pricing models.

Our findings have a number of implications. First, our evidence suggests that the pricing pressure of past stock returns is strong enough to result in systematic boundary condition violations, which are independent of any particular option pricing model. Consequently, our findings suggest that efforts to account for the observed biases in option prices through no-arbitrage-based option pricing models are not likely to be successful. Second, our findings indicate that it would be worthwhile to examine how taking into account past stock returns affects various biases that have been documented in different option pricing models (Bakshi, Cao and Chen (1997)). Third, given that implied volatility is widely in finance literature [14], our findings demonstrating the systematic variation in implied volatilities of calls and puts as a function of past stock returns can also be used to improve the quality of the implied

[14] For example, implied volatility is used to explore arbitrage opportunities (Manaster and Rendleman (1982)), to proxy the market's volatility (Schwert (1989, 1990), Canina and Figlewski (1993), and Lamoureux and Lastrapes (1993), or to measure the market's risk premia (Merton (1980), Poterba and Summers (1986)) etc.

volatility estimates used for these purposes. Finally, our findings have important investment implications. Following large stock price decreases, bets on further stock price increases are more expensive to implement using call options. Hence, investors wanting to place such bets may be better off using the futures contracts or underlying stocks. Conversely, following large stock price decreases, certain strategies such as covered put writing is likely to be more profitable.

Table 1.1 Distribution for Five Selected Stock Options Call-Put Pairs Matched on Time, Stock Price, Maturity and Strike Price

		Average Price		Number of Matched Trades		
Days to Maturity	Number of Days	Calls	Puts	Total	Average Per Day	Maximum Per Day
Panel A. GM Options: Dec 3 1979 through Dec 29 1995						
1-29	2260	$1.68	$1.38	55628	24.6	234
30-59	2406	3.01	2.24	71570	29.7	240
60-89	1351	3.75	2.90	43425	32.1	190
90 and more	3497	4.47	3.52	50647	14.5	266
All Options	3988	3.15	2.45	221270	55.5	497
Panel B. HWP Options: May 30 1980 through Dec 29 1995						
1-29	2131	2.41	1.74	33458	15.70	169
30-59	1935	3.64	2.62	28153	14.55	172
60-89	1026	4.74	2.97	21282	20.74	172
90 and more	2223	5.41	3.42	19149	8.61	134
All Options	3733	3.81	2.55	102042	27.34	277
Panel C: IBM Option: Dec 3, 1979 to Dec 29, 1995						
1-29	2830	2.87	2.16	456713	161.38	710
30-59	2924	4.51	3.31	290562	99.37	833
60-89	1445	6.09	3.98	149268	103.30	541
90 and more	3880	7.14	4.82	158192	40.77	502
All Options	3986	4.39	3.11	1054735	264.61	1459
Panel D: MRK Options: Jul 20 1981 through Dec 29 1995						
1-29	1916	2.65	2.04	20341	10.6	127
30-59	2044	3.64	2.82	15996	7.8	107
60-89	1118	4.45	3.18	6807	6.1	50
90 and more	2048	4.43	3.32	10382	5.1	85
All Options	3426	3.52	2.67	53526	15.6	248
Panel E: TXN Options: Jan 2 1981 through Dec 29 1995						
1-29	2031	$3.95	3.22	28497	14.0	267
30-59	835	6.33	5.52	23763	28.5	289
60-89	473	8.99	7.03	17235	36.4	222
90 and more	92	9.71	7.82	8875	96.5	112
All Options	3431	5.26	6.45	78370	22.8	320

Table 1.2 Put-Call Parity And Stock Option Boundary Conditions Tests based on Past 5-day Stock Returns: Entire Period

Past 5-Day Returns	No. of Trades	Mean B1	Prob (B1>0)	Mean (B1|B1>0)	Mean B2	Prob (B2>0)	Mean (B2|B2>0)
Panel A: GM Options							
All Data	221270	-1.043	0.056	0.399	-0.669	0.109	0.200
R<-0.15	86	-1.722	0.116	1.122	-0.635	0.302	0.851
R<-0.1	1769	-0.811	0.063	0.174	-0.929	0.023	0.420
R<-0.05	16713	-1.037	0.074	0.176	-0.823	0.059	0.155
R>0.05	29819	-1.099	0.034	3.206	-0.622	0.166	0.210
R>0.1	4159	-1.104	0.029	0.316	-0.224	0.351	0.228
R>0.15	1188	-0.892	0.022	0.221	-0.216	0.314	0.196
Panel B: HWP Options							
All Data	102042	-0.460	0.107	0.301	-0.505	0.131	0.171
R<-0.15	574	-0.223	0.289	0.328	-0.539	0.120	0.310
R<-0.1	1264	-0.289	0.210	0.224	-0.574	0.047	0.389
R<-0.05	12745	-0.393	0.131	0.126	-0.550	0.092	0.141
R>0.05	16664	-0.433	0.087	1.282	-0.527	0.173	0.186
R>0.1	3088	-0.542	0.091	0.319	-0.474	0.169	0.189
R>0.15	1549	-0.661	0.072	0.208	-0.437	0.114	0.301
Panel C: IBM Options							
All Data	1054735	-0.965	0.064	0.232	-0.771	0.105	0.145
R<-0.15	2089	-0.311	0.097	0.198	-0.327	0.273	0.085
R<-0.1	3537	-0.613	0.043	0.326	-0.476	0.268	0.112
R<-0.05	52218	-0.962	0.054	0.143	-0.604	0.194	0.134
R>0.05	85283	-0.872	0.092	0.182	-1.018	0.062	0.144
R>0.1	3928	-1.141	0.053	0.244	-1.420	0.032	0.149
Panel D: MRK Options							
All Data	53526	-0.516	0.157	0.181	-0.603	0.101	0.222
R<-0.15	3	-11.218	0.000	0.635	6.973	0.333	11.604
R<-0.1	252	-0.871	0.333	0.232	-1.032	0.119	0.657
R<-0.05	4307	-0.373	0.256	0.168	-0.664	0.084	0.348
R>0.05	5510	-0.649	0.075	0.101	-0.630	0.111	0.193
R>0.1	695	-0.781	0.033	0.635	-0.383	0.157	0.206
Panel E: TXN Options							
All Data	78370	-1.081	0.093	0.286	-1.028	0.124	0.275
R<-0.15	1898	-0.936	0.098	0.480	-1.290	0.066	0.540
R<-0.1	1586	-0.991	0.204	0.294	-1.094	0.129	0.907
R<-0.05	9629	-1.038	0.123	0.247	-1.219	0.083	0.231
R>0.05	12048	-1.174	0.078	0.318	-0.877	0.157	0.240
R>0.1	2314	-1.090	0.100	0.249	-0.937	0.152	0.323
R>0.15	918	-1.376	0.072	0.263	-1.088	0.115	0.293

Table 1.2a: Put-Call Parity And Stock Option Boundary Conditions Tests based on Past 5-day Stock returns: Pre-Crash Analysis

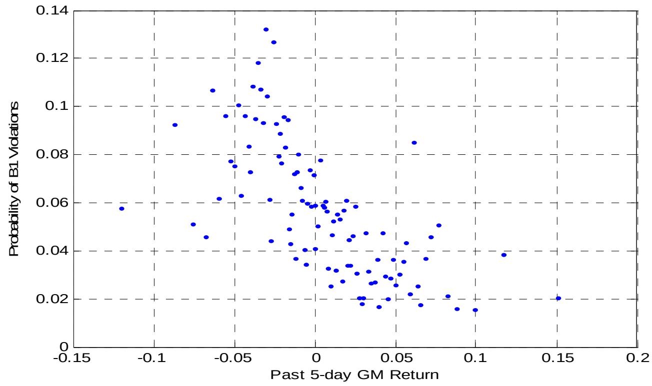
Past 5-Day Returns	No. of Trades	Mean B1	Prob (B1>0)	Mean (B1|B1>0)	Mean B2	Prob (B2>0)	Mean (B2|B2>0)
Panel A: GM Options							
All Data	166167	-1.248	0.032	0.823	-0.783	0.106	0.223
R<-0.1	899	-1.176	0.018	0.248	-1.344	0.012	0.893
R<-0.05	11876	-1.330	0.039	0.323	-1.012	0.054	0.183
R>0.05	21965	-1.329	0.020	7.518	-0.761	0.157	0.240
R>0.1	2699	-1.505	0.011	1.028	-0.219	0.423	0.256
R>0.15	937	-1.037	0.017	0.313	-0.217	0.343	0.211
Panel B: HWP Options							
All Data	76843	-0.549	0.074	0.455	-0.576	0.122	0.187
R<-0.15	281	-0.277	0.263	0.103	-0.687	0.007	0.066
R<-0.1	793	-0.334	0.203	0.301	-0.694	0.015	1.342
R<-0.05	9794	-0.466	0.094	0.127	-0.612	0.086	0.144
R>0.05	13030	-0.487	0.071	1.956	-0.616	0.157	0.202
R>0.1	2589	-0.610	0.077	0.315	-0.515	0.165	0.207
R>0.15	1150	-0.779	0.061	0.253	-0.513	0.078	0.432
Panel C: IBM Options							
All Data	627010	-1.235	0.065	0.317	-0.996	0.073	0.226
R<-0.05	22325	-1.461	0.965	0.268	-0.847	0.163	0.186
R>0.05	51005	-1.131	0.096	0.238	-1.363	0.028	0.289
R>0.1	2551	-1.472	0.056	0.309	-1.872	0.002	1.877
Panel D: MRK Options							
All Data	13120	-0.997	0.129	0.369	-0.154	0.093	0.364
R<-0.1	78	-0.117	0.551	0.695	-1.416	0.013	0.125
R<-0.05	1095	-0.805	0.192	0.447	-1.218	0.099	0.778
R>0.05	1510	-1.103	0.082	0.339	-1.145	0.093	0.283
R>0.1	168	-1.521	0.042	0.185	-0.685	0.167	0.218
Panel E: TXN Options							
All Data	63948	-1.277	0.058	0.372	-1.200	0.101	0.318
R<-0.15	1743	-0.997	0.078	0.375	-1.361	0.052	0.483
R<-0.1	859	-1.771	0.031	0.878	-1.787	0.041	4.389
R<-0.05	7398	-1.310	0.067	0.304	-1.499	0.050	0.286
R<0.05	42112	-1.231	0.058	0.371	-1.161	0.108	0.294
R>0.05	9592	-1.404	0.048	0.440	-1.040	0.128	0.269
R>0.1	1584	-1.446	0.066	0.324	-1.247	0.115	0.449

Table 1.2b: Put-Call Parity And Stock Option Boundary Conditions Tests based on Past 5-day Stock returns: Post-Crash Analysis

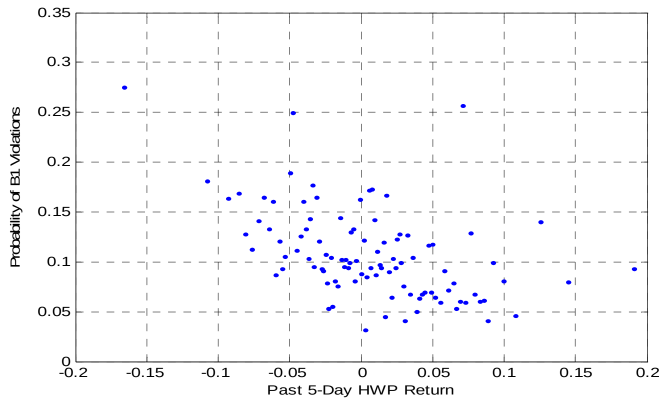
Past 5-Day Returns	No. of Trades	Mean B1	Prob (B1>0)	Mean (B1|B1>0)	Mean B2	Prob (B2>0)	Mean (B2|B2>0)
Panel A: GM Options							
All Data	53965	-0.418	0.129	0.083	-0.325	0.115	0.116
R<-0.1	831	-0.371	0.114	0.162	-0.491	0.024	0.139
R<-0.05	4761	-0.311	0.159	0.086	-0.359	0.071	0.102
R>0.05	7575	-0.445	0.073	0.065	-0.236	0.188	0.137
R>0.1	1460	-0.362	0.062	0.071	-0.234	0.217	0.126
R>0.15	251	-0.350	0.040	0.073	-0.213	0.207	0.103
Panel B: HWP Options							
All Data	23593	-0.193	0.198	0.123	-0.296	0.149	0.127
R<-0.15	119	-0.171	0.244	0.086	-0.262	0.168	0.119
R<-0.1	451	-0.202	0.226	0.105	-0.384	0.089	0.122
R<-0.05	2571	-0.167	0.236	0.119	-0.373	0.094	0.129
R>0.05	3308	-0.253	0.131	0.115	-0.215	0.226	0.145
R>0.1	390	-0.237	0.115	0.214	-0.253	0.164	0.097
R>0.15	355	-0.348	0.073	0.094	-0.239	0.200	0.153
Panel C: IBM Options							
All Data	415361	-0.574	0.061	0.097	-0.449	0.143	0.081
R<-0.15	2004	-0.315	0.083	0.076	-0.209	0.285	0.085
R<-0.1	3382	-0.625	0.027	0.093	-0.385	0.279	0.111
R<-0.05	27460	-0.605	0.063	0.090	-0.450	0.197	0.093
R>0.05	32810	-0.493	0.083	0.082	-0.519	0.099	0.083
R>0.1	1270	-0.525	0.036	0.043	-0.535	0.092	0.057
Panel D: MRK Options							
All Data	39506	-0.360	0.160	0.115	-0.420	0.100	0.158
R<-0.1	62	-1.006	0.000	0.153	-0.621	0.081	0.094
R<-0.05	2999	-0.240	0.266	0.110	-0.466	0.067	0.131
R>0.05	3973	-0.482	0.068	0.065	-0.435	0.118	0.166
R>0.1	527	-0.545	0.030	0.153	-0.286	0.154	0.202
Panel E: TXN Options							
All Data	13880	-0.215	0.245	0.186	-0.265	0.221	0.178
R<-0.15	95	-0.266	0.232	0.189	-0.311	0.168	0.164
R<-0.1	655	-0.070	0.398	0.230	-0.281	0.223	0.174
R<-0.05	2160	-0.143	0.302	0.203	-0.294	0.188	0.181
R<0.05	7724	-0.209	0.243	0.171	-0.259	0.218	0.175
R>0.05	2360	-0.280	0.190	0.201	-0.243	0.268	0.183
R>0.1	653	-0.333	0.173	0.160	-0.273	0.219	0.193

Figure 1-1 Relation between probability of B1 Boundary Condition Violations and Past 5-Day Stock Returns

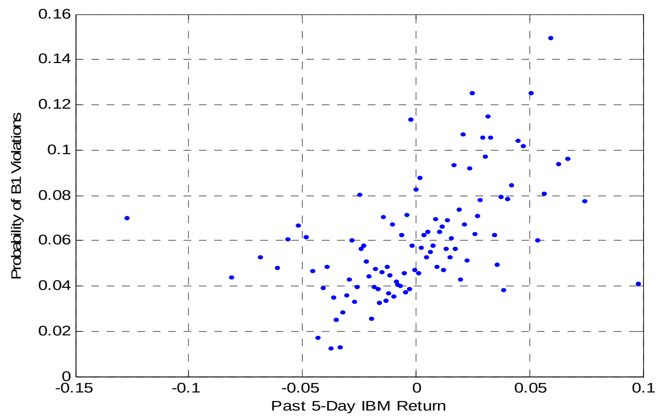
Panel A: GM Options



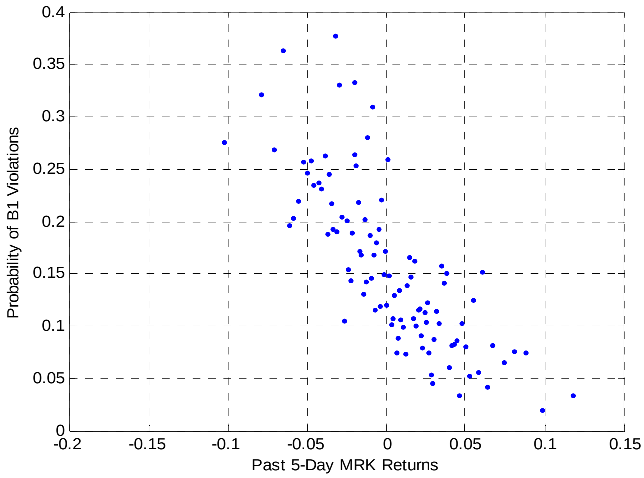
Panel B: HWP Options



Panel C: IBM Options



Panel D: MRK Options



Panel E: TXN Options

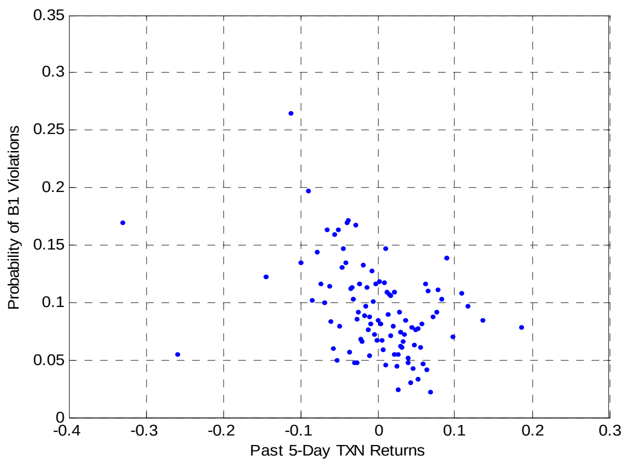
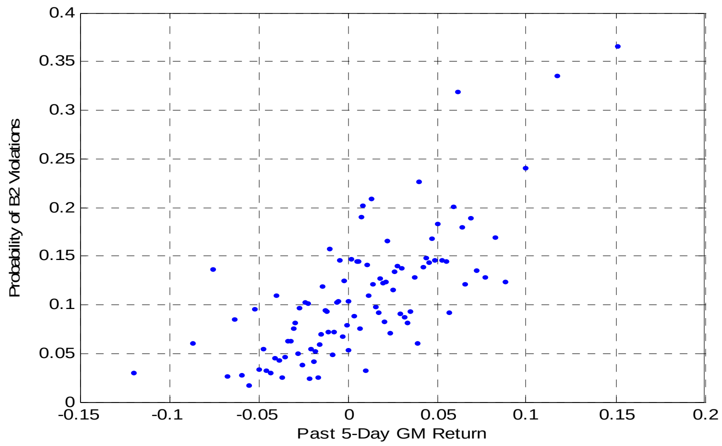
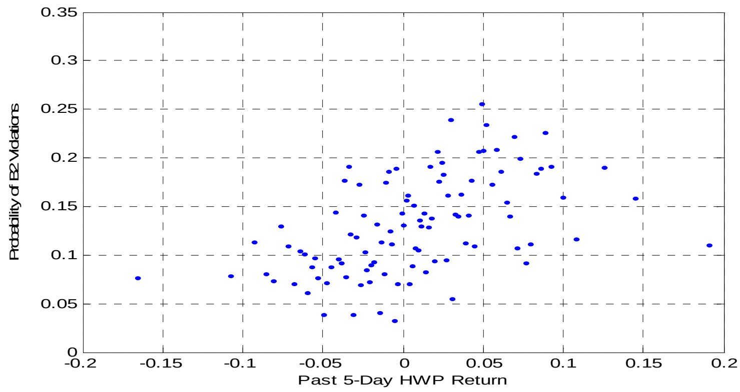


Figure 1-2 Relation between Probability of B2 Boundary Condition Violations and Past 5-Day Stock Returns

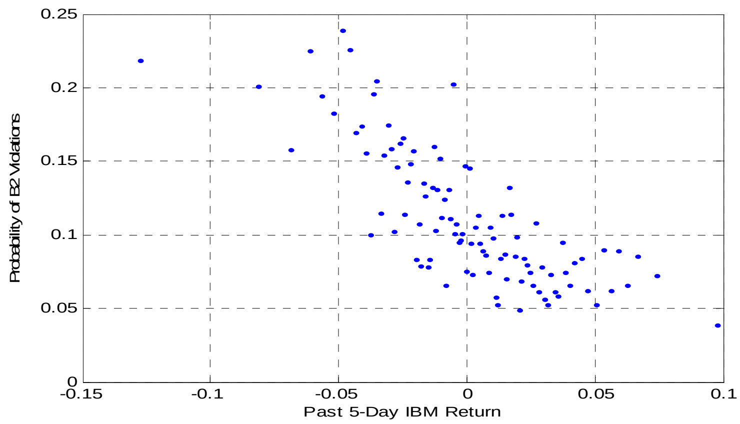
Panel A: GM Options



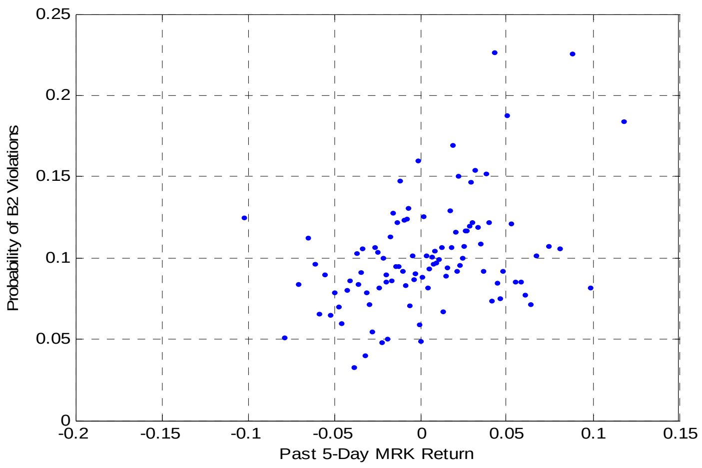
Panel B: HWP Options



Panel C: IBM Options



Panel D: MRK Options



Panel E: TXN Options

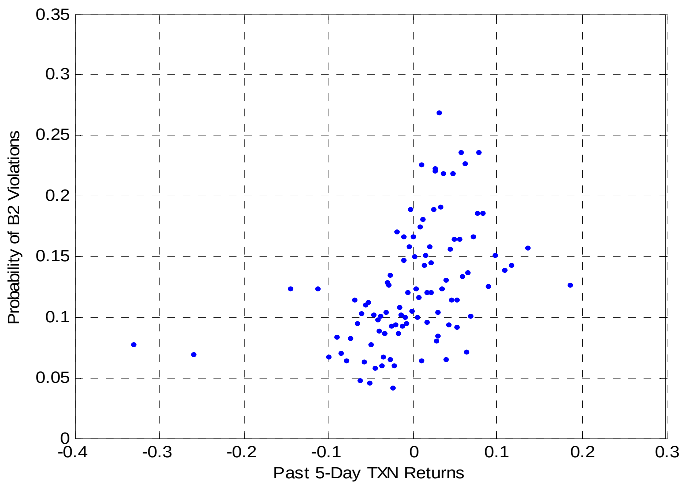


Table 1.3 First-Order Autocorrelation Coefficients For Five Selected Stocks and NYSE/AMEX/NASDAQ Index Returns

Horizon	TXN	IBM	MRK	GM	HWP	NTSE/AMEX/NASDAQ
5 days	-.0971 (.0075)	.0611 (.0811)	-.1094 (.0030)	-.0908 (.0096)	-.0293 (.4115)	.3000 (<.0001)
7 days	-.0519 (.2291)	.0586 (.1568)	-.0601 (.1699)	-.0862 (.0382)	-.0071 (.8660)	.3129 (<.0001)
9 days	.0147 (.7638)	.0771 (.1022)	-.0084 (.8659)	-.0130 (.7830)	-.0376 (.4331)	.2036 (<.0001)
10 days	-.0188 (.7160)	.0332 (.5055)	.0071 (.8918)	-.0185 (.7100)	.0018 (.9722)	.2292 (<.0001)
20 days	.0553 (.4494)	.1146 (.1037)	.0238 (.7504)	.1252 (.0745)	-.1245 (.0812)	.2171 (.0018)
30 days	-.0699 (.4398)	-.0033 (.9694)	-.0217 (.8128)	.0691 (.4241)	.0416 (.6384)	.2715 (.0014)
40 days	-.0365 (.7296)	.0581 (.5632)	.0109 (.9182)	-.0418 (.6737)	.0709 (.4874)	.1556 (.1187)
60 days	-.0197 (.8806)	.0747 (.5515)	.2119 (.1082)	-.1001 (.4181)	.0234 (.8549)	.1224 (.3219)

Table 1.4 Chi-Square Tests of the Relation between the Number of Option Pairs with Boudary Condition Violations and Past 5-Day Stock Returns

Critical level of Chi-Square distribution with 1 degree of freedom: @1%=6.63. The results of Chi-Square tests of whether B2 is violated more often after positive returns (call is overpriced relative to put), and B1 is violated more often after negative returns (put is overpriced relative to call). B1 and B2 denote the following conditions:

$$B1 = Callprice - Putprice - Stockprice + PV\,(strikeprice) \leq 0$$
$$B2 = Putprice - Callprice + Stockprice - PV\,(dividends) - Strikeprice \leq 0$$

The top number in each box is the number of option pairs in which a violation of that boundary condition was observed as a function of R = Rt-60, t-1, the stock return from calendar day t-60 to t-1. The bottom number in each box in parenthesis is the expected number of option pairs with violations, under the null hypothesis of no relation between past returns and boundary condition violations.

Panel A: GM Options

	A. Unadjusted Prices			B. Prices Net of Bid-Ask Spread		
	B1>0	B2>0	Total	B1>0	B2>0	Total
R<0	7877(5108)	7130(9899)	15007	3777(2497)	3298(4578)	7075
R>0	4599(7368)	17047(14278)	21646	2802(4082)	8764(7484)	11566
Total	12476	24177	36653	6579	12062	18641
	Chi-Square=3852.9			Chi-Square=1634.3		
R<-5%	1359(589)	1056(1826)	2415	736(340)	509(905)	1245
R>5%	1171(1941)	6786(6016)	7957	897(1293)	3836(3440)	4733
Total	2530	7842	10372	1633	4345	5978
	Chi-Square=1734.9			Chi-Square=800.9		
R<-10%	122(23)	66(165)	188	124(27)	26(123)	150
R>10%	147(246)	1833(1734)	1980	120(217)	1109(1012)	1229
Total	269	1899	2168	244	1135	1379
	Chi-Square=521.8			Chi-Square=487.9		

Panel B: HWP Options

	A. Unadjusted Prices			B. Prices Net of Bid-Ask Spread		
	B1>0	B2>0	Total	B1>0	B2>0	Total
R<0	5889(4840)	4837(5886)	10726	1836(1543)	1989(2282)	3825
R>0	5071(6120)	8491(7442)	13562	1858(2151)	3474(3181)	5332
Total	10960	13328	24288	3694	5463	9157
	Chi-Square=741.8			Chi-Square=160.1		
R<-5%	2100(1520)	1296(1876)	3396	593(466)	512(639)	1105
R>5%	1847(2427)	3577(2997)	5424	889(1016)	1521(1394)	2410
Total	3947	4873	8820	1482	2033	3515
	Chi-Square=652.1			Chi-Square=87.4		
R<-10%	432(279)	128(281)	560	105(71)	41(75)	146
R>10%	391(544)	699(546)	1090	218(252)	301(267)	519
Total	823	827	1650	323	342	665
	Chi-Square=252.1			Chi-Square=40.8		

Panel C: IBM Options

	A. Unadjusted Prices			B. Prices Net of Bid-Ask Spread		
	B1>0	B2>0	Total	B1>0	B2>0	Total
R<0	71234	24668	95902	27262	11911	39173
R>0	39484	42986	82470	17151	22866	40017
Total	110718	67654	178372	44413	34777	79190
	Chi-Square=13127.5			Chi-Square=5744.4		
R<-5%	11666	3163	14829	4390	1173	5563
R>5%	5369	8017	13386	2361	4178	6539
Total	17035	11180	28215	6751	5351	12102
	Chi-Square=4372.8			Chi-Square=2233.1		
R<-10%	1520	356	1876	419	51	470
R>10%	124	207	331	51	32	83
Total	1644	563	2207	470	83	553
	Chi-Square=280.9			Chi-Square=42.4		

Panel D: MRK Options

	A. Unadjusted Prices			B. Prices Net of Bid-Ask Spread		
	B1>0	B2>0	Total	B1>0	B2>0	Total
R<0	5593(4802)	2295(3086)	7888	1442(1339)	615(718)	2057
R>0	2796(3545)	3097(2306)	5893	998(1101)	693(590)	1691
Total	8389	5392	13781	2440	1308	3748
	Chi-Square=779.4			Chi-Square=50.2		
R<-5%	1187(937)	392(642)	1579	369(325)	103(148)	472
R>5%	436(686)	721(471)	1157	181(226)	147(103)	328
Total	1623	1113	2736	550	250	800
	Chi-Square=388.9			Chi-Square=47.6		
R<-10%	84(50)	32(66)	116	34(26)	10(18)	44
R>10%	23(57)	109(75)	132	10(18)	21(13)	31
Total	107	141	248	44	31	75
	Chi-Square=76.1			Chi-Square=15.2		

Panel E: TXN Options

	A. Unadjusted Prices			B. Prices Net of Bid-Ask Spread		
	B1>0	B2>0	Total	B1>0	B2>0	Total
R<0	4151(3345)	3653(4459)	7804	954(788)	881(1047)	1835
R>0	3149(3955)	6078(5272)	9227	908(1074)	1594(1428)	2502
Total	7300	9731	17031	1862	2475	4337
	Chi-Square=627.3			Chi-Square=106.5		
R<-5%	1693(1290)	1124(1527)	2817	403(318)	252(337)	655
R>5%	1234(1637)	2343(1940)	3577	327(412)	523(438)	850
Total	2927	3467	6394	730	775	1505
	Chi-Square=416.1			Chi-Square=78.7		
R<-10%	510(425)	329(414)	839	146(115)	57(88)	203
R>10%	298(383)	457(372)	755	68(99)	107(76)	175
Total	808	786	1594	214	164	378
	Chi-Square=72.2			Chi-Square=41.8		

Table 1.5 Implied Volatilities Separated by Call-Puts, Past 5-Day Returns, Maturity and Exercise Price

Panel A: Call Implied Volatility when R > 0.05

X*	<.95	.95-.97	.97-.99	.99-1.01	1.01-1.03	1.01-1.03	>1.05	All
Panel a: GM Options								
M=1	0.3711	0.3149	0.2686	0.2647	0.3523	0.3141	0.3342	0.3171
M=2	0.2832	0.2719	0.2584	0.2376	0.2295	0.2619	0.2936	0.2623
M=3	0.2517	0.2345	0.223	0.2266	0.2186	0.2531	0.251	0.2369
M=4	0.2501	0.2306	0.221	0.2095	0.207	0.2113	0.2207	0.2215
All	0.2890	0.2630	0.2428	0.2346	0.2519	0.2601	0.2749	0.2595
Panel b: HWP Options								
M=1	0.4016	0.37	0.3795	0.3717	0.3602	0.3897	0.4259	0.3855
M=2	0.3389	0.3458	0.3319	0.3252	0.3156	0.3288	0.3411	0.3325
M=3	0.3084	0.3232	0.3073	0.319	0.3168	0.3198	0.324	0.3169
M=4	0.2885	0.2858	0.2825	0.2935	0.2887	0.2883	0.299	0.2895
All	0.3344	0.3312	0.3253	0.3274	0.3203	0.3317	0.3475	0.3311
Panel c: IBM Options								
M=1	0.3778	0.3222	0.3056	0.2482	0.2613	0.2996	0.3499	0.3092
M=2	0.2918	0.2804	0.2441	0.2451	0.2333	0.2463	0.2952	0.2623
M=3	0.2559	0.231	0.2276	0.2223	0.2168	0.2197	0.2978	0.2387
M=4	0.2389	0.222	0.2245	0.2188	0.2116	0.2042	0.2382	0.2226
All	0.2911	0.2639	0.2505	0.2336	0.2308	0.2425	0.2953	0.2582
Panel d: MRK Options								
M=1	0.2491	0.2477	0.2525	0.2388	0.2469	0.2658	0.3069	0.2582
M=2	0.2741	0.2615	0.2689	0.2512	0.2567	0.2642	0.2505	0.2610
M=3	0.2843	0.2874	0.2871	0.2581	0.2591	0.2492	0.2965	0.2745
M=4	0.2648	0.2532	0.2552	0.2441	0.2562	0.2685	0.2465	0.2555
All	0.2681	0.2625	0.2659	0.2481	0.2547	0.2619	0.2751	0.2623
Panel e: TXN Options								
M=1	0.4353	0.3893	0.3858	0.3660	0.3791	0.4057	0.4502	0.4016
M=2	0.3710	0.3420	0.3415	0.3458	0.3406	0.3490	0.3742	0.3520
M=3	0.2994	0.2822	0.3113	0.2945	0.2829	0.3091	0.3263	0.3008
M=4	0.3078	0.2845	0.2859	0.2949	0.2776	0.2783	0.3115	0.2915
All	0.3534	0.3245	0.3311	0.3253	0.3201	0.3355	0.3656	0.3365

Panel B: Call-Implied Volatility when R < -0.05

X*	<.95	.95-.97	.97-.99	.99-1.01	1.01-1.03	1.01-1.03	>1.05	All
Panel a: GM Options								
M=1	0.3664	0.3361	0.3055	0.2984	0.3575	0.3308	0.3895	0.3406
M=2	0.2996	0.2979	0.292	0.2858	0.2678	0.2816	0.3579	0.2975
M=3	0.2711	0.257	0.2548	0.2516	0.2453	0.2519	0.2767	0.2583
M=4	0.2752	0.2584	0.2769	0.2628	0.2521	0.2443	0.2571	0.2610
All	0.3031	0.2874	0.2823	0.2747	0.2807	0.2772	0.3203	0.2894
Panel b: HWP Options								
M=1	0.4259	0.4024	0.382	0.3675	0.3751	0.3708	0.4131	0.3910
M=2	0.3582	0.3668	0.3513	0.3612	0.3577	0.3578	0.3839	0.3624
M=3	0.3213	0.3436	0.3276	0.3235	0.3241	0.3288	0.3344	0.3290
M=4	0.3076	0.3281	0.3104	0.3149	0.3184	0.3065	0.3239	0.3157
All	0.3533	0.3602	0.3428	0.3418	0.3438	0.3410	0.3638	0.3495
Panel c: IBM Options								
M=1	0.3936	0.3617	0.3353	0.3246	0.2986	0.3336	0.3926	0.3486
M=2	0.3253	0.2929	0.2831	0.2692	0.2494	0.2811	0.3531	0.2934
M=3	0.3213	0.3159	0.2809	0.3209	0.2352	0.284	0.4051	0.3090
M=4	0.2774	0.2761	0.2546	0.2284	0.2167	0.2253	0.2517	0.2472
All	0.3294	0.3117	0.2885	0.2858	0.2500	0.2810	0.3506	0.2996
Panel d: MRK Options								
M=1	0.3104	0.3148	0.3212	0.3014	0.3035	0.293	0.3133	0.3082
M=2	0.2549	0.261	0.2691	0.274	0.2818	0.2972	0.3183	0.2795
M=3	0.2838	0.2856	0.271	0.2446	0.2589	0.257	0.3004	0.2716
M=4	0.3104	0.2813	0.2955	0.2938	0.2808	0.2998	0.2849	0.2924
All	0.2899	0.2857	0.2892	0.2785	0.2813	0.2868	0.3042	0.2879
Panel e: TXN Options								
M=1	0.4886	0.496	0.4594	0.4057	0.4505	0.4609	0.4895	0.4644
M=2	0.3981	0.4238	0.3972	0.3754	0.3916	0.4034	0.4238	0.4019
M=3	0.3991	0.3292	0.3537	0.3588	0.3666	0.3502	0.4073	0.3664
M=4	0.3432	0.3376	0.3366	0.3207	0.3226	0.3228	0.3373	0.3315
All	0.4073	0.3967	0.3867	0.3652	0.3828	0.3843	0.4145	0.3911

Panel C: Put-Implied Volatility when R> 0.05

X*	<.95	.95-.97	.97-.99	.99-1.01	1.01-1.03	1.01-1.03	>1.05	All
Panel a: GM Options								
M=1	0.432	0.3678	0.3399	0.3261	0.36	0.4248	0.4269	0.3825
M=2	0.3589	0.3297	0.3228	0.3316	0.3372	0.3547	0.4084	0.3490
M=3	0.3669	0.3373	0.3575	0.3368	0.3308	0.3459	0.3927	0.3526
M=4	0.3553	0.3312	0.3276	0.3361	0.3585	0.3425	0.3587	0.3443
All	0.3783	0.3415	0.3370	0.3327	0.3466	0.3670	0.3967	0.3571
Panel b: HWP Options								
M=1	0.4616	0.4171	0.4029	0.4117	0.4107	0.4521	0.4807	0.4338
M=2	0.4141	0.3999	0.3805	0.3713	0.3676	0.3786	0.4053	0.3882
M=3	0.4103	0.3796	0.3775	0.3843	0.3922	0.3913	0.3926	0.3897
M=4	0.3834	0.3694	0.3705	0.3681	0.3778	0.3761	0.376	0.3745
All	0.4174	0.3915	0.3829	0.3839	0.3871	0.3995	0.4137	0.3965
Panel c: IBM Options								
M=1	0.3476	0.318	0.2899	0.2904	0.3022	0.3401	0.4545	0.3347
M=2	0.309	0.2951	0.2631	0.282	0.2826	0.2826	0.3305	0.2921
M=3	0.2857	0.2778	0.2544	0.2747	0.2733	0.28	0.3392	0.2836
M=4	0.2894	0.2755	0.275	0.2708	0.2854	0.2869	0.2997	0.2832
All	0.3079	0.2916	0.2706	0.2795	0.2859	0.2974	0.3560	0.2984
Panel e: MRK Options								
M=1	0.3832	0.3156	0.3008	0.3056	0.2969	0.3691	0.4454	0.3452
M=2	0.3285	0.2966	0.2914	0.2888	0.2865	0.3078	0.3484	0.3069
M=3	0.3309	0.2854	0.291	0.3059	0.2817	0.3046	0.3741	0.3105
M=4	0.2822	0.276	0.2706	0.2745	0.2582	0.2743	0.2916	0.2753
All	0.3312	0.2934	0.2885	0.2937	0.2808	0.3140	0.3649	0.3095
Panel e: TXN Options								
M=1	0.48	0.4331	0.4118	0.4008	0.4104	0.4519	0.4796	0.4382
M=2	0.4397	0.4023	0.394	0.3962	0.3908	0.4011	0.4369	0.4087
M=3	0.4155	0.3664	0.4097	0.3745	0.3531	0.3746	0.3998	0.3848
M=4	0.4058	0.3856	0.3778	0.3903	0.38	0.3819	0.3911	0.3875
All	0.4353	0.3969	0.3983	0.3905	0.3836	0.4024	0.4269	0.4048

Panel D: Put-Implied Volatility when R< -0.05

X*	<.95	.95-.97	.97-.99	.99-1.01	1.01-1.03	1.01-1.03	>1.05	All
Panel a: GM Options								
M=1	0.4705	0.3737	0.3706	0.3475	0.3447	0.3888	0.4936	0.3985
M=2	0.4384	0.381	0.3874	0.382	0.3643	0.38	0.4864	0.4028
M=3	0.3528	0.3494	0.3282	0.3246	0.3641	0.3609	0.4148	0.3564
M=4	0.3446	0.3571	0.3482	0.3421	0.3472	0.3306	0.357	0.3467
All	0.4016	0.3653	0.3586	0.3491	0.3551	0.3651	0.4380	0.3761
Panel b: HWP Options								
M=1	0.47	0.4484	0.4044	0.386	0.425	0.4385	0.4749	0.4353
M=2	0.4105	0.4028	0.3819	0.3925	0.3862	0.3839	0.4419	0.4000
M=3	0.4068	0.3835	0.3809	0.3682	0.3686	0.3708	0.399	0.3825
M=4	0.3789	0.3842	0.3798	0.3706	0.3702	0.3664	0.3852	0.3765
All	0.4166	0.4047	0.3868	0.3793	0.3875	0.3899	0.4253	0.3986
Panel c: IBM Options								
M=1	0.4443	0.3669	0.3382	0.3368	0.3262	0.3641	0.4477	0.3749
M=2	0.3884	0.3247	0.3111	0.2947	0.3138	0.306	0.3813	0.3314
M=3	0.3628	0.3072	0.2773	0.3049	0.3124	0.2972	0.5025	0.3378
M=4	0.3214	0.3035	0.2848	0.2743	0.272	0.2844	0.3088	0.2927
All	0.3792	0.3256	0.3029	0.3027	0.3061	0.3129	0.4101	0.3342
Panel d: MRK Options								
M=1	0.395	0.399	0.3923	0.3523	0.3449	0.4118	0.4769	0.3960
M=2	0.3699	0.3249	0.3276	0.326	0.302	0.3153	0.3858	0.3359
M=3	0.3895	0.385	0.3768	0.3665	0.3641	0.3934	0.5963	0.4102
M=4	0.3037	0.2953	0.3044	0.2996	0.2901	0.2889	0.3331	0.3022
All	0.3645	0.3511	0.3503	0.3361	0.3253	0.3524	0.4480	0.3611
Panel e: TXN Options								
M=1	0.538	0.492	0.4617	0.4356	0.4467	0.4725	0.4859	0.4761
M=2	0.4703	0.4411	0.4101	0.4083	0.4101	0.429	0.4544	0.4319
M=3	0.418	0.4003	0.4109	0.4065	0.4063	0.3942	0.4256	0.4088
M=4	0.4167	0.4019	0.3832	0.3705	0.3874	0.3938	0.3993	0.3933
All	0.4608	0.4338	0.4165	0.4052	0.4126	0.4224	0.4413	0.4275

Table 1.6 Sample Characteristics of Volatility Spread for Five Selected Stocks

	Mean	Std. dev.	max	90%	Medi-an	10%	min	ρ_1	ρ_2	ρ_3	No.
Panel A: GM Options											
ATM Options Only	-0.054	0.088	0.543	0.038	-0.050	-0.158	-0.365	0.586	0.235	0.120	3391
Equal-Weighted	-0.079	0.056	0.091	-0.017	-0.071	-0.156	-0.352	0.835	0.313	0.151	3995
Elasticity-Wtd	-0.073	0.056	0.110	-0.011	-0.064	-0.150	-0.347	0.817	0.293	0.152	3995
Vega-Weighted	-0.087	0.055	0.081	-0.025	-0.080	-0.162	-0.360	0.899	0.308	0.136	3995
Panel B: HWP Options											
ATM Options Only	-0.036	0.065	1.247	0.024	-0.032	-0.110	-0.342	0.491	0.265	0.184	3606
Equal-Weighted	-0.049	0.044	0.959	-0.011	-0.043	-0.099	-0.274	0.591	0.293	0.219	3832
Elasticity-Wtd	-0.050	0.045	0.961	-0.010	-0.044	-0.102	-0.301	0.575	0.272	0.210	3832
Vega-Weighted	-0.050	0.037	0.553	-0.016	-0.042	-0.095	-0.267	0.730	0.338	0.227	3832
Panel C: IBM Options											
ATM Options Only	-0.001	0.090	1.951	0.060	-0.006	-0.069	-0.284	0.388	0.183	0.152	3204
Equal-Weighted	-0.029	0.090	2.397	0.008	-0.029	-0.091	-0.253	0.379	0.175	0.176	3746
Elasticity-Wtd	-0.028	0.084	2.396	0.009	-0.026	-0.087	-0.270	0.347	0.116	0.139	3746
Vega-Weighted	-0.038	0.099	2.399	-0.008	-0.040	-0.099	-0.249	0.380	0.134	0.159	3746
Panel D: MRK Options											
ATM Options Only	-0.037	0.071	0.377	0.041	-0.039	-0.118	-0.353	0.682	0.336	0.200	3216
Equal-Weighted	-0.041	0.065	0.368	0.034	-0.046	-0.110	-0.355	0.797	0.362	0.170	3548
Elasticity-Wtd	-0.041	0.073	0.398	0.042	-0.047	-0.117	-0.328	0.674	0.361	0.171	3548
Vega-Weighted	-0.047	0.060	0.366	0.022	-0.051	-0.111	-0.307	0.889	0.339	0.170	3548
Panel E: TXN Options											
ATM Options Only	-0.047	0.064	0.576	0.024	-0.046	-0.120	-0.596	0.422	0.247	0.185	3418
Equal-Weighted	-0.054	0.041	0.236	-0.008	-0.049	-0.108	-0.385	0.643	0.233	0.180	3757
Elasticity-Wtd	-0.050	0.045	0.220	0.000	-0.048	-0.109	-0.388	0.591	0.250	0.124	3757
Vega-Weighted	-0.056	0.038	0.242	-0.016	-0.050	-0.110	-0.386	0.761	0.235	0.227	3757

Table 1.7 Cross-Correlation's of Volatility Spread for Five Selected Stocks Options by Weighting Type

Panel A: GM Options			
	Elasticity-weighted	equal-weighted	vega-weighted
At-the-money only	.438	.484	.528
Elasticity weighted	____	.910	.971
Equal weighted	____	____	.954
Panel B: HWP Options			
	Elasticity-weighted	equal-weighted	vega-weighted
At-the-money only	.658	.765	.674
Elasticity weighted	____	.965	.882
Equal weighted	____	____	.933
Panel C: IBM Options			
	Elasticity-weighted	equal-weighted	vega-weighted
At-the-money only	.624	.729	.646
Elasticity weighted	____	.931	.787
Equal weighted	____	____	.924
Panel D: MRK Options			
	Elasticity-weighted	equal-weighted	vega-weighted
At-the-money only	.829	.900	.845
Elasticity weighted	____	.935	.831
Equal weighted	____	____	.933
Panel E: TXN Options			
	Elasticity-weighted	equal-weighted	vega-weighted
At-the-money only	.510	.657	.603
Elasticity weighted	____	.947	.840
Equal weighted	____	____	.931

Table 1.8 Regression of Daily Volatility Spread on Past Stock Return for Five Selected Stocks

$$VolatilitySpread_t = \alpha_0 + \alpha_1 R_{t-k,t-1} + A(L)\varepsilon_t;$$

This table reports the results of time-series regressions of equally-weighted volatility spread (call-implied volatility – put-implied volatility) versus past 2-week (k=10) to 20-week (k=100) stock returns. An AR(5) model is fitted to eliminate the effect of autocorrelation in the residuals. The p-values are reported in parentheses. N is the number of observations. $R_{t-k,\,t-1}$ is the stock return from calendar date t-k to t-1; $A(L) = 1/\phi_0 - [\sum_{i=1}^{5} \phi_i L^i]$ and L is the lag operator.

	Overall Period 1/2/81-12/29/95			Precrash Period 1/2/80-10/18/87			Postcrash Period 1/19/88-12/29/95		
k days	α_0	α_1	R^2	α_0	α_1	R^2	α_0	α_1	R^2
Panel A: GM Options									
5	-.0507 (<.0001)	-.1061 (<.0001)	.0147	-.0634 (<.0001)	-.1196 (<.0001)	.0245	-.0393 (<.0001)	-.1133 (<.0001)	.0148
7	-.0507 (<.0001)	-.0863 (<.0001)	.0098	-.0633 (<.0001)	-.0958 (<.0001)	.0157	-.0392 (<.0001)	-.1095 (<.0001)	.0150
9	-.0507 (<.0001)	-.0680 (<.0001)	.0061	-.0633 (<.0001)	-.0831 (<.0001)	.0118	-.0392 (<.0001)	-.1000 (<.0001)	.0137
10	-.0505 (<.0001)	-.0847 (<.0001)	.0095	-.0632 (<.0001)	-.0886 (<.0001)	.0133	-.0390 (<.0001)	-.1171 (<.0001)	.0198
N	3757			1689			2005		
Panel B: HWP Options									
5	-.0494 (<.0001)	-.0654 (<.0001)	.0050	-.0633 (<.0001)	-.0707 (.0081)	.0040	-.0372 (<.0001)	-.0659 (<.0001)	.0082
7	-.0494 (<.0001)	-.0542 (.0003)	.0035	-.0631 (<.0001)	-.0850 (.0015)	.0057	-.0373 (<.0001)	-.0389 (.0110)	.0032
9	-.0495 (<.0001)	-.0330 (.0262)	.0013	-.0630 (<.0001)	-.0695 (.0101)	.0037	-.0374 (<.0001)	-.0228 (.1206)	.0012
10	-.0494 (<.0001)	-.0429 (.0039)	.0022	-.0630 (<.0001)	-.0660 (.0152)	.0033	-.0372 (<.0001)	-.0409 (.0041)	.0041
N	3832			1764			2005		
Panel C: IBM Options									
5	-.0287 (<.0001)	.1916 (.0003)	.0035	-.0288 (<.0001)	.2814 (.0116)	.0036	-.0275 (<.0001)	.1023 (.0062)	.0039
7	-.0289 (<.0001)	.2602 (<.0001)	.0073	-.0296 (<.0001)	.4151 (<.0001)	.0088	-.0275 (<.0001)	.1401 (<.0001)	.0079

9	-.0291 (<.0001)	.2753 (<.0001)	.0092	-.0301 (<.0001)	.4181 (<.0001)	.0100	-.0275 (<.0001)	.1680 (<.0001)	.0121
10	-.0291 (<.0001)	.2420 (<.0001)	.0074	-.0300 (<.0001)	.3525 (.0003)	.0076	-.0275 (<.0001)	.1523 (<.0001)	.0100
N			3746		1759		1924		
Panel D: MRK Options									
5	-.0399 (<.0001)	-.0264 (.4106)	.0002	-.0380 (.0017)	-.1749 (.0004)	.0081	-.0380 (<.0001)	.0492 (.2457)	.0007
7	-.0402 (<.0001)	.0292 (.3555)	.0002	-.0381 (.0016)	-.1166 (.0193)	.0035	-.0383 (<.0001)	.0895 (.0319)	.0024
9	-.0400 (<.0001)	.0029 (.9271)	.0001	-.0383 (.0014)	-.0700 (.1602)	.0013	-.0379 (<.0001)	.0194 (.6492)	.0001
10	-.0404 (<.0001)	.0394 (.2212)	.0004	-.0386 (.0012)	-.0348 (.4873)	.0003	-.0382 (<.0001)	.0508 (.2351)	.0007
N			3548		1557		1928		
Panel E: TXN Options									
5	-.0507 (<.0001)	-.1061 (<.0001)	.0147	-.0634 (<.0001)	-.1196 (<.0001)	.0245	-.0393 (<.0001)	-.1133 (<.0001)	.0148
7	-.0507 (<.0001)	-.0863 (<.0001)	.0098	-.0633 (<.0001)	-.0958 (<.0001)	.0157	-.0392 (<.0001)	-.1095 (<.0001)	.0150
9	-.0507 (<.0001)	-.0680 (<.0001)	.0061	-.0633 (<.0001)	-.0831 (<.0001)	.0118	-.0392 (<.0001)	-.1000 (<.0001)	.0137
10	-.0505 (<.0001)	-.0847 (<.0001)	.0095	-.0632 (<.0001)	-.0886 (<.0001)	.0133	-.0390 (<.0001)	-.1171 (<.0001)	.0198
N			3757		1689		2005		

Table 1.9 Regression of Volatility Spread on Past Stock Returns, Historical Volatility, Skewness and Kurtosis Measures for Five Selected Stocks

$$VolSpread = \alpha_0 + \alpha_1 R_k + \alpha_2 E(\sigma_{k+1}) + \alpha_3 E(Skewness_{k+1}) + \alpha_4 E(Kurtosis_{k+1}) + \varepsilon_{1t}$$
$$\sigma_k = b_0 + b_1\sigma_{k-1} + b_2\sigma_{k-2} + b_3\sigma_{k-3} + b_4\sigma_{k-4} + b_5\sigma_{k-5} + \varepsilon_{2t}$$
$$Skewness_k = c_0 + c_1 Skewness_{k-1} + c_2 Skewness_{k-2} + c_3 Skewness_{k-3} + c_4 Skewness_{k-4} + c_5 Skewness_{k-5} + \varepsilon_{3t}$$
$$Kurtosis_k = d_0 + d_1 Kurtosis_{k-1} + d_2 Kurtosis_{k-2} + d_3 Kurtosis_{k-3} + d_4 Kurtosis_{k-4} + d_5 Kurtosis_{k-5} + \varepsilon_{4t}$$

Estimates are from GMM. The p-values for the estimated coefficients are in parentheses, while the Wald statistics tests the hypothesis that all estimated coefficients are equal to zero. Volatility spread is computed from elasticity-weighted options for each day. R_k is the stock return from date t-k to t-1. σ_k is the estimated historical volatility of the stock returns from day t-k to t-1. Skewnessk is the estimated skewness coefficient of the stock returns from day t-k to t-1, and Kurtosisk is the estimated kurtosis coefficient of the stock returns from day t-k to t-1. Data are sampled once every 20 days.

k (days)	α_0	α_1	α_2	α_3	α_4	Wald
Panel A: GM Options						
5	-.1401 (<.0001	-.6102 (.0653)	4.7667 (.0003)	-.0061 (.5450)	.0145 (.0725)	409.90 (<.0001)
7	-.1774 (.1255)	-.4102 (.3363)	9.5630 (.0054)	-.0002 (.9910)	-.2574 (.7109)	28.30 (<.0001)
9	-.1512 (<.0001)	-.3374 (.2827)	5.8851 (.0021)	-.0162 (.5616)	-.0441 (.2156)	248.09 (<.0001)
10	-.1283 (<.0001)	-.3661 (.0628)	3.6252 (.0004)	.01418 (.4040)	.0174 (.4083)	371.27 (<.0001)
Panel B: HWP Options						
5	-.0460 (<.0001)	-.03566 (.0465)	-.2200 (.6866)	.0086 (.3811)	.0026 (.6110)	734.40 (<.0001)
7	-.0517 (.0007)	-.1530 (.4296)	-.1347 (.8325)	.0939 (.2905)	.0156 (.0195)	142.20 (<.0001)
9	-.0795 (.0007)	-.03786 (.0457)	1.8003 (.1239)	-.0016 (.9374)	.0021 (.7478)	406.68 (<.0001)
10	-.1053 (<.0001)	-.2867 (.0213)	2.8219 (.0150)	.0286 (.2242)	.0125 (.2414)	318.19 (<.0001)
Panel C: IBM Options						
5	.0557 (<.0001)	.7355 (.2191)	-6.0503 (<.0001)	-.1098 (.5028)	-.0027 (.7997)	103.95 (<.0001)
7	.0571 (<.0001)	-.0898 (.7661)	-6.1763 (<.0001)	-.0130 (.7008)	-.0019 (.8918)	155.42 (<.0001)

9	.0204 (.3121)	.2657 (.4986)	-3.5440 (.0146)	-.0431 (.2338)	-.0029 (.7402)	105.32 (<.0001)
10	.0477 (.0009)	-.1061 (.6060)	-5.7510 (<.0001)	.0133 (.3304)	.0275 (.1383)	136.54 (<.0001)
Panel D: MRK Options						
5	.0666 (.0014)	1.2657 (.1158)	-7.9493 (<.0001)	-.0300 (.3741)	-.0413 (.1526)	86.31 (<.0001)
7	.0326 (.5055)	.1987 (.6762)	-7.6225 (<.0001)	.2024 (.4123)	-.1013 (.5108)	52.46 (<.0001)
9	.0478 (.0351)	.8412 (.0527)	-6.3853 (<.0001)	-.0763 (.2249)	.0131 (.5279)	111.96 (<.0001)
10	.0219 (.5756)	1.1943 (.0249)	-5.7219 (.0210)	.0578 (.2742)	-.0179 (.3134)	108.20 (<.0001)
Panel E: TXN Options						
5	-.0495 (<.0001)	-.5161 (.0304)	.08945 (.8702)	-.0181 (.3644)	.0122 (.3526)	486.46 (<.0001)
7	-.0461 (.0078)	-.3911 (.1502)	.2903 (.6872)	-.0554 (.2311)	.0039 (.7516)	301.30 (<.0001)
9	-.0612 (<.0001)	.0850 (.6680)	.7061 (.1862)	-.0273 (.3076)	.0118 (.2809)	295.03 (<.0001)
10	-.0586 (<.0001)	-.1522 (.3736)	.5421 (.3248)	.0058 (.7450)	-.0040 (.4707)	477.94 (<.0001)

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Chapter 2 Time-Varying Liquidity Trading, Private Information And Insider Trading

2.1 Introduction

One fundamental question in market microstructure is how private information about underlying assets gets incorporated into asset prices through the trading process. It is now generally accepted that such private information is usually revealed through trades by informed traders and learning from these trades by other market participants such as market makers and uninformed traders. In this sense, studies on the interaction between informed traders and uninformed traders (a.k.a liquidity traders) are especially important for a better understanding of the private information incorporation process. Using corporate insiders as proxies for informed traders[15], this paper studies insider trades around two distinct settings, i.e., scheduled versus unscheduled corporate announcements to investigate how insiders trade differentially based on their private information when there is a dispersion in the amount of liquidity trading around such announcements.

Scheduled and unscheduled announcement events are defined by whether the timing information as to when an announcement will be issued is publicly available or not. Scheduled announcements are those where such information is publicly available whereas unscheduled announcements refer to cases where such information is not publicly available. Classification of major corporate events into scheduled and

[15]Corporate insiders are quite natural proxies for informed traders. The fact that there are plenty of corporate information events makes this proxy even more appealing when we examine insider trades under asymmetric information.

unscheduled announcements has one important advantage for our purposes: it provides us with a unique setting of timing-varying liquidity trading where we can examine how insiders respond to time-variation in liquidity trading. More specifically, when timing information is available, discretionary liquidity traders in the sense of Admati and Pfleiderer (1988) know that a large flow of information will be released on a specific date. Since they do not know what the information is, they can respond by changing the timing of their trades. For example, they might postpone their trading if they anticipate adverse price movements associated with the information release. In contrast, when timing information is not available, liquidity traders might not change the timing of their trades and trade just as usual. We believe this differential trading pattern has important implications for insider trading. As predicted by the strategic trading literature, informed traders will try to hide themselves among liquidity trading to prevent their private information being revealed fully and too quickly[16]. To the extent that the amount of liquidity trading is time-varying around scheduled versus unscheduled announcements, they provide different covers for informed trading. Our empirical results provide direct evidence that such informed trading actually manifests itself in the trading volume and profitability of insider trades around such announcement events.

Following Chae (2005), we use earnings announcements as scheduled announcements and M&A announcements as unscheduled announcements. Quarterly earnings announcements are usually routinely made by listed companies and involve a release of information in which the timing is publicly known[17]. In comparison, neither the timing nor the magnitude and direction of the merger announcements is public

[16]See Kyle (1985, 1989), Adamati and Pleiderer (1988), Holden and Subramanyam (1992), Foster and Viswanathan (1994, 1996), Huddart, Hughes and Levine (2001) for an incomplete list of strategic trading literature.

[17]The evidence in Bagnoli, Kross and Watts (2002) is that, by and large, firms do announce earnings on the planned-and-disclosed date, which suggests that earnings announcement dates are known in advance and sticky. Chordia, Roll and Subramanyam (2001) also mention that earnings announcements are among the best candidates for scheduled announcements involving a release of relevant pricing information.

information. As noted by Chae (2005), these two types of announcements are chosen because they represent major corporate events that have substantial impacts on stock prices[18].

Our paper fits into the insider trading literature. Existing insider trading literature has separately investigated insider trading around earnings announcements and M&A announcements[19]. While these studies provide lots of insights into the informational content of insider trades around such announcement events, none of them exploit the unique feature of time-varying liquidity trading to investigate insider trading around these two types of announcements simultaneously. Availing ourselves of the striking difference in the degree of information asymmetry that results from time-varying liquidity trading around such announcement events, our paper is the first one to examine insider trading patterns under such asymmetric information settings. In a paper closely related to our study, Aboody and Lev (2000) hypothesize that research and development (R&D) activities increase the information asymmetry between insiders and investors, thereby allowing insiders at firms with high R&D spending to reap higher profits from their trading than insiders at other firms. Consistent with their hypothesis, they report greater excess stock returns between the transaction date and the reporting date for insider trades at firms with high R&D spending compared with other firms. Our paper differs from theirs in that we do not reply on R&D spending as a proxy for information asymmetry. Instead, we focus directly on the nature of two distinct types of corporate announcements that are uniquely characterized by different degrees of information asymmetry. Roulstone (2006) also studies the relationship between insider trading and the informational content of earnings announcement. But

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[18]See Ball and Brown (1968), Jensen and Ruback (1983), Foster et. al. (1984), Dennis (1986), Bamber (1987), Bernard and Thomas (1989), Jarrell and Poulsen (1989), Ball and Kothari (1991), Hand et. al. (1992), Keown and Bolster (1992), Mitchell and Stafford (2004), Clara (2006) and others for studies on stock prices around such events.

[19]See Sivakumar and Waymire (1994), Ke, Huddart and Petroni (2003), Huddart et. al. (2006), Roulstone (2006) and others for insider trading around earnings announcements; See Keown (1981), Jarrell and Poulsen (1989), Melbroek (1992), Cornell and Sirri (1992), Arshadi and Eyssell (1993) and others for insider trading around mergers and acquisitions.

his focus is on whether the net effect of insider trading promotes more accurate stock pricing by conveying insiders' private information to market participants. While in this paper, we are more focused on how corporate insiders trade differentially based on time-varying liquidity trading and the dispersion of information asymmetry. Huddart et. al. (2007) also examines a variety of information asymmetry measures to investigate the relationship of such measures to aspects of insiders' trades. Unlike our present paper, they focus exclusively on earnings announcements.

Our paper is also related to other strands of literature. Firstly, the strategic trading literature. To the extent that informed traders trade strategically by either spreading their trades over time or trading when liquidity trading is most intensive, our paper provides direct evidence that insiders trade more heavily and profitably when liquidity trading provides better camouflages for their trades. Secondly, the empirical literature about PIN measure and its application in corporate finance context; Given the increasing prevalence of applying PIN measure in corporate finance studies, it is interesting to ask whether PIN measure captures the information structure associated with these two distinct types of corporate events. Our findings suggest that PIN measure performs quite well in this case. Thirdly, our paper is also closely related to the trading volume literature around major corporate information events. George et. al. (1994) propose that high trading volume immediately after corporate announcements is a result of increased liquidity trading. Kim and Verrecchia (1991) and Atiase and Bamber (1994) offer another explanation of increasing trading volume on/after corporate announcements. Our paper differs from their work in that we focus on insider trading volume both before and after announcement events. To the extent that liquidity trading volume increases after corporate announcement events, we need to control for this increase when we examine insider trading volume.

Perhaps our paper is most closely related to Chae (2005), which investigates trading volume before scheduled and unscheduled corporate announcements to explore how traders respond to private information. He finds that cumulative trading volume decreases prior to scheduled announcements. In contrast, trading volume before unscheduled announcements increases dramatically. And the opposite relation holds for volume after the announcements. Our analysis differs from his in that we examine insider trading volume instead of total trading volume. To the extent that total trading volume increases (decreases) before unscheduled (scheduled) announcements, his paper provides a basis for our analysis. As shown by Jeng et. al. (2003), insider trading volume only accounts for a very limited portion of total trading volume. Given this fact, we argue that the increase (decrease) in total trading volume before unscheduled (scheduled) announcements can reliably translate to increase (decrease) in the amount of liquidity trading. In this sense, we believe Chae (2005) provides a first-pass test for our main hypotheses. Given that discretionary liquidity traders do change their trading behavior depending on the availability of timing information around scheduled versus unscheduled announcements, it is meaningful to ask whether insiders respond to and internalize such trading behavior.

Our main contributions are mainly two-fold: first, by resorting to the argument of time-varying liquidity trading, we are able to show that the degree of information asymmetry differs across scheduled versus unscheduled announcements. We further test directly whether the recently emerged PIN measure (probability of information-based trading) (Easley et. al. (1996, 2002)) captures information asymmetry around such announcement events. Since the widely-used market microstructure PIN measure is derived from an well-specified structured model, it is not surprising that the majority of the asset pricing literature presumes that PIN captures information asymmetry and provides direct evidence that PIN is actually priced in asset returns (Easley, Hvidkjaer and O'Hara (2002, 2004)). However, little is yet known as to how PIN fares when it is used to capture information asymmetry around material corporate events. Clara (2006) is among the few studies that examine the performance of PIN in corporate finance context. Using earnings announcement as the main information events, she finds that stocks with higher PIN values have smaller post-earnings-announcement drift and thus seem to have more informative pre-earnings-announcement prices. In this paper we investigate whether PIN measures characterizes informed trading as a response to time-varying liquidity trading around major announcement events. We find that PIN is much higher before unscheduled announcements than before scheduled announcements[20]. We interpret this evidence as consistent with the notion of strategic trading by corporate insiders.

Second, given that liquidity trading is time varying and information asymmetry is much higher before unscheduled announcements than before scheduled announcements as suggested by PIN, it is quite natural to ask whether corporate insiders make use of this differential information structure and trade accordingly. The comprehensive insider trading dataset we use in this paper, combined with the rich sets of corporate announcements, provides an ideal setting for such studies. We investigate whether there are differential patterns in insider trading volume and profitability. More specifically, we examine whether insiders trade more intensively before unscheduled announcements than before scheduled announcements and whether insider trades before unscheduled announcements are more profitable. For both of these two conjectures, we find supportive evidence.

The rest of the paper is organized as follows: Section 2 formally develops the main hypotheses; In Section 3 we describe the data and methodology that are used to test the main hypotheses. Section 4 contains the main empirical results for insider trading volume and insider trading profitability. Section 5 concludes.

2.2 Hypothesis Development

Many event studies about corporate announcements, such as earnings and takeovers,

[20]What surprises us is the finding that PIN is much higher after target(acquiror) announcements than before target(acquiror)announcements. While this finding itself is puzzling, it is consistent with Aktas et. al. (2006). They also find similar patterns in PIN around M&A announcements. Several possible reasons are suggested in their paper to reconcile this puzzle.

indicate that a considerable amount of information is released around these announcements. These releases of information often generate large price changes. For example, the absolute daily price change on earnings announcements, acquisition announcements, target announcements is about 56%, 45%, 287% higher than the average absolute price changer on other days in the same month respectively. Therefore, it seems quite plausible that there exists severe information asymmetry between informed and uninformed investors immediately before such announcements. Moreover, we argue that the degree of information asymmetry differs substantially around scheduled versus unscheduled announcements. This is due to the direct effect of the different nature of these announcements on the amount of liquidity trading. As we argue in the introduction, quarterly earnings announcements are often routinely scheduled. As shown in Bagnoli et. al. (2002), lots of firms announce earnings on planned-and-disclosed date, which suggests that earnings announcement dates are usually known in advance [21]. In contrast, merger announcements are usually unscheduled and abrupt. Uninformed investors can not predict when such announcement will be made until it becomes public information.

As a consequence, the amount of liquidity trading varies around these two types of announcements. Consider scheduled announcements first. Knowing that there is a high possibility of trading with informed traders, uninformed traders will participate less in the market, or in an extreme case, exit the stock market before such announcements is made [22]. Consequently, the amount of liquidity trading might decrease. A necessary condition for this to happen is that uninformed investors perceive a high level of information asymmetry and rationally expects that they might be ripped off by informed traders. This is more so for scheduled announcements than for unscheduled announcements, since uninformed traders knowingly expect lots of

[21] They also show that any delay in scheduled earnings announcements leads to significantly negative stock price reactions and economic losses for such firms.

[22] See Milgrom and Stokey (1982), Black (1986) and Wang (1994) for the famous no-trade theorem and its extension.

information will be released prior to scheduled announcements whereas he has no such expectation out of unscheduled announcements. In other words, before scheduled announcements, uninformed traders acknowledges the possibility that trading demand from informed traders and the adverse selection of trading might be high and hence, avoid unnecessary trading. In contrast, since uninformed traders can not predict when unscheduled announcements will take place, they will trade just as usual. An outcome of this scenario is that liquidity trading is much higher before unscheduled announcements than before scheduled announcements. Consistent with this argument, Chae (2005) finds a more than 15% decrease in cumulative trading volume before scheduled announcements and a steady increase before unscheduled announcements[23].

Now consider what happens to informed traders. Strategic trading models predict that insiders always want to hide their private-information trading among liquidity trading. Now that there will be thinner liquidity trading to sustain insider trading before scheduled announcements, insiders are less able to hide their trading before scheduled announcements than before unscheduled announcements. All else equal, they will choose to trade more heavily before unscheduled announcements for information reasons[24]. In contrast, if insiders trade solely for liquidity reasons, they will not need to hide themselves in the first place. Our hypothesis 1 formalizes this intuition.

Hypothesis 1: Insider trading before scheduled announcements is more likely to be liquidity-motivated rather than information-motivated than insider trading before unscheduled announcements, and hence, less profitable.

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[23] As further corroborative evidence, Chae (2005) also shows that over a cross section of stocks, decreases in trading volume before scheduled announcements are correlated with the extent of information asymmetry. In contrast, no such relation holds before unscheduled announcements.

[24] Other factors may also play a role when examining insider trading volume before these announcements. For example, litigation concern is one such factor. Huddart et. al. (2006) provides convincing evidence in this regard. We will discuss more about this in our Hypothesis 3.

Our second hypothesis is a direct corollary of Hypothesis 1. Now that more private information-based trading is expected before unscheduled announcements as compared to scheduled announcements, we would expect any measure that captures information asymmetry should be higher before unscheduled announcements. Relating this argument to the PIN as an information asymmetry measure in the sense of Easley et. al. (1996, 2002), our Hypothesis 2 is stated as follows.

Hypothesis 2: If PIN captures information asymmetry, PIN measure should be much higher before unscheduled announcements than before scheduled announcements[25].

Our third hypothesis examines insider trading volume. Note first that even if insider trades are more profitable before unscheduled announcements, insider trading volume may or may not be different across these two types of announcements. This is because many other factors can also affect insider trading volume around such events, among which litigation concerns resulting from federal regulation and corporate restrictions arguably have the most important effect. As shown by Bettis et. al. (2000), it is not uncommon that many companies have initiated and implemented restrictions that discourage or prohibit insiders from trading around major corporate events. Huddart et. al. (2006) also provides compelling evidence that insiders condition their trades on foreknowledge of price-relevant public disclosures and avoid profitable trades when jeopardy due to trade is high. In other words, insiders may avoid profitable trades before announcement events if the offsetting effect from litigation concerns is high enough. Taking this into account, we leave it an empirical question to determine whether there is difference in insider trading volume before schedule versus unscheduled announcements.

[25]We want to emphasize that Hypothesis 2 is, in essence, a joint hypothesis of PIN measure as an information asymmetry measure and informed trading before announcement events. The rejection of Hypothesis 2 can mean: either PIN does not capture information asymmetry in this case; or informed trading does not concentrate more before unscheduled announcements.

Hypothesis 3: Insider trading volume before scheduled announcements is not different from that before unscheduled announcements.

Our last hypothesis pertains to insider trading volume and profitability after scheduled/unscheduled announcements. Again we start by considering liquidity trading after such events. To the extent that discretionary liquidity traders' liquidity demands are exogenous and have to be satisfied eventually, the amount of liquidity trading should be much higher after scheduled announcements than after unscheduled announcements. This is because liquidity traders refrain from trading before scheduled announcements whereas they do not do so before unscheduled announcements. This could mean that better camouflages are available after scheduled announcements. On the other hand, information asymmetry associated with these announcements is largely resolved once these announcements are made public. Taking this into account, we may presume that much higher liquidity trading after scheduled announcements does not translate directly to higher profitability for insider trades after scheduled announcements. Similarly, insider trading volume may not differ across these two types of announcement events.

Hypothesis 4: Insider trading volume and profitability after scheduled announcements is not different from those after unscheduled announcements.

2.3 Data and Methodology

2.3.1 CRSP,I/B/E/S and SDC Data

The data used in this study come from five sources. From the Center for Research in Securities Prices (CRSP) we obtain the daily returns, daily trading volume and other supportive variables for both the announcement events and insider trades. I/B/E/S data from 1993-2005 are used for the earnings announcement dates. Reporting dates for quarterly earnings announcements are extracted from the I/B/E/S actuals file. After matching with other databases through CUSIP numbers, we are left with a total number of 289,099 earnings announcements dates for about 15,000 firms during this period. Acquisition and target announcements for NYSE, AMEX and NASDAQ stocks are collected from SDC plantium complied by Thomson Financial Securities Data. SDC's merger and acquisition database provides us with an initial number of 24,650 target announcements and 59,121 acquiror announcements from 1993-2005[26]. Since we need to estimate PIN around these announcement events, we further require that any two successive announcements events be at least 3 months apart. We are left with a total of 179,311 announcement events for 17,224 firms after imposing this restriction.

2.3.2 Insider Trading Data

Insider trading data are obtained from First Call/Thomson Financial Insider Research Services Historical Files. The insider trading records are the transactions of persons subject to the disclosure requirements of Section 16(a) of the Securities and Exchange Act of 1934 reported on Form 4 and 5[27]. Among the information required on Form 4 are: name and address of reporting address, issuer name and ticker or trading symbol, relationship of reporting person to the issuer (officers, directors or other positions held by the reporting persons in issuers), whether it is a purchase or sale, the transaction date, price, trade size. Since it has been documented that this database contains a number of data errors[28], we impose a number of filters to purge this database and obtain a clean version of insider trades. First, we require that trading records have a matching CUSIP with data available from CRSP. Second, we only focus on open market transactions in equity securities. Third, we require that any reported trades

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[26]In comparison, Chae (2005) obtain a total of 25,087 and 12,485 announcements for acquiror and target announcements respectively between 1986 and 2000.

[27]According the Securities and Exchange Act of 1934, the term "corporate insiders" refers to corporate officers, directors and large shareholders who own more than ten percent of the firms' stock. If insiders buy or sell their firms' stock, they are mandated to file with the Securities and Exchanges Commission (SEC) within the first 10 days of the next month after their transactions. Starting from August 29, 2002, insiders are required to report their trades within two business days.

[28]See Appendix A in Jeng et. al. (2003) for more details.

have a transaction price that is within daily price range as recorded in CRSP for the corresponding trading day. We also delete any trading records with transaction price less than 1 dollar and shares traded less than 100 shares. As suggested by Jeng et. al., we also purge duplicate transactions (i.e., those with identical entries in all categories). Finally, we only examine trades by top executives and officers and directors. Insider trades by large shareholders are excluded from our analysis[29].

2.3.3 PIN estimation

To estimate PIN measure, we make use of TAQ database available from NYSE. Each trade record in TAQ contains information on ticker symbol of the traded stocks, transaction price, trade size, trade time and the exchange on which the trade occurred. Each quote record in TAQ contains information on ticker symbol of the quoted stocks, bid/ask price, bid/ask depth, quote time and the exchange on which the quote occurred. The estimation of PIN measure requires each trade be signed as either buy-initiated or seller-initiated trades. We use Lee and Ready (1991) algorithm to achieve this purpose[30]. We require that all trades and quotes must take place between 9:30 AM and 4:00 PM. We also focus on trades and quotes that come from the exchange on which the stock is listed.

The PIN measure is a private information measure because it is a function of abnormal order flow. The underlying assumption is that public information is directly incorporated into prices without going through the trading process, whereas private information presumably should be reflected in excess buying or excess selling pressure (abnormal order flow). Not surprisingly, estimation of PIN measure requires detailed information on the structure of order flow. What follows is a brief summary

[29] Since our intent is to use corporate insiders as proxies for informed traders to analyze the trades motivated by private information, it is appropriate to exclude trades by entities that statue defines as insiders for the sole reason that the entity owns a block of ten percent or more of the corporation's stock. Aboody and Lev (2000), among others, also exclude those trades.

[30] Recently, there have been concerns about the misclassification issues of Lee and Ready (1991) algorithm.

of the model. Please refer to Easley and O'Hara (1992) for an extensive discussion of the structure of the model.

The model consists of three types of players: liquidity traders, informed traders and a market maker. The main assumptions are: all players are risk neutral; there are no transaction costs and there is no discounting by traders. Liquidity traders buy or sell shares for reasons that are exogeneous to the model. Suppose the daily arrival rates of noise traders that submit buy and sell orders are ε_b and ε_s respectively. The probability that an information event occurs is α, in which case the probability of bad news is δ and the probability of good news is 1-δ. If an information event occurs, the arrival rate of informed traders is μ. Informed traders submit a sell order if they get bad news and a buy order if they get good news. Thus, on a day with no information event with probability 1-α, the arrival rate of buy order will be ε_b and the arrival rate of sell order will be ε_s. On a day with a bad information event with probability α δ, the arrival rate of a buy order will be ε_b, and the arrival rate of sell order will be $\varepsilon_s + \mu$. On a day with a good information event with probability α (1-δ), the arrival rate of a buy order will be $\varepsilon_b + \mu$ and the arrival rate of a sell order will be ε_s. Let θ = { ε_s, ε_b, α, δ }. The likelihood function for a single trading day is given by:

$$L(\theta \mid B,S) = (1-\alpha)e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}e^{-(\varepsilon_s+\mu)}\frac{(\varepsilon_s+\mu)^S}{S!}$$

$$+\alpha(1-\delta)e^{-\varepsilon_b+\mu}\frac{(\varepsilon_b+\mu)^B}{B!}e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!}$$

Here, B is the number of buy orders and S is the number of sell orders in a single trading day. Using trading information over J days and assuming cross-trading-day independence, we can estimate the parameters of the model (ε_s, ε_b, α, δ) by maximizing the following likelihood function:

$$V = L(\theta \mid M) = \prod_{j=1}^{J} L(\theta \mid B_j, S_j)$$

Then, the probability of informed trading in a given stock for a given period, which determines the PIN measure, will be:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s}$$

Intuitively, PIN is low for stocks with less fluctuations of daily buy and sell orders. If a stock receives roughly balanced buy and sell orders from day to day, these orders are more likely to originate from investor's independent liquidity needs or liquidity trading. The law of large numbers will smooth out these orders and consequently the probability of information events is small. In comparison, for stocks that exhibit frequent large deviations from their normal order flows, PIN measure will be much higher. Also notice that in the above equation, PIN increases monotonically in α (the probability of an information event) and μ (the arrival rate of informed traders). We will discuss more about this in our empirical tests.

Since our research question aims at investigating information asymmetry around scheduled and unscheduled announcement events, we require that a minimum number of 20 trading days for PIN estimation. Also, 30 trading days centered around the announcement dates are used for both pre and post event period time windows. Maximization of the above likelihood function involves numerical optimization. For some announcement events, the numerical algorithm does not converge. In this case, we delete such announcement events from our sample. Summary statistics of these PIN estimates are provided in the following section.

2.4 Empirical Results

2.4.1 Liquidity Trading Around Scheduled Versus Unscheduled Announcements

Before we proceed to our main empirical results, we'd like to show that there is indeed a dispersion in the amount of liquidity trading around scheduled versus unscheduled announcements. This is critical to our analysis since our hypotheses about profitability of insider trades and information asymmetry stem from liquidity trading patterns associated with such events. We rely on two recent findings in the literature to prove that this is indeed the case. Firstly, using turnover as a measure for trading volume, Chae (2005) showed that the time series pattern of turnover before unscheduled announcements exhibits clear differences from the pattern before scheduled (earnings) announcements. Instead of the negative abnormal trading volume seen before scheduled announcements, he observed positive abnormal trading volume prior to unscheduled announcements.

Figure 2-1 provides a graphical summary of this striking difference in total trading volume around such announcement events.

The above graph can be quite misleading in that the above trading volume is the total trading volume around such events. In other words, it could include both informed trading and liquidity trading around these periods. Before this trading volume can be translated reliably to liquidity trading, we need to assess how much out of the trading volume is due to informed trading. Given that informed traders are hardly recognized in reality, this is almost impossible. However, we do observe the trading volume that comes from corporate insiders. This should at least give us a rough idea of the proportion of total trading volume accounted for by insider trading. As documented by Jeng et. al. (2003), over their sample period from 1975 to 1996, the average monthly ratio of value-weighted insider sales to all trades is 0.22 percent, whereas the average monthly ratio of insider purchases to all trades is 0.03 percent. Thus, an outsider making a purchase would expect 0.22 cents per dollar to have an insider as counterparty, whereas outsiders making sales would expect only 0.03 cents per dollar to be with insiders. Consequently, it is relatively safe to argue that trading volume contributed by corporate insiders account for a fairly small proportion of the total trading volume.

2.4.2 Profitability of Insider Trades

Having established that there is indeed time-varying liquidity trading around scheduled versus unscheduled announcements, we now turn to formal tests of the above four hypotheses. Our first hypothesis is mainly about the profitability of insider trades around such announcements. To the extent that corporate insiders trade more on their private information prior to unscheduled announcements than prior to scheduled announcements, insider trades before unscheduled announcements are more likely to be information-motivated than liquidity-motivated. Consequently, insider trades before unscheduled announcements are more profitable.

To examine the profitability of insider trades, it is critical to choose an appropriate time horizon over which to cumulate stock returns. In our analysis, we mainly use six months horizon. We measure returns over a six-month period for three reasons. First, six months is the shortest plausible trading horizon for an insider because Section 16(b) of the Securities and Exchange Act of 1934 stipulate that insiders must disgorge profits attributable to offsetting purchases and sales that occur within six months of each other. Second, several studies of US data find that abnormal returns extend for six or more months following insider trades. Thus, a return horizon of at least 6 months is indicated. Third, while the abnormal returns that follow insider trades can be detected 12 or more months after the trade, the price effect is greatest immediately after the trade and is quite small in months 9 through 12 (Seyhun, 1998, p48). This suggests computing return over a horizon much longer than six months may introduce noise into our profitability measure. Combined altogether, these facts suggest that six months is a reasonable period over which to measure profitability of insider trades[31]. Jeng (2003) and Huddart et. al. (2006), among others, also employ six-month horizon

[31]Results are similar and our conclusions are unaffected if returns are computed over 12 months.

to examine the profitability of insider trading.

2.4.3 Univariate Analysis

Table 2.1 provides the distribution of insider trades around such announcements. We examine three measures of insider trading activity: the number of trades, number of shares traded and value of shares traded. We use 30 calendar days to compute pre and post event insider trading activities[32]. One thing we immediately observe is that insider trading activity is more balanced around target and acquiror announcements as compared to earnings announcements. More specifically, the number of shares traded, total number of shares traded and total value of shared traded before target (acquiror) announcements all account for more than 40 (41) percent of the total insider trading activity around target (acquiror) events. In contrast, they only account for 18, 12 and 10 percent of total insider trading activity respectively around earnings announcements. Moreover, this pattern is persistent for both insider purchases and sales. We think this is consistent with the notion that insiders' trading activity is less concentrated before earnings announcements as compared to target and acquiror announcements.

Table 2.2 provides the mean market-adjusted returns over 6 months following trade dates. Panel A and Panel B of Table 2.2 computes the mean returns of insider trades over six months following the transaction dates. Returns are market-adjusted by subtracting the NYSE/AMEX/NASDAQ value-weighted index return from the raw returns. Several observations are in order. First, insider purchases, regardless of whether these purchases are conducted before or after the announcements, are always followed by positive returns. This is consistent with the notion that insiders tend to buy shares ahead of good news. Second, insider sales are followed by negative returns only when these sales are conducted before target and acquiror announcements. In contrast, insider sales are always followed by positive returns when these sales are

[32]The choice of 30 calendar days amounts to one month. We have also tried alternative definitions of pre and post event time window. Our conclusions are qualitatively the same.

conducted after the announcements of such events. While this finding is only partially consistent with the notion that insiders tend to sell shares ahead of bad news, several other researchers find the same pattern. Lakonishok and Lee (2001) also find that insider sales are not necessarily associated with low returns. Huddart et. al (2006) document that insiders sell after good news earnings announcements due to reasons such as litigation concerns. Aktas et. al. (2007) also find positive abnormal returns following insider sales[33].

More importantly, we notice that mean market-adjusted returns for insider purchases that are transacted before target and acquiror announcements, 8.37 percent and 6.84 percent respectively, are higher than that before earnings announcements, which is only 4.15 percent, whereas the mean market-adjusted returns for insider purchases that are conducted after target and acquiror announcements, 2.03 percent and 4.26 percent respectively, are lower than that after earnings announcements, which is 6.42 percent. This suggests that at transaction level, insider purchases, on average, are more profitable when they are conducted before unscheduled announcements than before scheduled ones. And this pattern reverses for insider purchases after such announcements. In contrast, insider sales that are conducted before target and acquiror announcements are followed by a negative return of 1.06 percent and 2.83 percent respectively, whereas insider sales before earnings announcements are followed by a positive return of 1.84 percent. To the extent that insiders avoid loss when their sales are followed by negative returns, insiders gain more by selling before target and acquiror announcements than by selling before earnings announcements. Formal statistical tests show that the difference in means is mostly statistically significant at 5 percent significance level. Thus, the most profitable purchases are insider purchases before target and acquiror announcements, followed by insider purchases after

[33]There are at lease two reasons why insider sales are followed by positive abnormal returns. First, insider sells are likely to be driven by other motives such as diversification and liquidity reasons rather than private information. See Lakonishok and Lee (2001), Jeng et. al. (2003) and Fidrmuc et. al. (2006) for more details. Second, insiders can have market timing ability, as shown in Jenter (2005) and Piotroski and Roulstone (2005).

earnings announcements. Insider purchases before earnings announcements and after unscheduled announcements are the least profitable trades, even though they are still followed by positive returns. In contrast, the most profitable sales are those conducted before target and acquiror announcements. On a semi-annual basis, insiders gain an additional 4.2 (2.9) percent of market-adjusted returns from purchasing (selling) before target announcements as compared to purchasing (selling) before earnings announcements.

The above trade and return data are consistent with our main hypotheses: insider trades are more profitable before unscheduled announcements than before scheduled announcements. However, this univariate analysis suffers from several limitations. First, there are overlapping trades around scheduled versus unscheduled announcements. That is, some trades are classified as both trades around scheduled and unscheduled announcements. However, Panel B of Table 2.2 shows that this actually does not change our main findings. When non-overlapping trades are allowed, the results, if any changes, are actually stronger. Second, the transaction data are not independent. It is often the case that there are multiple trades per firm. Moreover, firms attributes (e.g., risk, firm size) related to these announcements may affect the documented returns, in addition to the hypothesized difference in insider trading strategies around such events. Accordingly, the return data in Table 2.2 should be viewed as descriptive and tentative. In the following section, we proceed to multivariate analysis to further investigate the cause of the difference in insider trading profitability.

2.4.4 Cross-Sectional Multivariate Analysis

We first examine whether the profitability of insider trades depends on the timing of such trades after controlling for certain firm and trade characteristics. The literature has documented a number of such characteristics that can affect the profitability of insider trades. First, insider trades in smaller firms are often more profitable than those in large firms (Seyhun (1998) etc.). To control for this size effect, we include market capitalization around the time insider trades in our analysis. Second, Rozeff and Zaman (1998) document past returns are associated with the direction of insider trading activity and its profitability. They find that the proportion of buying transactions in insider trades is negatively related to prior stock returns. Taking this into account, we include the raw buy and hold return cumulated over a six-month period up to the transaction dates, PreRet6. Third, trading volume prior to insider trades might also provide camouflages for their trades (Kyle 1985, Admati and Pfleiderer (1988) etc) in addition to the timing of their trades. For this purpose, we include the standard deviation of daily trading volume, scaled by total shares outstanding, over a six-month period up to the transaction dates, StdVol. Our cross-sectional transactional level regression specification is as follows:

$$Abret_i = \beta_0 + \beta_1 SrcIdx_i + \beta_2 LnMV_i + \beta_3 StdVol_i + \beta_4 PreRet6 + \varepsilon_i$$

where SrcIdx is an indicator variable that takes a value of 1 if the trade takes place around unscheduled announcements and 0 otherwise; LnMV is the natural log of the market value prior to the insider trades; PreRet6 is the raw buy-and-hold return over a six-month period up to the transaction dates; StdVol is the standard deviation of daily trading volume, scaled by total shares outstanding over a six-month period up to the transaction dates.

Separate regressions are run conditional on the type of insider trades (purchases or sales) and timing of insider trades (before and after scheduled versus unscheduled announcements). Our predictions are that, controlling for other firm and trade characteristics that are known to affect the profitability of insider trades, slope coefficient estimates before the above indicator variables should be statistically significant.

Table 2.3 provides the results for the above regressions. As we can see clearly from the table, slope coefficient estimates before firm size variable are always negative and statistically significant for insider purchases. In contrast, they are positive and usually statistically insignificant for insider sales. This is consistent with Seyhun (1998)'s findings, among others, that smaller firms tend to be subject to higher level of information asymmetry and hence insider trades in small firms are usually more profitable. We also notice that the slope coefficient estimates before the scaled trading volume variable are negative and statistically significant for insider sales. While they are always positive, they are only statistically significant for insider purchases that are conducted before the announcements. This suggests that insider purchases earn higher market-adjusted returns when these trades are conducted at times when the variation of liquidity trading increases, and hence, provides better camouflages. We interpret this evidence as consistent with the predictions of strategic trading models.

To examine whether the timing of trades matters for the profitability of insider trades, we find that the the majority of the slope coefficient estimates before the indicator variables are statistically significant and the magnitude of these slope coefficient estimates are very close to the return differences in Table 2.2. For example, insider purchases before acquiror announcements, on average, earns an extra return of 2.7 percent as compared to those before earnings announcements, which is close to 2.69 percent as indicated in Table 2.2. Insider purchases after acquiror announcements, on the other hand, on average, earns an extra return of negative 2.17 percent, which is also close to negative 2.1 percent in the univariate case. In addition, the statistical significance is quantitatively the same after controlling those firm and trade characteristics that have been documented to affect insider trade profitability.

2.4.5 Time-Series Multivariate Analysis

We also wish to examine the association between the profitability of insider trades around scheduled and unscheduled announcements and other risk factors. To accomplish this we construct several monthly portfolio conditional on the timing of the insider trades and the type of insiders' transaction (purchase or sale). These portfolios are: (1) $PreEarn_p$ for insider purchases that are conducted before earnings announcements; (2) $PostEarn_p$ for insider purchases that are conducted after earnings announcements; (3)$PreTarget_p$, $PreAcq_p$ for insider purchases that are conducted before target and acquiror announcements; (4) $PostTarget_p$, $PostAcq_p$ for insider purchases that are conducted after target and acquiror announcements. Similarly, $PreEarn_s$, $PostEarn_s$, $PreTarget_s$, $PreAcq_s$, $PostTarget_s$ and $PostAcq_s$ are constructed for insider sales around such announcement events.

We calculate returns for each of the above portfolios as follows. For each calendar month (January 1993 through December 2005), we compute firm-specific mean raw returns over a six-month period following the transaction dates of insider trades that are defined as pre and post event trades. These firm-specific mean six-month-period returns are averages over all the individual insider trades that occurred during the month. We then compute calendar-time equally weighted portfolio returns over all the firms with insider trades in a given month, defined as the pre and post event trades in the above. We thus focus on the portfolio returns conditional on the timing of insider trades around such announcement events.

To examine the extent to which the profitability of insider trades differ conditional on the timing of these trades, we employ an intercept test using the Fama-French model augmented with the well-documented momentum factor (MOM). The dependent variable is the difference between the calendar-time portfolio returns of insider trades conditional on the timing of such trades around scheduled and unscheduled announcements ($PreTarget_{pt}$ -$PreEarn_{pt}$ and $PreAcq_{pt}$ - $PreEarn_{pt}$ for insider purchases and $PreTarget_{st}$ - $PreEarn_{st}$ and $PreAcq_{st}$ - $PreEarn_{st}$ for insider sales). The independent variables are the four factors: market return, size, book to market and momentum factor. The regression equation is as follows. Similar regressions are run for portfolios formed conditional on insider trades around acquiror and earnings announcements.

$$PreTarget_{pt} - PreEarn_{pt} = \alpha_p + \beta_p (R_{mt} - R_{ft}) + \delta_p SMB_t + \sigma_p HML_t + \lambda_p MOM_t + \varepsilon_p$$

$$PreTarget_{st} - PreEarn_{st} = \alpha_s + \beta_s (R_{mt} - R_{ft}) + \delta_s SMB_t + \sigma_s HML_t + \lambda_s MOM_t + \varepsilon_s$$

Panel A of Table 2.3 provides the univariate raw returns of the constructed portfolios. Notice that these returns are raw returns instead of market-adjusted returns. As hypothesized above, the mean returns of the portfolios of firms that have insider purchases prior to target (acquiror) announcements are significantly higher than returns for portfolios of firms that have insider purchases prior to earnings announcements. Investing long in the target (acquiror) portfolio and short in the earnings portfolio yields a mean excess return of 7.55 (3.07) percent over a six-month period. What is different from the transaction level return is that this pattern persists after the announcement events. On average, PostEarn_p continues to earn a lower return than PostTarget_p and PostAcq_p, even though the return differences become statistically insignificant. Looking at insider sales, the return difference between portfolios formed conditional on insider sales around scheduled and unscheduled announcements becomes statistically insignificant. Combined together, this suggests that insider purchases are more informative than insider sales around such events. And the timing of insider purchases also matters for portfolio performances.

Panel B and C of Table 2.3 presents estimates from Fama-French four-factor model for the above two equations. As hypothesized above, the estimated intercept from time-series regressions of the difference in returns between target portfolios and earnings portfolios is statistically significant with a p-value of 0.02. And the estimated intercepts (8 percent) are close to the univariate returns in Panel A (7.55 percent). In contrast, the intercept estimate from the time-series regressions of the differences in returns between acquiror and earnings portfolios is only marginally significant with a p-value of 0.12, even though the magnitude of such return difference preserves the positive sign. Overall, this portfolio approach renders us less significant results. Nonetheless, insider purchase before target announcements indeed yield much higher returns than those before earnings announcements even at portfolio level.

To sum up our main findings, we find that insider purchases before target announcements earn much higher returns than insider purchases before earnings announcements. And this much higher return is robust to firm and trade characteristics and risk factors.

2.4.6 Information Asymmetry around scheduled versus unscheduled announcements

Our previous analysis shows that insider purchases prior to unscheduled announcements are more profitable than those prior to earnings announcements. A direct corollary is that if insiders trade more heavily and profitably before unscheduled announcements than before earnings announcements, this relative concentration of informed trading should be inferred from the trading process. After all, private information only gets incorporated when informed traders execute their trades. In this sense, our second hypothesis provides a supplementary test as to whether insiders actually exploit their private information conditional on the time-varying liquidity trading.

Table 2.5 reports the mean and median PIN estimates obtained from maximizing the above equation (2) and (3). A 30-day event window is used to define pre and post event periods. The choice of this time window is based on early findings about the information leakage in the literature. Keown and Pinkerton (1981), Dennis and McConnell (1986) and Melbroek (1992) use a window covering the period from 20 days before the announcement dates to one day before the announcement date. In contrast, Jabbour et. al. (2000) find insider trading occurring 45 to 60 days before the announcement dates. To the extent that we want to have enough number of trading days between consecutive earnings announcement dates for numerical optimization and convergence and also account for the fact that information leakage occurs primarily from -1 to - 45 days, we choose 30-day time window[34]. Estimating PIN requires the daily number of buys and sells for each event period. To obtain this statistic, we employ Lee and Ready (1991) algorithm to sign each eligible trade for each trading day in the subject event period. As we can see from Table 2.5, on average,

[34]Our results are qualitatively the same for an alternative 45-day time window.

PIN estimates ranges from 23 percent to 26 percent. This is very close to what others have obtained using similar or longer time window. We also notice that mean PIN estimates are a little higher before earnings and acquiror announcements than after. This is consistent with the notion that information asymmetry is higher before such events are made public. However, we also find that mean PIN estimates are much higher after target announcements than before such announcements. Though this result itself is puzzling, our finding is consistent with Aktas et. al (2007). These authors also find that PIN dropped before merger and acquisition announcements and increased after the information release[35].

Turning to Hypothesis 2, we notice that mean PIN estimates before target and acquiror announcements are always higher than those before earnings announcements. And these differences are always statistically significant at one percent significance level. Also the median of PIN estimates also have the same pattern. In untabulated tables, the differences in median are also significant. Interestingly, the mean and median of PIN estimates after target and acquiror announcements are also significantly higher than those after earnings announcements. Overall, this suggests that information asymmetry as captured by PIN is always higher around unscheduled announcements than around scheduled announcements.

2.4.7 Trading Volume

Our last two hypotheses are related to insider trading volume around scheduled and unscheduled announcements. After all, if insiders time their trades around such events, insider trading volume is indispensable in addition to the profitability of their trades. Table 2.1 in the above only provides summary statistics for three measures of insider trading activities. While insider trading activities are shown to be more intense and concentrated around unscheduled announcements, the evidence in Table 2.1 is far

[35]They offered two plausible reasons. First, PIN only considers the number of buys and sells. It does not consider the number of shares involved in a given transaction or the value of the transaction. Second, PIN might also incorporate public information instead of private information only.

from conclusive. We now turn to formal statistical tests of insider trading volume.

To examine insider trading volume around announcement events, it is important to notice many factors may also play a role in determining how much insiders want to trade around such announcements, even though such trades are quite profitable. There are at least two factors that can affect insiders' desire to trade around material corporate announcement events. First, corporate restrictions and regulations prohibit insiders from trading in blackout periods. Bettis et. al. (2000) shows that such blackout periods successfully suppress trading by insiders and narrow bid-ask spread. The only exception to such blackout periods is the open trading window during the period three through 12 trading days after quarterly earnings announcements. Second, insiders have litigation risk and litigation concerns. Huddart et. al. (2006) argues that since insiders have discretion over whether and how much to trade, they tend to avoid risks stemming from jeopardies established by past regulatory actions, shareholder class-action suits and adverse publicity.

To accommodate these factors and make insider trading volume comparable around earnings and target (acquiror) announcements, we examine abnormal insider trading volume defined over a different set of time windows around announcement events. Abnormal trading volume has been widely used in the literature as an indication of information leakage to control for other factors that affect normal trading volume in previous studies (Keown et. al. (1992), Meulbroek (1992)). To compute abnormal trading volume, the mean trading volume over some estimation window is usually subtracted from the trading volume in the event window. Similarly, we define four time intervals around each announcement, with the closest one being the event window and the three further ones being the estimation window. We subtract mean trading volume over the estimation windows from the trading volume in the event window to obtain our measure of abnormal trading volume. Also since we want to capture insider trading volume as a proportion of the daily stock trading volume to examine insider trading volume around major events, we define trading volume to be the shares traded by insiders divided by the daily share trading volume for that stock.

Table 2.6 presents the computed mean abnormal trading volume around earnings and target (acquiror) announcements. Notice that these numbers are pretty small since they are measuring insider trading volume as a proportion of daily trading volume. As we can see clearly, the abnormal trading volume prior to all announcements are negative, which suggests that the closer it gets to the announcements, the less insider trades. We think this is consistent with the litigation risk hypothesis. After all, any immediate insider trades right before the announcement dates suffer more from adverse publicity and presumably, litigation risk for such trades are higher. Interestingly, abnormal trading volume increases substantially and become positive for earnings announcements, even though it remains negative for target and acquiror announcements. While this is consistent with Huddart et. al.(2007), among others, who find that insiders trade aggressively after earnings announcements, we think there are many plausible explanations. As suggested by Bettis et. al. (2000), many corporate insiders are essentially disallowed to trade except during the period three to 12 trading days after the earnings announcement dates. However, we want to point out that over all the different definition of event window, abnormal trading volume is always higher before unscheduled announcements than before earnings announcements. More importantly, this pattern is reversed after these announcements are made. Combined with the descriptive statistics provided in Table 2.1, we believe this constitutes strong evidence that insiders trade more heavily before unscheduled announcements and after earnings announcements.

2.5 Conclusions

This paper provides direct empirical evidence that insiders trade more aggressively and profitably around certain corporate announcements than around others. We find that insiders trade more heavily before unscheduled corporate announcements as compared to scheduled announcements. Moreover, insider trades before unscheduled announcements are much more profitable than those before scheduled announcements.

This evidence clearly suggests that corporate insiders time their trades around material corporate information events based on the amount of liquidity trading available to camouflage their trades. We argue that the striking differences between the amount of liquidity trading available to camouflage their trades, as predicted by the strategic trading models, can be used to explain this findings.

Figure 2-1 Cumulative Abnormal Volume Around Announcement Events

This figure plots the cumulative abnormal volume from t = -15 to t = 15 around scheduled and unscheduled announcement events. For each announcement, the benchmark average log turnover is computed from t = - 40 to t = -11 days, where turnover is defined as daily trading volume scaled by shares outstanding.

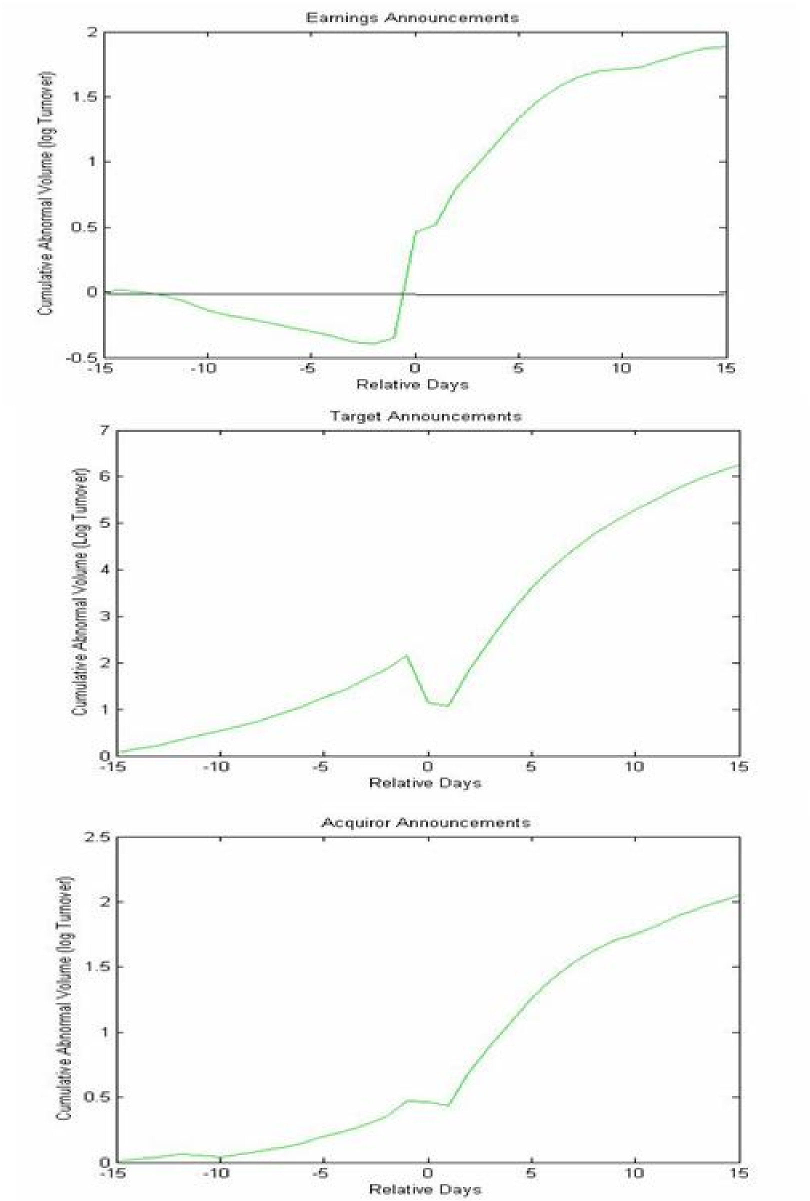

Table 2.1 Distribution of Insider Trades Jan 1993 - Dec 2005

This table presents aggregate insider trading data around earnings, target and acquiror announcements. Number of trades, number of shares traded and dollar value of shares traded by corporate insiders are provided in Panel A, Pane B and Panel C respectively for both pre and post event periods.

	Earnings		Target		Acquiror	
	Pre	Post	Pre	Post	Pre	Post
Panel A. Number of Trades						
No. of Purchases	9447	37882	3624	4051	4797	6866
No. of Sales	49373	237662	13431	18213	25034	35587
Total No. of Trades	58820	275504	17055	22264	29831	42453
Panel B. Number of Shares Traded						
No. of Shares purchased (MM)	77.2	258.0	34.2	33.1	24.5	43.4
No. of Shares sold (MM)	372.4	3009.0	142.4	229.0	305.1	359.9
Total No. of shares traded (MM)	449.6	3267.0	176.6	262.1	329.6	403.3
Panel C. Dollar Value of Shares Traded						
Val. of shares purchased (MM$)	1056.2	3358.2	488.9	569.7	389.3	620.2
Val. of shares sold (MM$)	12055.7	114600.5	5394.1	8106.8	11220.9	13830.7
Val. of shares traded (MM$)	13111.9	117958.7	5883.0	8676.5	11610.2	14450.9

Table 2.2 Average Market-Adjusted Returns of Insider Trades

This table presents the average market-adjusted returns for insider purchases and sales over the 6 months following the transaction date. Panel A allows for overlapping trades between scheduled and unscheduled announcements. In Panel B there are no such overlapping trades. Market-adjusted returns are the raw returns minus the return on a value-weighted NYSE/AMEX/NASDAQ index. ***, ** and * denote that means or the differences in means are statistically significant at 1, 5 and 10 percent level respectively.

Panel A. Overlapping Trades				
	Insider Purchases		Insider Sales	
	Pre	Post	Pre	Post
Earnings Announcements	4.15%***	6.42%***	1.84%***	0.24%***
Target Announcements	8.37%***	2.03%***	-1.06%***	0.42%***
Acquiror Announcements	6.84%***	4.26%***	-2.83%***	1.57%***
Target minus Earnings	4.22%***	-4.39%***	-2.90%***	0.18%***
Acquiror minus Earnings	2.69%***	-2.17%***	-4.68%***	1.33%***
Panel B. Non-Overlapping Trades				
	Insider Purchases		Insider Sales	
	Pre	Post	Pre	Post
Earnings Announcements	4.35%***	6.70%***	1.86%***	0.27%***
Target Announcements	9.39%***	3.80%***	-2.91%***	2.00%***
Acquiror Announcements	7.30%***	3.80%***	-2.91%***	2.00%***
Target minus Earnings	5.04%***	-2.89%***	-3.02%***	0.76%**
Acquiror minus Earnings	2.95%**	-2.90%***	-4.77%***	1.73%***

Table 2.3 Transaction-level Return Regression Controlling for Firm and Trade Characteristics

This table presents the empirical results for the following regression specifications:

$$Abret_i = \beta_0 + \beta_1 SrcIdx_i + \beta_2 LnMV_i + \beta_3 StdVol_i + \beta_4 PreRet6_i + \varepsilon_i$$

Separate regressions are run conditional on the type of insider transactions (insider purchases/sales) and the timing of insider trades (before/after scheduled and unscheduled announcements). SrcIdx is an indicator variable that takes a value of 1 if the trade takes place around unscheduled announcements and 0 otherwise; LnMV is the natural log of market value prior to the insider trades; PreRet6 is the raw buy-and-hold return over a six-month period over to the transaction dates; StdVol is the standard deviation of daily trading volume, scaled by total shares outstanding, over a six-month period up to the transaction dates. Panel A compares trades around earnings and target announcements; Panel B compares trades around acquiror and earnings announcements. Robust standard errors are obtained from GMM estimates and p-values are reported in parentheses.

Panel A. Comparing Target and Earnings Trades					
	β_0	β_1	β_2	β_3	β_4
Pre-Event Purchases	0.253 (<.001)	0.031 (.003)	-0.019 (<.001)	0.004 (<.001)	0.006 (.729)
Post-Event Purchases	0.325 (<.001)	-0.039 (<.001)	-0.021 (<.001)	0.000 (<.001)	0.023 (.002)
Pre-Event Sales	-0.058 (<.001)	-0.032 (<.001)	0.005 (<.001)	-0.001 (<.001)	0.047 (<.001)
Post-Event Sales	0.004 (0.596)	0.002 (0.322)	0.000 (0.882)	-0.001 (<.001)	0.025 (<.001)
Panel B. Comparing Acquiror and Earnings Trades					
	β_0	β_1	β_2	β_3	β_4
Pre-Event Purchases	0.199 (<.001)	0.027 (.002)	-0.014 (<.001)	0.003 (<.001)	0.019 (0.292)
Post-Event Purchases	0.295 (<.001)	-0.021 (0.001)	-0.019 (<.001)	0.000 (0.269)	0.009 (.230)
Pre-Event Sales	0.013 (0.280)	-0.049 (<.001)	0.001 (0.276)	-0.001 (<.001)	0.019 (<.001)
Post-Event Sales	-0.001 (.927)	0.013 (<.001)	0.000 (.440)	-0.001 (<.001)	0.019 (<.001)

Table 2.4 Portfolio Returns from Going Long on Insider Trading Around Unscheduled Announcements and Short Around Scheduled Announcements

This table presents mean percentage raw returns earned on portfolios formed as follows: For each month between January 1993 and December 2005 we calculate, for each sample firm, the mean six-month raw returns following the transaction dates over all insider transactions during the month. We calculate the mean returns separately for firms that have insider trades around earnings, target and acquiror announcements. In Panel B and C, the intercept (alpha) of the augmented Fama French four-factor model in equation (5) is presented. It is the estimated intercept from a time-series regression of the portfolio returns formed in the above on the market excess return, size, book-to-market and momentum factors. P-Values are reported in parentheses.

Panel A. Univariate Portfolio Returns				
	Insider Purchases		Insider Sales	
	Pre	Post	Pre	Post
Earnings Portfolio	10.53% (<.001)	9.93% (<.001)	5.11% (0.02)	4.44% (0.002)
Target Portfolio	18.08% (<.001)	13.78% (<.001)	6.08% (0.02)	5.70% (<.001)
Acquiror Portfolio	13.60% (<.001)	10.59% (<.001)	5.54% (0.001)	5.81% (<.001)
Target minus Earnings	7.75% (<.001)	3.85% (0.124)	0.97% (0.871)	1.26% (0.431)
Acquiror minus Earnings	3.07% (<.001)	0.66% (0.124)	0.43% (0.001)	1.37% (<.001)

Panel B. Four Factor Model: Pre Event Portfolios						
	Intercept	R_{mt} - R_{ft}	SMB_t	HML_t	MOM_t	Adj. R^2
$PreTarget_p$ - $PreEarn_p$	0.080 (0.020)	-0.292 (0.702)	1.653 (0.089)	0.888 (0.263)	-0.244 (0.711)	0.03
$PreAcq_p$ - $PreEarn_p$	0.035 (0.118)	-0.779 (0.110)	0.124 (0.841)	0.176 (0.729)	0.162 (0.694)	0.03
$PreTarget_s$ - $PreEarn_s$	0.013 (0.616)	0.395 (0.490)	0.389 (0.590)	-0.119 0.846)	-0.737 (0.134)	0.03
$PreAcq_s$ - $PreEarn_s$	0.010 (0.701)	0.139 (0.812)	0.295 0.690)	0.428 (0.497)	-0.762 (0.132)	0.03

Panel C. Four Factor Model: Post Event Portfolios						
$PostTarget_p$ - $PostEarn_p$	0.031 (0.154)	0.135 (0.778)	1.186 (0.054)	1.097 (0.036)	-0.407 (0.324)	0.032
$PostAcq_p$ - $PostEarn_p$	0.000 (0.992)	-0.165 (0.624)	0.303 0.476)	-0.077 (0.832)	0.187 (0.517)	0.015
$PostTarget_s$ - $PostEarn_s$	0.016 (0.257)	0.040 (0.899)	-0.065 (0.872)	-0.144 0.676)	-0.349 (0.202)	0.015
$PostAcq_s$ - $PostEarn_s$	0.022 (0.111)	-0.492 (0.117)	0.417 0.288)	-0.312 0.346)	-0.592 0.027)	0.017

Table 2.5 Probability of Informed trading around scheduled and unscheduled announcements

This table presents the mean and median of PIN estimates around earnings, target and acquirer announcements. A 30-day event window is used to define pre and post event period. To obtain these estimates, likelihood function as indicated in equation (2) is maximized using numerical algorithm. Lee and Ready (1991) is used to sign each eligible trades for each of the event period. The bottom two rows report the difference between these mean estimates.

	Pre		Post	
	Mean	Median	Mean	Median
Earnings Announcements	0.234	0.206	0.231	0.203
Target Announcements	0.252	0.222	0.261	0.227
Acquiror Announcements	0.241	0.209	0.239	0.206
Target minus Earnings	0.018 (<.001)		0.030 (<.001)	
Acquiror minus Earnings	0.007 (<.001)		0.008 (<.001)	

Table 2.6 Abnormal trading volume around scheduled and unscheduled announcements

This table presents mean abnormal trading volume around earnings, target and acquirer announcements. Panel A, B, C provides abnormal trading volume over a 30-day, 21-day, 14-day event period respectively. To compute abnormal trading volume, subtract the mean trading volume over the 3 further estimation windows from the mean trading volume over the event window. The bottom two rows report the difference between these mean estimates. P-values, based on robust standard errors obtained from GMM estimates, are reported in parentheses.

Panel A: Abnormal Trading Volume: 30-day Event Window		
	Pre	Post
Earnings Announcements	-0.0124	0.0045
Target Announcements	-0.0060	-0.0021
Acquiror Announcements	-0.0062	-0.0027
Target minus Earnings	0.006 (<.001)	-0.0067 (<.001)
Acquiror minus Earnings	0.0062 (<.001)	-0.0072 (<.001)
Panel B: Abnormal Trading Volume: 21-day Event Window		
	Pre	Post
Earnings Announcements	-0.0118	0.0055
Target Announcements	-0.0041	-0.0011
Acquiror Announcements	-0.0048	-0.0017
Target minus Earnings	0.008 (<.001)	-0.0066 (<.001)
Acquiror minus Earnings	0.007 (<.001)	-0.0072 (<.001)
Panel C: Abnormal Trading Volume: 14-day Event Window		
	Pre	Post
Earnings Announcements	-0.0055	0.0019
Target Announcements	-0.0021	-0.0012
Acquiror Announcements	-0.0033	-0.0012
Target minus Earnings	0.0034 (<.001)	-0.003 (<.001)
Acquiror minus Earnings	0.0022 (<.001)	-0.0031 (<.001)

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Chapter 3 Informed Option Trading Around Merger Announcements

3.1 Introduction

This paper studies informed trading in options markets around merger announcements. It is motivated by the following three considerations.

The first consideration stems from the usefulness of the options market as a setting where informed trading can be better examined as compared to stock market. Existing literature has documented significant pre-takeover stock price runup on target stocks. Both illegal insider trading hypothesis and market anticipation hypothesis have been proposed to explain the price runup. While much has been done to investigate how to disentangle these two alternative hypotheses using anomalous stock returns and trading volume, less has been devoted to the options market to examine how anomalous option trading can help detect illegal insider trading. My paper makes the first attempt to bridge the gap. I argue that the options market provides an ideal setting to investigate informed trading for a number of reasons. First, while private information about the target stock is the same, the options market provides a whole package of instruments, i.e., options with different strike prices and maturities. In comparison, the stock market only provides one stock for informed traders to trade. Moreover, different option instruments with the same underlying are usually associated with different liquidity and leverage characteristics. This will certainly allow us to examine informed traders' trading strategies in greater depth and help increase our chances of recognizing informed trading ex post. Second, options provide higher leverage than stocks. Astute investors are more likely to use highly-levered options to utilize their private information; third, pre-takeover stock trading can be motivated by a variety of reasons such as media expectation, bidders' toehold strategies, event arbitrageurs and private information (Jarrell and Poulsen (1989)), whereas pre-takeover option trading is less subject to such different trading motives. Higher leverage and lower liquidity associated with the options market makes options speculative vehicle in nature. Merger announcement simply magnify this effect.

The second consideration is related to the information event nature of merger announcements. I argue that merger announcements constitute the most natural events to study informed trading in options market for at lease three reasons. First, mergers often involve a change of corporate control and are usually associated with large and immediately realizable price premiums. Private information about merger deals is often material and potential awards from utilizing it are substantial[36]; second, neither the timing nor the magnitude of merger announcement is public information; third, extant literature has documented that illegal insider trading seems to be predominantly occurring in merger deals. In all, merger announcements present the most plausible setting where I can thoroughly examine how information and price are discovered through option trading around such events.

My last consideration is motivated by the perceived increase in illegal insider trading around merger deals. This paper comes at a time when there is growing concern about whether illegal insider trading in merger deals has increased or not in recent years. Anecdotal evidence suggests that this might be the case. For instance, *Financial Times* reports that suspicious trading ahead of US mergers and acquisitions has risen four-fold in the past five years. Almost 60 percent of the 27 big merger deals announced in North America in 2006 were preceded by unexplained spikes in trading in the stock of the target company. As a matter of fact, the United States Senate Committee on Judiciary have held two hearings on Sept. 26, 2006 and Dec. 5, 2006 respectively to discuss how widespread illegal insider trading is and whether there is adequate

[36]On average, announcement returns are about 18 percent in my merger sample. Notice these abnormal returns accrue within only two days.

enforcement against such illegal trading, especially considering the fact that hedge funds are becomingly increasingly involved in insider trading [37]. As documented by Meulbroek (1992), about 80 percent of the illegal insider trading in her sample is related to takeover transactions. Thus, investigation of insider trading around merger announcements certainly captures a fairly large part of illegal insider trading and hence helps inform regulators.

Using a broad sample of merger announcements, I find that there is abnormal option trading prior to such announcements after controlling for merger characteristics. This abnormal option trading is mainly concentrated in short-term and at-the-money options. Trading volume in these options leads stock market order imbalances and strongly contributes to the pre-takeover stock price runup. Implied volatility spread[38] calculated from these options is strongly positively associated with the abnormal option volume. Finally, I also investigate whether option trading volume can be used to predict takeover targets. I find strong predictive power of option volume for takeover targets.

My paper is closely related to two separate brands of literature. First, the literature about the information content of option trading volume. Finance literature has established that option prices lead stock prices and option trading volume conveys information about future stock price movements (Manaster and Rendleman (1982), Easley, O'Hara and Srinivas (1998), Cao, Chen and Griffin (2005), Chakravarty and Mayhew (2005), Schlag and Stoll (2005), Pan and Poteshman (2006)). Unfortunately, existing studies have predominantly focused on regular times. Few papers have investigated informed trading in option market prior to significant information events such as merger announcements. Chakravarty et. al. (2004) find that on average option

[37] For information about these two hearings see http://judiciary.senate.gov/hearing.cfm?id=2405 and http://judiciary.senate.gov/hearing.cfm?id=2437.

[38] Implied volatility spread is defined as call implied volatility minus put implied volatility. It has been used an empirical proxy to capture the pricing pressure of calls relative to puts. I will dwell on its motivation and usage in my context in the empirical section.

market's contribution to price discovery is about 17 percent in the sense of Hasbrouck (1995). However, their analysis is based on 60 most actively traded stock options from 1988-1992 at regular times. I suspect the level of price discovery will probably increase for option trading immediately prior to merger announcements. Similarly, Easley at. al (1998), Pan and Poteshman (2006) also find that their constructed option trading volume measure (positive versus negative volume in Easley et. al. and put-call ratios in Pan and Poteshman) predicts future stock returns at regular times. However, none of them cast their research questions around significant information events.

Perhaps the only exception is Cao, Chen and Griffin (2005). They find that ahead of takeover announcements, the option market plays an important role in information revelation, whereas during normal market times, the stock market is the primary place of price discovery. My paper resembles their paper in that I also study option trading around merger announcements. However, my paper differs from theirs in two important aspects: first, I show that cross-sectionally, abnormal option trading volume immediately prior to takeover announcements is strongly positively associated with implied volatility spread, which I motivate as relative pricing of calls and puts. This association is especially strong for short-term and at-the-money (ATM) options. That is to say, short-term and ATM call options are becoming more and more expensive and experience the largest increase in trading volume simultaneously. I interpret this as strong evidence that price effect and volume effect are unified under the common roof of informed trading for these options. Second, I investigate directly whether option volume leads stock volume immediately before merger announcements. I show that relative option volume has strong predictive power on next-day stock market order imbalances. A one standard deviation increase in relative option volume leads to about 0.015 standard deviation increase in next-day stock market order imbalance. More interestingly, I show that this predictive power is especially strong for those mergers that have experienced accumulated implied volatility spread.

My paper also contributes to the M & A literature in two important aspects. First, my paper examines the implications of option trading on stock price runup. Using a novel control for market anticipations, I show for the first time that abnormal option trading volume strongly contributes to the pre-takeover stock price runup in a cross-section of merger announcements. Thus, not only merger announcements affect how informed traders trade options, but also option trading shapes merger deals in return. Second, using a fairly large sample of 3,878 firms in an 11-year period, I estimate a hazard model that forecasts takeover targets using option trading volume as a predictor. The estimation result shows that option trading volume has strong predictive power on takeover targets even after controlling for a broad set of time-varying covariates. Thus, what happens in the options market can actually be used to predict whether firms will be acquired or not. This certainly has important implications for both practitioners and researchers.

The rest of the paper is organized as follows. In section 2 I develop the main empirical hypotheses. Section 3 describes data sources for this study. I discuss the main results of empirical tests in Section 4. Section 5 concludes.

3.2 Hypothesis Development

Option trading can be motivated by a number of reasons. Absent significant information events, liquidity reasons such as hedging and portfolio diversification might be the most common reason why both informed and uninformed traders trade options. In contrast, in the presence of large and significant information events, information reasons might be the driving force for option trading around such events. Option market is also the main venue for volatility information trading since traders with volatility information can only use non-linear securities such as options if they learn that stock price will change but they are not sure whether stock price will go up or go down[39]. In this section I intend to provide more background discussion on how

[39]An incomplete list of volatility trading literature includes: Whaley (1993), Chakravarty, Gulen and Mayhew (2004), Blasco, Corredor and Santamaria (2006), Ni, Pan and Poteshman (2006).

these different trading motives shape option trading in the context of merger announcements and formally derive my main hypotheses.

Hypothesis 1: There is abnormal option trading volume in target stocks immediately prior to merger announcements.

My first research question is: immediately before merger announcements, is there abnormal trading volume in options for target stocks? Motivation for this question is very simple. As mentioned in the introduction, existing literature (Easley et. al. (1998), Chakravarty et. al. (2004), Pan and Poteshman (2006) etc.) has documented that option market plays a role in price discovery and option trading volume carries information about future stock price movements in regular market times. This being the case, it is meaningful to examine the implications of option trading in a setting where a significant information event is pending. I argue that a careful examination of option trading volume is the first step in understanding the implications of option trading around merger announcements. My first hypothesis formalizes this intuition.

Hypothesis 2a: Informed option trading volume is more likely to be concentrated in ATM and short-term options.

Informed traders can choose to trade either stocks or options to take advantage of their private information. Whether informed traders choose to trade options is largely shaped by the trade-off between leverage and liquidity effects of trading in alternative markets. Easley et. al. (1998) among others shows that the market choice of informed traders is not a straightforward one. Both liquidity factor and leverage factor can enter into informed traders' choice of alternative markets. First of all, stock trading is generally more liquid. In contrast, options are generally thinly traded and bid-ask spreads in option markets are much wider (Vijh (1990)). Higher stock trading liquidity has two important implications for informed traders when they decide whether to trade stocks or options. First, higher liquidity trading and lower transaction costs imply that execution costs for informed trading can be lower, and hence, a larger incentive for informed traders to trade stocks. Second, higher stock trading liquidity also provides a better camouflage for informed trading in the sense of Admati and Pfleiderer (1988). The higher stock trading liquidity is, the more likely informed traders choose to trade stocks for stealth trading[40] purpose. Combined together, the liquidity arguments predicts that, all else equal, there should be an inverse relation between underlying stock trading liquidity and informed option trading around merger announcements.

Secondly, option markets offer higher leverage as compared to the stock market and the downside risk when trading options is often limited. Black (1975) argues that informed investors may be attracted to the option market by the high leverage achievable through options. Consequently, this leverage effect implies that informed traders might prefer options to stocks, and hence, a positive relationship between option leverage and informed option trading.

The above trade-off argument can be generalized to trading options with different strike prices in a similar fashion. This is because options with different strike prices are associated with distinct leverage and liquidity characteristics. More specifically, while out-of-the-money (OTM) options offer an informed trader the greatest leverage, bid-ask spreads and commissions also tend to be widest for OTM options. On the other hand, while ATM options provide mild leverage, bid-ask spreads also tend to be lowest. In contrast, in-the-money (ITM) options provide the least leverage. But commissions tend to be lowest for these options (Vijh (1990), Kaul et. al. (2002), Chakravarty et. al. (2004)). Chakravarty et. al. (2004) find that in regular market time, information shares estimates in the spirit of Hasbrouck (1995) average higher for OTM options across the 60 stocks in their sample from 1988-1992, which is consistent with the notion that leverage may be the primary force driving price

[40] An incomplete list of the stealth trading literature includes Kyle (1985), Admati and Pfleiderer (1988), Barclay and Warner (1993), Chakravarty (2001).

discovery in the options market. However, this does not necessarily rule out the role of liquidity effect. As further evidence, these authors also find that ATM information shares are higher, compared to OTM information shares when ATM options have high volume and narrow spreads as compared to OTM options. Thus, if informed traders value both liquidity and leverage, they will more likely choose to trade ATM options as compared to ITM and OTM options.

Now let's consider option maturities. In general, short-term options are much more liquid than long-term options. More importantly, informed trader's private information about merger announcements is often short-lived and quickly gets incorporated into stock prices soon after the announcements are made. For these two reasons, I conjecture that any abnormal option trading volume immediately prior to merger announcements, if it is informed, will be mainly concentrated in short-term options. Hypothesis 2a formalizes this intuition.

Hypothesis 2b: pricing effects and volume effects immediately before merger announcements are strongly correlated[41].

My second part of Hypothesis 2 is derived by investigating the simultaneity between pricing effects and volume effects before merger announcements. Gao and Oler (2004) also examine the simultaneity between pricing effects and volume effects in the stock market using a sample of merger announcements and find that there exists a non-synchronicity between these two effects. More specifically, they find that higher-than-normal volume precedes significant share price movement by about seven days in their merger sample. The reason is that over this period, active buyer-initiated trades are offset by active seller-initiated trades. They ascribe this pre-announcement selling

[41]It is noteworthy to point out that rejection of the second part of Hypothesis 2 does not necessarily rule out the possibility of informed trading. This is because informed traders may employ very sophisticated option trading strategies to prevent themselves from being recognized. Anand and Chakravarty (2003) present direct evidence that there is indeed stealth trading in option market. The propensity of stealth trading by informed traders is a function of leverage and the underlying liquidity of the option contracts.

to arbitrageurs. My paper extends this analysis into option trading and examines the simultaneity between option pricing effects and option volume effect. I argue that the informed option trading hypothesis predicts simultaneity between the option pricing effects and trading volume effects. The reason is as follows. If abnormal option trading volume right before merger announcements mainly originates from informed traders, option prices should move concomitantly. After all, informed traders' private information will get incorporated into prices before the announcement dates. On the other hand, if abnormal option trading is spurred by other reasons such as hedging rather than information reasons, then option prices may or may not move in line with trading volume simultaneously. In particular, option prices may significantly lag option trading volume since volume that originates from liquidity motives does not carry new information in the first place. This constitutes my second part of Hypothesis 2.

Hypothesis 3: Pre-takeover option trading volume leads stock volume.

My third hypothesis examines the lead-lag relationship between option volume and stock volume around merger announcements. The literature has already investigated the lead-lag relationship between stock prices and option prices (Manaster and Rendleman (1982) etc), between option volume and stock prices (Easley et. al. (1998), Pan and Poteshman (2006) etc.). However, less has been devoted to the lead-lag relationship between option volume and stock volume. To the extent that it takes volume to move prices, a direct examination of the lead-lag relationship between stock and option volume certainly helps a understanding of the price discovery process. Theoretically speaking, stock volume can either lead or lag option volume depending on whether informed traders choose to trade stocks or options first. The detailed mechanism can be as follows. If informed traders choose to trade stocks first, what happens is that market makers in the stock market will observe an increased imbalance of order flow. More specifically, buy orders will outgrow sell orders to reflect this informed trading in stocks. As market makers stand ready to make the markets, they will have to sell stocks to informed traders. As a result, stock market makers will want to hedge their positions or maintain their desired inventory level. One thing they can do is that they can buy call options in the options market. Consequently, an increase in the stock market order imbalance will translate to an corresponding increase in option volume via market makers' market-making and hedging behavior. In other words, we will observe stock volume leads option volume if informed traders choose to trade stocks first. If on the contrary, informed traders choose to trade options first, then the above mechanism will reverse and we will observe option volume leads stock volume. Due to its information event nature, merger announcement provides a most natural setting where option volume is expected to lead stock volume.

Hypothesis 4: Cross-sectionally, pre-announcement stock price runup should be higher for merger deals that have experienced larger abnormal option trading volume.

My last two hypotheses aim at understanding the implications of option trading on merger deals per se from two different perspectives. More specifically, I first investigate whether and how pre-takeover option trading relates to pre-takeover stock price runup in merger announcements. Existing literature has documented significant stock price runup immediately prior to merger announcements (Keown and Pinkerton (1981), Jarrell and Poulsen (1989), Sanders and Zdanowicz (1992), Meulbroek (1992), Ascioglu et. al. (2002), King et. al. (2005)). Depending on data sample and time period, stock price runup index ranges from 27 percent to as high as 60 percent. Pre-takeover stock price runup warrants its own discussion for at least two reasons. First, studies on pre-takeover stock price runup are meaningful for bidding firms. Schwert (1996) argue that pre-announcement stock price runup and takeover premia are generally unrelated. With no substitution between the runup and the markup, the runup is an extra cost to the bidders. Thus, it is economically important for bidders to explore the source of such significant stock price runup. Second, understanding what causes the pre-bid runup is also important for regulators. As mentioned in the introduction, both market anticipation hypothesis and illegal insider trading hypothesis have been advocated in the literature to explain such significant stock price runup. If pre-bid runup is mainly driven by illegal insider trading, then it makes sense for securities regulators to spend more regulatory efforts to bring down such illegal trading.

Surprisingly little has been done to understand whether and how option trading immediately before merger announcements affects the pre-bid runup. I extend the existing literature into the options market and directly test the above two alternative hypotheses. I argue that if information leakage is the main reason for pre-announcement stock price runup and if abnormal option trading is spurred by informed traders, then in a sample where market anticipation about these mergers is controlled for, higher pre-announcement abnormal returns should be observed for those mergers that have experienced larger abnormal option trading volume. After all, higher informed option trading volume helps faster incorporation of leaked information into stock prices, thus leading to a higher pre-announcement abnormal return. This constitutes my hypothesis 4.

Hypothesis 5: Pre-takeover option trading volume has predictive power on takeover targets.

In my last hypothesis, I attempt to investigate whether option trading volume is predictive of takeover targets that have options traded on them. If pre-takeover option trading volume mainly stems from informed traders who have already learnt of the merger deals and traded in options market, then option trading volume immediately prior to merger announcements should have predictive power on whether firms will be announced to be acquired or not. Regardless of what kind of option trading strategies informed traders will adopt, aggregate option trading volume will nonetheless carry information about firms being takeover targets. It is in this sense that I can safely rely on aggregate option trading volume instead of abnormal option trading volume in my survival analysis that is employed to forecast the takeover targets. I now formalize hypothesis 5 as follows:

It is worthwhile to point out that the above hypotheses are closely related. More specifically, if informed option trading is mainly concentrated in short-term and ATM options as predicted by Hypothesis 2, I would expect that any positive results for Hypotheses 3 and 4 should be stronger for short-term options. More importantly, hypothesis 5 will flow naturally from the first four hypotheses. It is in this sense that I argue the power of my empirical tests actually relies on the joint support of the above five hypotheses. More about this will be discussed in the empirical section.

3.3 Data and Methodology

3.3.1 M & A Data

Merger announcement data are obtained from SDC platinum M & A database. For a merger deal to be included in my sample, I impose several restrictions. First, I require that both target and acquiror firms be US public firms. Second, the dollar value of the merger deal is at least one billion US dollars. These two restrictions ensure that my research question will be examined in a setting where private information can possibly make the largest difference in relatively large merger deals. In total, 1919 merger announcements with target stocks being optioned are obtained after these data filters from 1996-2006.

It is known that announcement dates from SDC platinum Merger and Acquisition databases can be erroneous sometimes. Jarrell and Poulsen (1989) and Sanders and Zdanowicz (1992), among others, show that exact announcement date is critical to evaluate whether the pre-takeover stock price runup is due to illegal insider trading or market anticipations. To ensure that I have the precise announcement dates, I cross check the SDC announcement dates against the announcement dates from SEC

Schedule 13D and 14D-1 filing wherever applicable[42] for each of the merger deal in my sample. I find that the majority of the SDC announcement dates for our sample are accurate. There are indeed a few cases where the SDC announcement dates are one day behind the 13D or 14D-1 dates. I replace them with the earlier dates in these cases.

Since my research question aims at understanding how pre-takeover option trading impacts the way private information about these merger deals is incorporated into stock price, it is crucial to control for market expectation associated with these merger deals. This is because pre-takeover option trading can either be motivated by private information about these merger deals or by market anticipations about these deals. Jarrell and Poulsen (1989) find that the presence of rumors in the news media about an impending tender offer is the strongest explanatory variable in accounting for the pre-bid runup in the stock market. King and Padalko (2005) also find that pre-takeover stock price-volume dynamics are more consistent with market anticipation than illegal insider trading. Consequently, it is reasonable to conjecture that pre-takeover option trading could also be spurred by market rumors and anticipations about these deals. To control for market rumors and anticipations, I construct a Media variable as follows. I first obtain all the business news reports about the merger deals in Factiva database[43] starting from one year ahead leading up to the announcement date. Any news report that includes: a report that a target firm is negotiating a change in control or seeking strategic alternatives, whether a buyer is named or not; an report that the target firm will look for buyer or merger partner to “maximize shareholder value”; a report that target firm's major shareholder intends to sell a controlling block of shares; a report that target firm had been negotiating a merger or takeover that failed earlier; a report that acquirer expresses a takeover intention; a report that target

[42]The SEC requires Scheduled 13D filings by five percent or more equity owners within 10 days of acquisition event. Schedule 14D-1 filings are required by the SEC at the time a tender offer is made to holders of equity securities of the target company if acceptance of the offer would give the bidder over five percent ownership of the subject securities.

[43] I search through the two main business news databases: *the Wall Street Journal* and *Dow Jones News Service*. Presumably these two databases provide a timely and comprehensive coverage of merger deals.

firms have been conducting stock repurchases with significant corporate control implications will make Media be coded as 1 and 0 otherwise.

3.3.2 Stock Market Order Flow Data

Data on stock market order flow are obtained from NYSE Trade & Quote database. Standard Lee and Ready (1991) algorithm is employed to sign each trade. More specifically, a trade is a classified as a buyer/seller-initiated trade if the price is above/below the prevailing quote midpoint. For midpoint trades, tick tests are employed and buyer/seller initiation is classified if the most recent price change is positive/negative. For each firm in my sample, I compute a time-series of the stock market order imbalance going back to as far as 180 days before the announcement dates.

3.3.3 Options Data

Volume data for option trading are obtained from OptionMetrics database. OptionMetrics provides daily trading volume for both calls and puts from Jan 1996 to December 2006. I match each optioned target stock into OptionMetrics by CUSIP numbers. OptionMetrics also provides the end-of-day trading volume for each option contract, which further allows me to compute the trading volume for options classified by maturities and moneyness[44].

Another important feature of OptionMetrics database is that it also provides implied volatility estimates for each traded option contract. According to the documentation file of OptionMetrics database, the implied volatility estimate is computed using a proprietary pricing algorithm that is based on the industry-standard Cox-Ross-

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[44]Following the standard practice in the literature, we classify options with maturities less than 60 days as short-term options. Options with maturities greater than 60 days are classified as long-term options. Option moneyness is defined as follows: call options are: in-the-money if strike price is less than 90 percent of the underlying stock price; at the money if strike price falls between 0.9*stock price and 1.1*stock price; out-of-the-money if strike price greater than 1.1*stock price. Similarly for put options. For robustness check I also experiment with cutoff levels 0.95 and 1.05 for moneyness definition. The majority of my empirical results are unchanged.

Rubinstein (CRR) binomial tree model. Numerical optimization is run iteratively until the CRR model price of the option converges to its market price, which is the defined as the midpoint of the option's best closing bid and best closing offer prices. The final value of σ is the option's implied volatility.

Implied volatilities estimated this way accommodate underlying securities with either discrete or continuous dividend payments and American options with early exercise features. However, it is also noteworthy that these implied volatility estimates are model dependent. There can be an unknown bias in these estimates, especially considering the fact the market price is defined as the midpoint of the best closing bid and best closing offer prices. For this reason, I employ implied volatility spread in the following analysis. The notion is that a lot of the estimation bias in these volatility estimates might cancel each other out if I subtract the put implied volatility from the call implied volatility, thus leaving me a clean estimate of call option pricing relative to puts. I will further motivate the use of implied volatility spread in Section 4.

OptionMetrics database also provides an exchange file that contains a historical record of changes to the active exchange for a security and new listing and delisting information. This file allows me to construct the takeover target prediction sample. Firms can drop out of my sample due to mergers and other reasons. Alternatively, firms may last throughout the sample period. Table 3.1 provides a detailed decomposition of the number of firms for each case. In total 3,878 firms are included in the final takeover target prediction sample.

3.4 Empirical Results

3.4.1 Abnormal Option Trading Volume

My empirical analysis starts from examining whether there is abnormal option trading before announcement dates and if so, the determinants of the abnormal trading volume. More importantly, I am interested in examining how pre-takeover option trading translates to informed trading after controlling for merger characteristics and underlying stock trading liquidity.

Following the standard event methodology in the literature, I employ the fixed mean model to compute abnormal option trading volume. More specifically, [t-30, t+10] and [t-90, t-31] are defined as event window and estimation window respectively[45]. Normal trading volume is then computed over the estimation window by taking the average of the natural log of the raw trading volume[46]. Chae (2005), among others, argues that log transformation can make the trading volume variable closer to be normally distributed. Daily abnormal trading volume is computed by subtracting the normal trading volume from the daily trading volume in the event window. Cumulative abnormal trading volume is then computed by cumulating the daily abnormal trading volume over the 30 days leading up to the announcement dates. Abnormal trading volume for options with different maturities and moneyness are computed in a similar fashion.

Panel a in Table 3.2 presents the abnormal trading volume for options conditional on maturities and moneyness. I provide the cumulative average abnormal option trading volume on target stocks for three samples: the whole sample, the sub sample where there is no media expectation and the sub sample where there is no acquiror's toeholds in target firms. By constructing these sub samples, I provide a preliminary control for two important factors that have been hypothesized to affect abnormal option volume around merger announcements: media expectation and acquiror's toeholding positions. I also compute the abnormal trading volume separately for calls and puts[47]. All the

[45]For a robustness check, I also experiment with a [t-20, t+10] for event window in all my empirical analysis. The main results remain unchanged.

[46]See Lo and Wang (2000) for a comprehensive discussion of different trading volume measures.

[47]Two reasons for us to separate call volume from put volume: first, the literature documents that puts are relatively less liquid than calls; second, takeover premium is more likely to have pricing pressure on calls as compared to puts.

numbers are statistically significant at one percent significance level.

Several results are immediately observed. First, for call options, the largest increase in cumulative abnormal trading volume occurs in ATM options, followed by ITM and OTM calls. Looking at options with different maturities, I observe that short-term calls experience a much larger increase in cumulative abnormal trading as compared to long-term calls. Moreover, the difference between options with different maturities is much wider than that for options with different moneyness. This is consistent with the notion that since informed traders' private information is short-lived, they will choose to trade short-term options before their private information gets public. Second, the above pattern is robust across the whole sample and the two sub samples. However, it does appear to be the case that media expectation about merger deals contributes to higher abnormal trading volume across options with different maturities and moneyness. Abnormal call option trading volume is indeed higher for the whole sample than for the no-media subsample. In contrast, the fact that the abnormal volume for the no-toehold subsample is a little higher than that for the whole sample seems to suggest that acquiror's toeholding actually tends to decrease the abnormal option trading. Third, notice that for put options with different moneyness and maturities, the abnormal option volume is much lower as compared to calls. This is consistent with the notion that calls are generally more liquid and hence, informed traders trade calls more than they trade puts to capitalize on their private information. Moreover, the largest increase occurs in OTM puts, followed by ATM puts. ITM puts experience the least increase in abnormal volume. Additionally, the difference in the increase between short-term and long-term puts is less striking as compared to calls. Overall, this is consistent with the notion that trading interests are more concentrated in calls as compared to puts around merger announcements.

To assess the economic significance of the increase in cumulative abnormal option trading, notice that the numbers in Table 3.2 are in natural logs. To convert them back to the raw trading volume, I have to take the exponential. Take the short-term calls for an example. The cumulative abnormal trading volume for short-term calls within 30 days before the announcement date averages around ten million contracts. Such magnitude of accumulation in the trading volume is economically significant by all means[48]. Overall, the results in Table 3.2 suggest that there is abnormal option trading volume before merger announcements even after controlling for media expectation and acquiror's toeholds associated with such mergers. And this abnormal option trading volume is both statistically and economically significant, thus lending support to hypothesis 1. The fact that short-term calls experience much larger increase than long-term calls also provides initial support for informed option trading hypothesis[49].

The liquidity argument in the previous section argues that there should be an inverse relation between underlying stock trading liquidity and informed option trading. To investigate whether this is indeed the case, I compute the abnormal option volume, this time conditional on stock trading liquidity. Since liquidity has many different dimensions, many different liquidity measures have been proposed in the literature. Given that my research interests mainly lie in how stock trading liquidity affects informed traders' stealth trading purposes and better execution purposes, I use log volume as a proxy for stock liquidity[50]. More specifically, for each merger in my sample, I compute the average log volume over the benchmark period [t-240, t-60]. All firms are then sorted into five quintiles based on the average log volume over this period. I then compute the abnormal option trading volume for each quintile in a similar fashion.

Cumulative abnormal option volume computed this way is presented in Panel b of

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[48] In comparison, the average trading volume for 100 most liquid options from 1996 to 2006 is 14,300 contracts.

[49] As further evidence, I also compute the abnormal option trading volume conditional on both moneyness and maturities. Not surprisingly, I find that the short-term ATM calls experience the most significant increase in trading volume, followed by short-term ITM calls.

[50] I also use an alternative proxy for liquidity: log turnover, defined as the natural log of the shared traded scaled by shares outstanding. The results remain unchanged.

Table 3.2. As we can see clearly for call options, going from the least liquid quintile to the most liquid quintile, the cumulative average option volume decreases monotonically. The cumulative average abnormal option volume for quintile 1 (least liquid) is more than three times that for quintile 5 (most liquid). In addition, this pattern is robust across the whole sample, the no-media sample and no-toehold sample. In contrast, for put options, the abnormal option volume decreases, albeit not monotonically, as stock trading liquidity increases. Overall, these results strongly support the negative relation between stock trading liquidity and informed option trading and speak to the importance of controlling for underlying stock liquidity when I examine the determinants of abnormal option volume in multivariate analysis.

To further relate the above abnormal option volume pattern to the option characteristics, I examine the liquidity and leverage associated with options of different moneyness and maturities. More specifically, I use option delta as a proxy for option leverage and log volume as a proxy for option trading liquidity. Again, I compute these two metrics over the benchmark period [t-240, t-60]. Table 3.3 presents the cross-sectional averages of the time-series averages for both option delta and log volume. Not surprisingly, I find that indeed, ATM options are associated with mild leverage and highest liquidity. While OTM options provide the greatest leverage, it is also the least liquid. In comparison, ITM options offer the least leverage and are more liquid at the same time. Additionally, this leverage-liquidity characteristic is robust across both calls and puts. For options with different maturities, I observe that short-term options are more liquid than long-term options. And this is true for both calls and puts. While short-term calls have slightly lower leverage than long-term calls, short-term puts have higher leverage than long-term puts. Figure 3-1 provides a graphical representation of the options within different maturities and moneyness on the leverage-liquidity quadrant. These leverage and liquidity characteristics, combined with the abnormal option volume pattern, is strongly consistent with the notion that informed traders value both liquidity and leverage when trading options around merger announcements.

3.4.2 Simultaneity Between Pricing Effects and Volume Effects

The previous section establishes that there is abnormal option trading volume immediately before merger announcements. The distribution of abnormal volume across options with different moneyness and maturities lends initial support to the informed option trading hypothesis. In this section I motivate one important measure of relative option pricing: implied volatility spread. I further investigate the simultaneity between this pricing measure and the abnormal option volume to test the hypothesis 2b.

Implied volatility is now a widely accepted paradigm for empirical tests of option valuation (Jarrow and Wiggins (1989)). Implied volatility spread is defined as the call implied volatility minus put implied volatility. The motivation of using implied volatility spread as a measure for the relative pricing of call and put options is as follows: under perfect market conditions and for a given maturity date, the volatility implicit in call options must be equal to the volatility implied in put options. On the other hand, higher called-implied volatility relative to put-implied volatility indicates that calls are overpriced relative to puts. Therefore I can measure the relative overpricing or underpricing of call and put options by their implied volatilities[51]. In my context, positive implied volatility spread is alternatively interpreted as additional pricing pressure on calls relative to puts right before announcement date.

Implied volatility spread is an ideal measure to capture the pricing pressure in option market prior to takeover announcements. This is because merger announcements have been documented to have directional implications on the stock price movements. Target stocks often experience significant takeover premiums. If informed traders choose to trade options to utilize their private information, the directional move in target stock prices will certainly be reflected in the relative overpricing of call options.

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[51] A similar procedure has been adopted by Figlewski and Webb (1993) to investigate the pricing pressures in options market as a function of short interest. Therefore, I am not the first one to advocate this measure.

More specifically, call options will be more expensive relative to puts if target stock price is expected to increase substantially in the near future. Consequently, I can expect there is an accumulation of implied volatility spread immediately prior to takeover announcements.

Previous literature suggests that option pricing models systematically misprice options with respect to maturity and moneyness (Whaley (1982), Stein (1989) and Bakshi et. al. (1997)). Short-term options are typically underpriced by Black-Scholes relative to long-term options. Similarly, deep in-the-money and deep out-of-the money options are underpriced relative to at-the-money options. Consequently, I need to control for option moneyness and maturities when I employ implied volatility spread as a pricing pressure measure. To achieve this purpose, I sort each traded option contract by maturity and moneyness. Call and put options are then matched by the same underlying stock price, maturity and moneyness. I then subtract the put-implied volatility from the call-implied volatility to obtain my estimate of the implied volatility spread for each matched call and put pair. Implied volatility spreads are averaged by maturity and moneyness to obtain a daily series for each target stock. I also compute the implied volatility spread from long-term/short-term options, ITM/ATM/OTM options in a similar fashion.

To capture the accumulation of implied volatility spread, I compute the abnormal implied volatility spread as follows: for each day in the event window ([t-30, t+10]), I first take the average of the implied volatility spread in the prior 60 days. I then subtract the average from the implied volatility spread in the event window. These abnormal volatility spreads are then cumulated over the event window.

Figure 3-2 plots the cumulative abnormal implied volatility spread for the whole sample, the no-media subsample and no-toehold subsample. As we can see clearly, there is an obvious accumulation of the implied volatility spread immediately prior to the announcement dates in all three samples. Cumulative abnormal implied volatility spread keeps increasing before the announcement dates and reaches the highest level around announcement dates. Thus, calls are indeed overpriced relative to puts right before the announcement dates.

I further examine what kind of option contracts experience the accumulation of the implied volatility spread before announcement dates. As predicted by the informed option trading hypothesis, short-term calls are more likely to attract informed traders than long-term calls due to its liquidity and leverage characteristics, hence I expect the accumulation of implied volatility spread to be concentrated in short-term options. Similarly for options with different moneyness, ATM calls are more likely to attract informed trades due to its leverage and liquidity characteristics as shown in Table 3.3. Hence, I expect the accumulation of implied volatility spread to be more striking in ATM options than for ITM and OTM options.

In Figure 3-3, I plot the computed cumulative abnormal implied volatility spread for option contracts classified by moneyness and maturity for the whole sample[52]. Interestingly, I find that the accumulation of the implied volatility spread is indeed concentrated in ATM options. In contrast, accumulation of the implied volatility spread is less obvious for ITM and OTM options. Moreover, visual examination clearly shows that the accumulation of volatility spread is even more striking for short-term options than for long-term options. Thus, short-term and ATM calls are becoming more and more expensive immediately before merger announcements. This is consistent with the notion that informed traders' concentrated trading in these options exerts the largest pricing pressure on these options.

So far, the above graphical results demonstrate that short-term and ATM call options are encountered with the largest pricing pressures before announcement dates. However, the above evidence is at most descriptive and qualitative. More importantly,

[52]Results are similar for the no-media subsample and no-toehold subsample. For brevity reasons I do not present these results here.

it is silent as to whether and how this pricing pressure on call options is related to abnormal option trading volume over the event period. To formally examine the simultaneity between the pressure and the volume effect, formal statistical tests are necessary. In what follows I employ regression analysis. My regression specification is as follows:

$$CumAbvol_{opt} = \alpha + \beta \cdot Media + \gamma \cdot Toehold + \eta \cdot StkLiq + \omega \cdot OrderFlow_{stk} + \upsilon \cdot Volspread + \varepsilon$$

Where Media is the constructed media variable that takes the value of one if there is news report about the merger deal one year ahead of the announcement date and zero otherwise; Toehold is acquiror's toeholding position in target firms; StkLiq is the log volume over the benchmark period [t-240, t-60] proxying for underlying stock trading liquidity; $OrderFlow_{stk}$ is the cumulative stock market order imbalance defined as buyer-initiated volume minus seller-initiated volume; $Cumabvol_{opt}$ is the cumulative abnormal option volume; Volspread is the computed cumulative abnormal implied volatility spread.

The above independent variables are motivated by factors that may affect abnormal option trading volume immediately before merger announcements. First of all, if there is market anticipation about the merger deal ahead of the announcement date, higher abnormal option trading volume might be expected from Jarrell and Poulsen (1989). In addition, cumulative option volume could also be affected by acquiror' toeholding positions in target firms as shown in the above univariate results. Secondly, it is crucial to control for the stock market order flow imbalances given that there are many channels through which stock trading volume relates to option trading volume. For instance, informed traders trade in stock market and hence market makers hedge their positions in options market. More importantly, as I argue in Section 2, the informed option trading hypothesis predicts simultaneity between the relative pricing of calls versus puts and the cumulative abnormal option trading volume. Consequently, I expect the slope efficient estimates before Volspread to be positive and significant. Moreover, I expect that both the economic and statistical significance should be much stronger for implied volatility spread computed from short-term and ATM options.

Table 3.4 presents the estimation results for the above regression specification. I estimate a total number of 6 models, which differ from each other in the Volspread variable. More specifically, Volspread variable in model 1 is computed from the whole sample, whereas in Model 2 to Model 6 the Volspread is computed from ITM, ATM, OTM, short-term and long-term options respectively.

Several observations are immediately noticed. First, the slope efficient estimates before Media variables are positive and statistically significant except for model 6, where the Volspread variable is computed from long-term options. Thus, I do find evidence that news report and media coverage about merger deals stimulate trading volume in options market. This is consistent with the univariate result in Table 3.2 where cumulative abnormal option volume for the no-media sample is lower than that for the whole sample; Second, the slope coefficient estimates before Toehold are negative and statistically significant for the whole sample and for model 5 and 6 where Volspread is computed from short-term and long-term options. Again, this negative sign is consistent with the univariate results in Table 3.2; Third, the slope coefficient estimates before the stock trading liquidity variable StkLiq are always negative and statistically significant except for model 2, where Volspread is computed from ITM options. Hence, lower option volume is usually associated with higher stock trading liquidity. This is consistent with both the univariate results and the predictions of the liquidity argument. Fourth, the $OrderFlow_{stk}$ variable that captures the stock market order imbalances is always positive and significant. Hence, higher stock market order imbalance is associated with higher cumulative abnormal option volume. This is quite intuitive given that pre-takeover trading volume in these two markets is strongly correlated. However, it is unclear whether stock volume leads option volume or vice versa. Formal causality tests are needed before I can come to a conclusion.

More importantly, I notice that even after I control for the above merger characteristics and stock market order imbalances and liquidity that have been shown to affect abnormal option volume, the slope coefficient estimates before my focal variables are always positive and statistically significant except for Model 2, where this variable is computed from ITM options. Thus, higher abnormal option volume is associated with larger cumulation of implied volatility spread, indicating that calls become more expensive and volume increase more at the same time. These results constitute favorable evidence that short-term and ATM option pricing pressures are strongly correlated with abnormal option trading volume. Overall the above graphical results and regression analysis lend strong support to the predictions of the informed option trading hypothesis that pricing effects and volume effects are unified under informed option trading for ATM and short-term options.

3.4.3 Option Volume Leads Stock Volume

The previous two sections show that abnormal option volume pattern is consistent with informed option trading hypothesis. However, it does not address whether price is first discovered in stock market or options market. Option volume leading stock volume would certainly reinforce the above results. In this section, I test directly the lead-lag relation between stock volume and option volume.

To capture what is taking place in the stock market around merger announcements, I propose a metric of stock market order imbalance, StkOrderFlow, defined as the difference between buyer-initiated volume and seller-initiated volume. This metric is more appropriate as compared to raw stock volume given that I am not interested in the total shares traded, but rather how buy/sell orders become out of balance as a result of informed trading and how this order imbalance relates to option trading. To capture the options market, I also propose a metric of relative option volume, OptVol, defined either as short-term volume minus long-term volume or ATM volume minus ITM/OTM volume. This relative option volume metric is motivated by the above findings that short-term and ATM options exhibit the largest increase in abnormal volume before merger announcements. Consequently, I argue that short-term and ATM volume, net of long-term and ITM/OTM volume, is more meaningful in that it sifts out any possible maturity or moneyness effect when I examine the informativeness of option volume[53]. I then estimate the following regression:

$$StkOrderFlow_t = \alpha + \beta_1 \cdot StkOrderFlow_{t-1} + \beta_2 \cdot OptVol_{t-1} + \varepsilon, t \in [t-30, t-1]$$

where StkOrderFlow and OptVol are stock market order flow and relative option volume respectively.

Since for each event in my sample, at most I have 30 observations, to increase the statistical power, I pool all the observations together. For this purpose, I first standardize both the stock market order flow imbalance series and relative option volume series using its mean and standard deviation over the benchmark window [t-150, t-30]. Cao et. al. (2005) also standardizes their option volume series using a similar procedure. I control for the lagged stock market order imbalance since the literature has documented that stock market order flow tends to be positively autocorrelated.

Panel A in Table 3.5 provides the estimation results for the whole sample. I report each of the two relative option volume series. Notice first that stock market order imbalances are positively autocorrelated. A one standard deviation increase in stock market order imbalances leads to about 0.090 standard deviation increase in next-day order imbalance. This is consistent with what the literature has documented. More importantly, after controlling for lagged stock market order imbalances, the slope coefficient estimates before the lagged relative option volume are always positive and statistically significant for both relative option volume series. On average, a one

[53] Ideally, I would like to use option market order flow imbalance similar to $StkOrderFlow$. However, this requires high-frequency option trade & quote data, which unfortunately is not available. For robustness check I also use log volume for short-term, long-term, ITM, ATM and OTM options and re-run the regressions. The main results remain unchanged.

standard deviation increase in lagged relative option volume leads to about 0.015 standard deviation increase in next-day stock market order imbalance. Thus, option volume indeed leads stock volume for the mergers in my sample. This complements Cao et. al. (2005) and speaks to the informativeness of option volume before merger announcements.

To further investigate the source of the predictive power of relative option volume and relate it to the pricing effects as measured by implied volatility spread, I cut the sample into two sub samples based on whether there is accumulation of implied volatility spread. Panel B and Panel C in Table 3.5 report the estimation results for these two sub samples. As we can see clearly, both the magnitude and the statistical significance of the predictive power decrease substantially for the sub sample where there is no accumulation of implied volatility spread. In sharp contrast, lagged relative option volume series are always positive and highly significant when there is accumulation of implied volatility spread. On average, a one standard deviation increase relative option volume results in 0.021 standard deviation increase in next-day stock market order imbalances. Overall, I interpret this as strong evidence that option volume leads stock volume the most when there is simultaneous pricing effects as indicated by the implied volatility spread.

3.4.4 Implications of Option Volume on Mergers Per Se

In this section I examine how pre-takeover abnormal option trading affects merger deals per se. More specifically, I investigate both how option trading affects pre-takeover stock price runup and whether option trading volume has any predictive power on takeover targets. Investigation of the implications of option trading on stock price runup is meaningful for at least bidding firms. Schwert (1996) argues that there is no association between pre-bid stock price runup and the post-announcement increase in the target's stock price (the markup). Consequently, runup is an added cost to bidding firms. Thus, if option trading accounts for the pre-bid runup, option trading may actually hurt bidding firms from this perspective. Examination of whether option trading volume can be used to predict takeover targets is of vital interests for both market professionals and ordinary investors given that mergers often induce significant stock price movements.

Hypothesis 4 predicts that in a cross section of merger announcements, higher pre-announcement returns should be observed for mergers that have experienced larger abnormal option trading if option trading mainly originates from informed traders. This is because information contained and hence revealed in option trading will be incorporated into stock prices before the announcement dates.

To compute abnormal returns, I follow the standard event study methodology. Event window is defined as [t-30,t+10]. A market model is then estimated using estimation window data running from [t-240, t-31]. Market model parameter estimates are then applied to compute abnormal returns. Daily abnormal returns are then cumulated over the the time period 30 days before the announcement date to obtain the prior cumulative abnormal returns. The following regression equation is then estimated:

$$PriorRet = \alpha + \beta \cdot Media + \gamma \cdot OrderFlow_{stk} + \eta \cdot Cumabvol_{opt} + \varepsilon$$

Where PriorRet is the computed cumulative abnormal returns over the pre-announcement period; $\text{OrderFlow}_{\text{stk}}$ and $\text{Cumabvol}_{\text{opt}}$ are stock market order imbalances and cumulative abnormal option volume respectively. Media is the constructed media variable that captures the market anticipations of the merger deals;
The above explanatory variables are motivated as follows. Stock market order imbalance is incorporated since I want to investigate whether stock market order imbalance before merger announcement is conducive to stock price runup in the presence of option trading volume. The fact that option trading volume leads stock volume does not necessarily rule out the role of stock trading volume. It is possible that stock market order imbalance also conveys information about the forthcoming merger deals. Thus, while I expect the sign of this variable to be positive for pre-announcement returns, I leave its statistical significance to be determined empirically.

Larger media coverage and massive market anticipations certainly help discover the price and hence, I expect a positive sign for the Media variable.

Estimation results are presented in Table 3.6 for pre-announcement return equation. which differ from each other in the $Cumabvol_{opt}$ variable. More specifically, $Cumabvol_{opt}$ variable in model 1 is computed from the whole sample, whereas in Model 2 to Model 6 the $Cumabvol_{opt}$ is computed from ITM, ATM, OTM, short-term and long-term options respectively.

Notice that: (1). Media variable is usually positive but only statistically significant for pre-announcement returns for Model 4 and Model 6. Thus, I find weak evidence that media coverage and market anticipations do help spread the word about the forthcoming merger deals and contribute to the pre-takeover stock price runup. (2). $OrderFlow_{stk}$ is always positive and statistically significant in explaining the pre-announcement returns across all the models I have estimated, which suggests that higher pre-takeover stock market order imbalance does lead to higher stock price runup in the stock market. (3). More importantly, $Cumabvol_{opt}$ is always positive and statistically significant except for Model 4, where this variable is computed from OTM options. Furthermore, I notice that the magnitude of the slope coefficient estimates for short-term options is larger than that for long-term options. While the slope coefficient estimate before ATM options is smaller than that before ITM options, it is significant at one percent level. Combined altogether, this provides strong supportive evidence that abnormal option trading volume is conducive to pre-takeover runups and the contribution mainly stems from short-term and ATM options.

3.4.5 Forecasting Takeover Targets Using Option Volume

Hypothesis 5 predicts that informed option trading volume is predictive of takeover targets. To test hypothesis 5, I employ a hazard model to forecast takeover targets using option trading volume as my main focal variable. In the hazard model, a firm's risk of being taken over changes through time and its survival is a function of its latest financial data. As argued by Shumway (2001), hazard models are econometrically more appropriate than single-period model in forecasting corporate events such bankruptcy or mergers for a number of reasons. First, traditional static model fails to control for each firm's period at risk. Hazard model automatically adjusts for the fact that some firms are taken over after many years of being at risk while other firms are acquired in their first year; second, hazard model exploits each firm's time-varying data by including monthly observations as time-varying covariates. Hazard model allows each firm's financial data to reveal its changing risk of being acquired; third, hazard model is also more preferable in that it may produce efficient out-of-sample forecasts by utilizing much more data. It is for these reasons that I rely on hazard model in forecasting takeover targets in the following. More specifically, my hazard model specification is as follows:

$$H(t) = H_0(t) \cdot \exp(\alpha \cdot Vol_{opt} + \beta \cdot Controls)$$

where $H_0(t)$ is the baseline hazard at time t representing the hazard for the firm being taken over with value 0 for all the predictor variables; Vol_{opt} and Controls are monthly option trading volume and a set of time-varying predictors reflecting the firm's financial data and thus its changing risk of being taken over.

Control variables in the above model specification are motivated by economic theories. Palepu (1989) searches an exhaustive list of both financial and accounting predictors based on economic stories. My sets of predictors are determined in a similar fashion. More specifically, I include the following control variables in the hazard model estimation[54]: (1). Firm size. Economic theories suggest that the likelihood of being acquired decreases with the size of the firm. This is because there are several size-related transaction costs associated with acquiring a firm. These costs are likely to increase with the target size. Hence, I expect the size variable to be

[54]I also experiment with several other accounting and financial variables including leverage, return on equity and price-earning ratios. These variables are not significant at all even in the univariate hazard model. Hence, I do not incorporate them in the multivariate hazard model.

negative; (2). book-to-market ratios. Firms whose market values are low compared to their book values are likely acquisition targets. Growth firms are more likely to be ``cheap" buys. Hence, I expect the book-to-market variables to be positive; (3). Stock returns. The inefficient management hypothesis argues that firms with bad management are likely targets. If stock returns are used as proxies for management efficiencies, then a negative sign is expected of this variable; (4). stock trading volume. This variable is included for the obvious reason that volume in the stock market and options market might be correlated. (5). Open interest. This variable is motivated by business news that report significant change in open interest in options market immediately prior to merger announcements.

Estimation results for the hazard model are provided in Table 3.7. Several observations are in order. First, parameter estimates for Mktcap variable are negative and statistically significant. Thus, smaller firms are more likely to be acquisition targets; second, slope coefficient estimates for Btm variables are positive and significant across all the models I estimated. Thus, growth firms are more likely to be acquired; third, parameter estimates for StkVol are positive and significant. Thus, anomalous trading in the stock market can be indicative of a forthcoming merger; fourth and more interestingly, slope coefficient estimates for Ret are positive and significant. Thus, it seems to be the case that firms with better performance in the stock market are likely acquisition targets. This is opposite to what has been expected if stock returns are viewed as a proxy for management efficiency. I think one possible explanation might be that firms with strong performance in the stock markets might catch attention from potential acquirors for the consideration that acquisition of such firms implies immediately available cash flows. More importantly, I find that parameter estimates for my focal variable Volume are positive and statistically significant for the whole sample as well as for option volume computed from options with different moneyness and maturities.

3.5 Conclusions

This paper documents that abnormal option trading immediately before merger announcements contains private information about the merger deals. Informed traders do trade options to capitalize on their private information and their private information gets revealed through option trading. I show that such information revelation is mainly achieved through short-term and ATM call options. The simultaneity between the pricing pressures on these call options and the large increase in abnormal trading volume, along with the fact that option volume leads stock market order imbalances, further corroborates this informed option trading story. More importantly, I show that this abnormal option trading has important implications for both pre-bid stock price runup and takeover target predictions. The fact that larger pre-takeover abnormal option trading volume is associated with higher stock price runup, combined with the fact that pre-takeover stock price runup is an added cost to the bidding firms, implies that bidders should at least keep an close eye on option trading in target stocks immediately before the public announcement. It makes sense for them to investigate whether there is serious information leakage about the merger deals and how this can affect the way they structure the merger deals. Moreover, using a sound econometric model, I show that option trading volume can actually be used to predict whether firms will be acquired or not. I believe this is the first paper that shows the implications of option trading on takeover target predictions.

At least the following three questions can be further examined in future studies. The first question is, to what extent is the level of price discovery in merger context different from that in regular market times? An answer to this question will certainly help us achieve a understanding of the price discovery process both around significant information events and in ordinary times. While the evidence presented in this paper seems to suggest that information shares in the spirits of Hasbrouck (1995) might be higher for option trading around significant events, high-frequency data are required before I can draw any quantitative conclusions. Second, from a market microstructure perspective, how is the private information discovered through the option trading process? While the results in this paper prove that such information is indeed revealed before announcement date, it is silent on how market makers recognize the increased probability of informed trading and hence adjust their quoting strategies. It is also unclear how other liquidity traders might respond to informed trading. Third, how is option trading related to stock trading around merger announcements? Is it simply that informed traders choose to trade options when there is a significant information event pending? Or is there much more interesting and complicated interaction between trading in these two different markets? While this paper demonstrates that abnormal option trading is informative in that it predicts stock market order imbalances, it is agnostic on any detailed mechanism that links stock and option trading in a way that generates further insights into multi-market trading around information events. I intend to further pursue these questions in the future.

Figure 3-1 Leverage and Liquidity Characteristics for Calls and Puts

This figure presents the leverage and liquidity characteristics for options with different moneyness and maturities. The X-axis represents option trading liquidity and is defined as the natural log of the raw trading volume over the benchmark period [t-240, t-60]. The Y-axis represents option leverage and is defined as option delta. Cross-sectional averages of these two metrics are computed for short-term, long-term, ITM, ATM and OTM respectively. Figure 3.1a presents call options and Figure 3.1b presents the put options.

Figure 3.1a Call Options

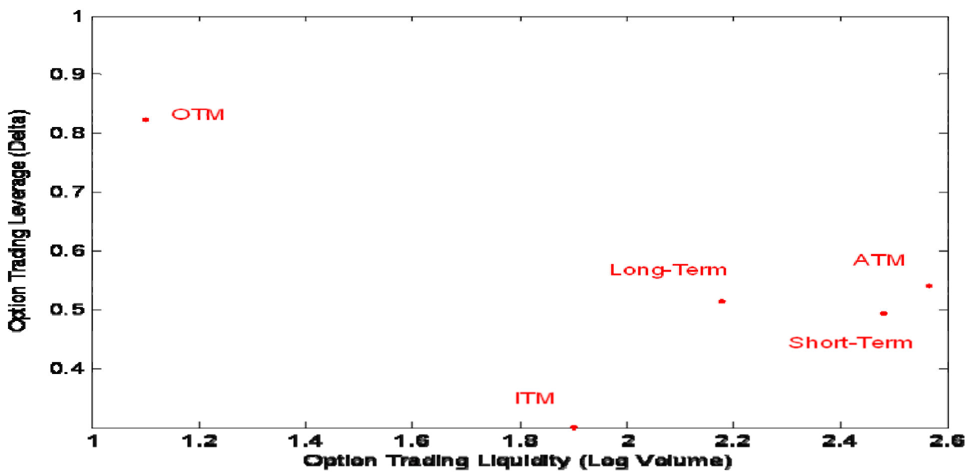

Figure 3.1b Put Options

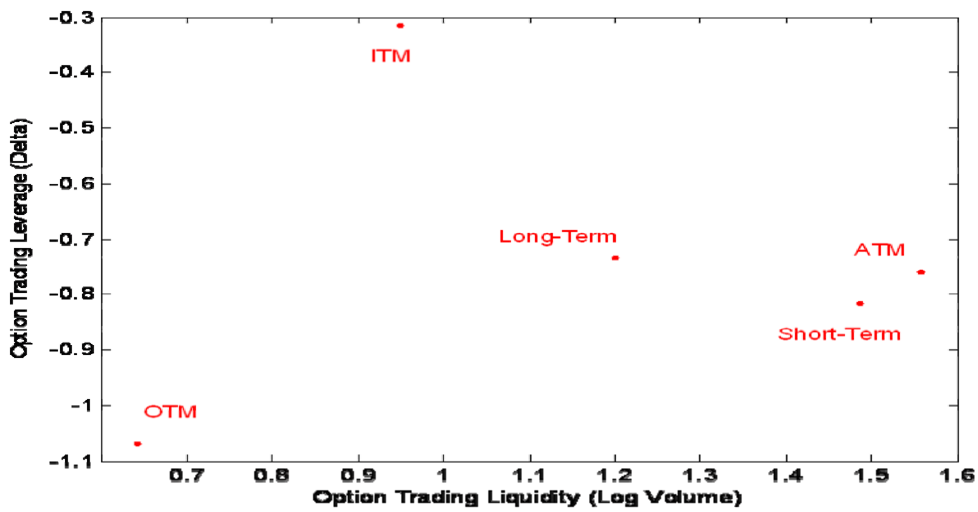

Figure 3-2 Cumulative Abnormal Volatility Spread Immediately Prior to Takeover Announcements

This figure presents the cumulative abnormal volatility spread immediately prior to the takeover announcements in my sample. Volatility spread is defined as call implied volatility minus put implied volatility. Call options and put options are matched by the same underlying stock, strike prices and maturities. Figure 3.2a presents the cumulative abnormal volatility spread for the whole sample. Figure 3.2b and Figure 3.2c present the cumulative abnormal volatility spread for those takeover announcements where no media expectation about the merger deal is present and where acquirors have no toehold positions in target firms.

Figure 3.2a All Sample

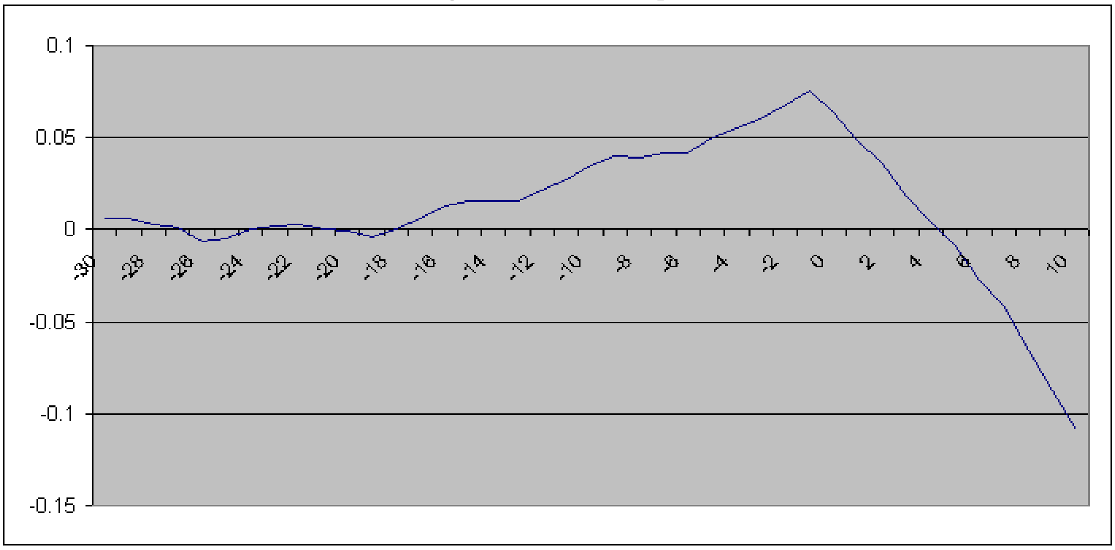

Figure 3.2b Controlling for Media Expectation

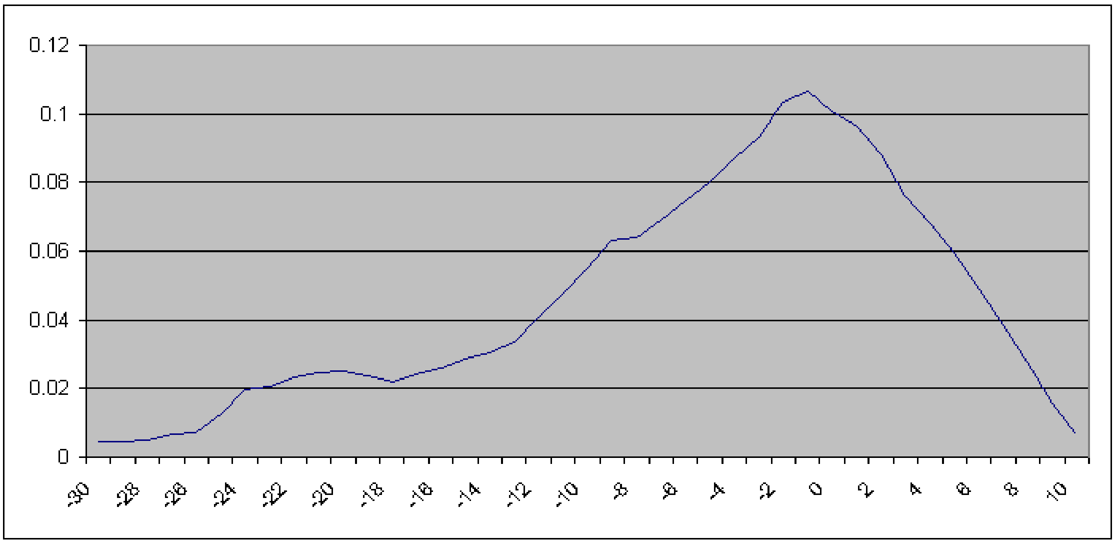

Figure 3.2c Controlling for Acquiror Toeholds

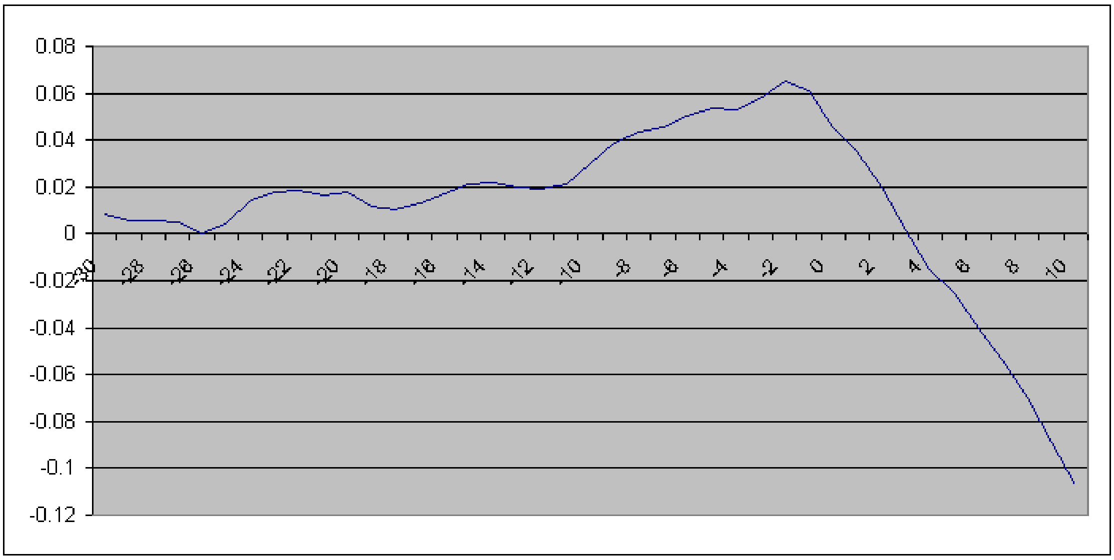

Figure 3-3 Cumulative Abnormal Volatility Spread Immediately Prior to Takeover Announcements Conditional on Option Moneyness

This figure presents the cumulative abnormal volatility spread immediately prior to the takeover announcements conditional on option moneyness. Volatility spread is defined as call implied volatility minus put implied volatility. Call options and put options are matched by the same underlying stock, strike prices and maturities. Figure 3.3a, figure 3.3b and figure 3.3c presents the cumulative abnormal volatility spread computed from ITM, ATM and OTM options respectively. Figure 3.3d and figure 3.3e presents the cumulative abnormal volatility spread computed from short-term and long-term options respectively.

Figure 3.3a In-the-Money Options

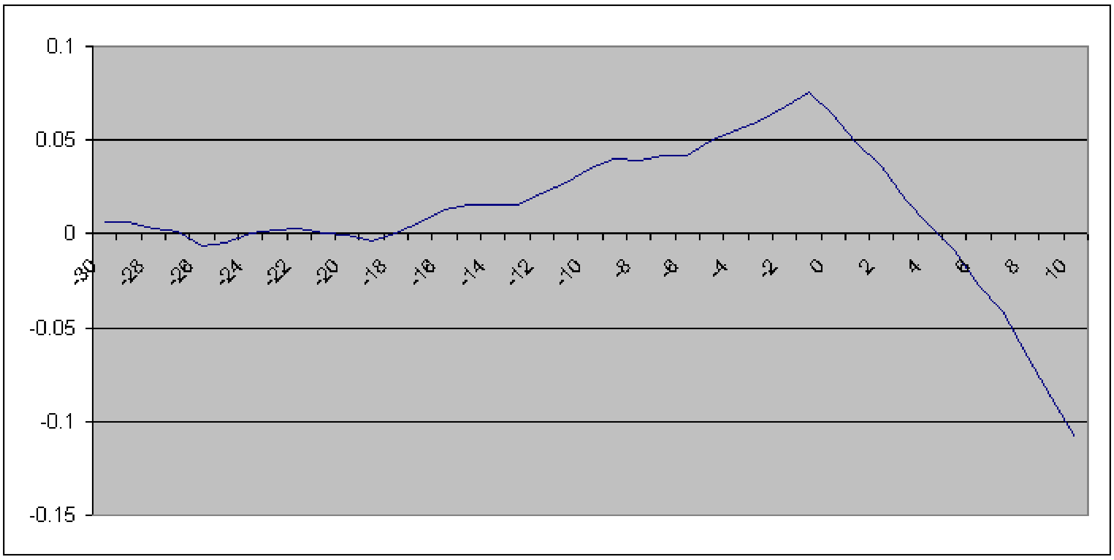

Figure 3.3b At-the-Money Options

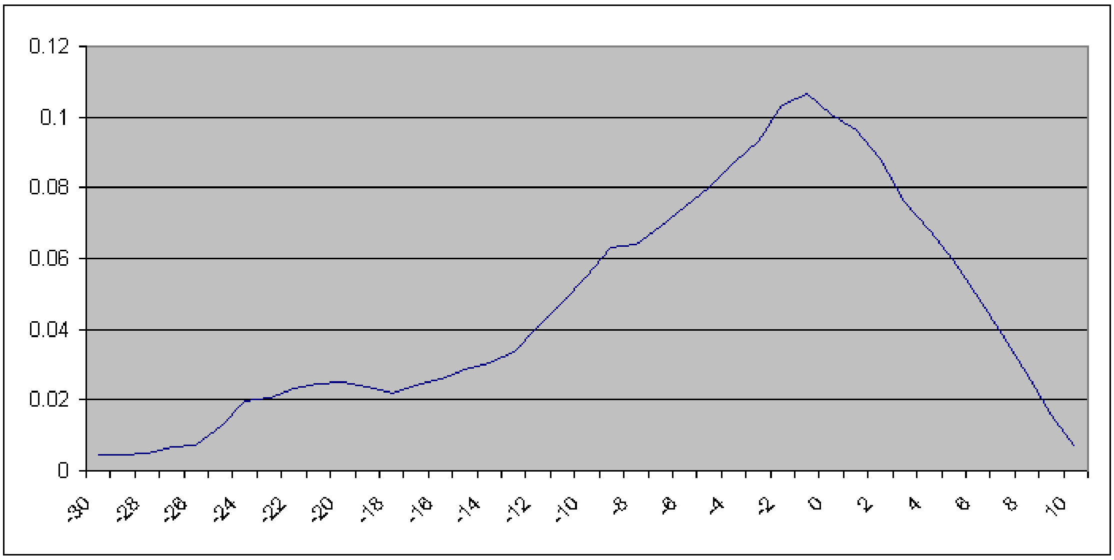

Figure 3.3c Out-of-the-Money Options

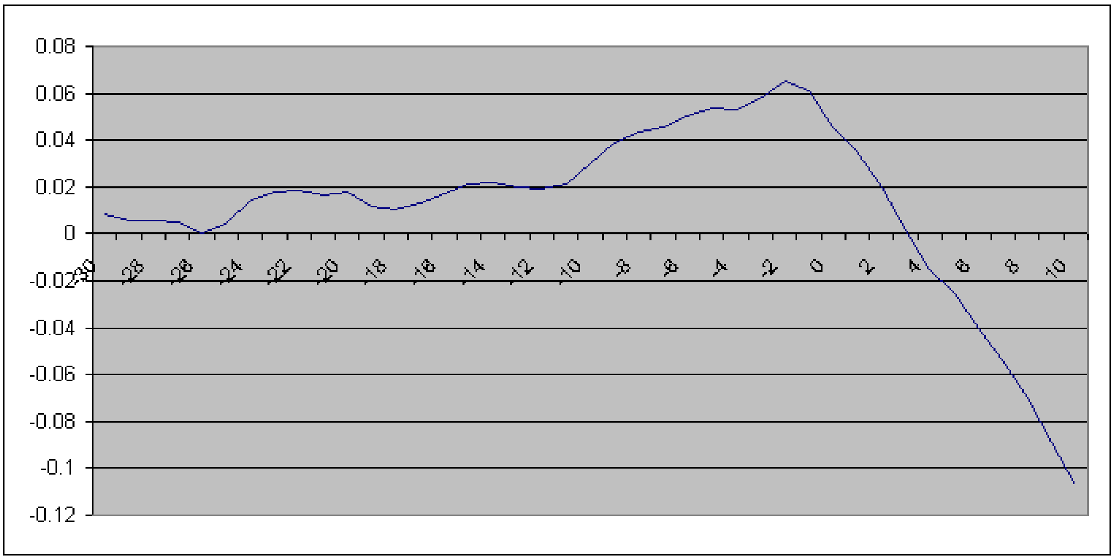

Figure 3.3d Short-term Options

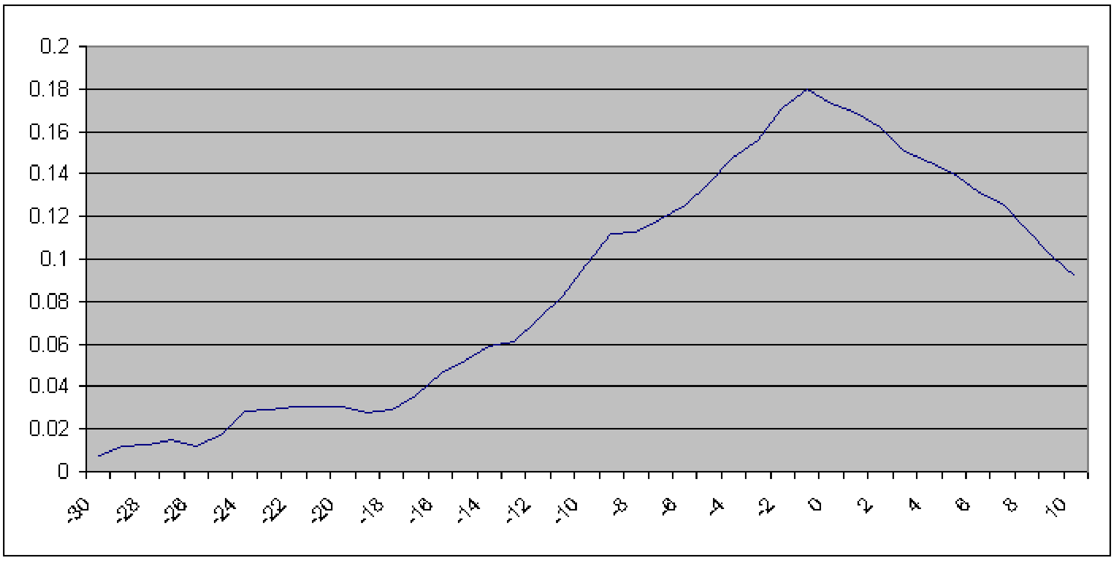

Figure 3.3e Long-term Options

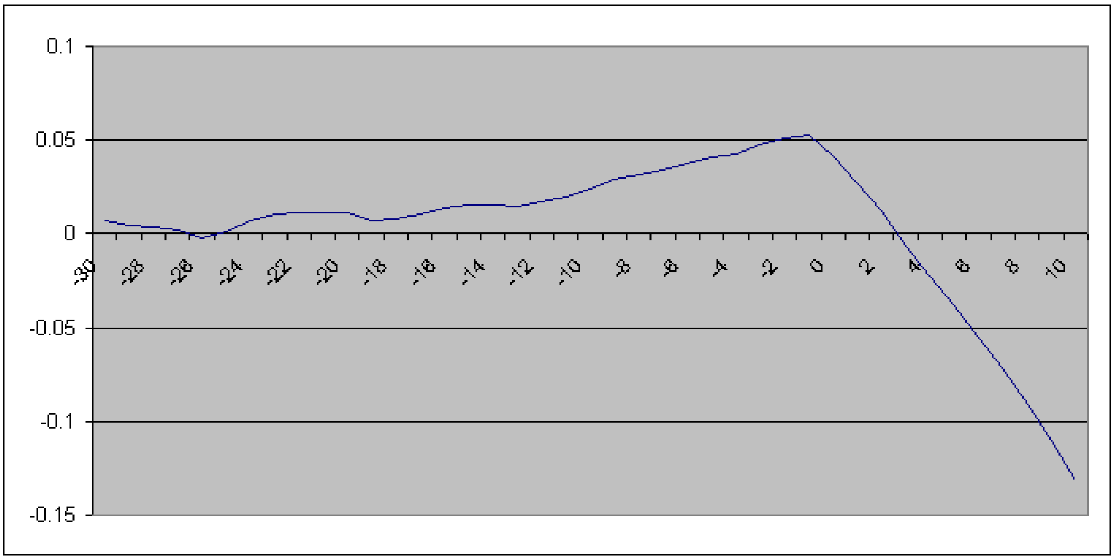

Table 3.1 Takeover Target Sample Construction

This table provides detailed information on the construction of the takeover target prediction sample. All data are from OptionMetrics database.

Data Filters	Number of firms
NYSE/AMEX/NASDAQ firms with available data from OptionMetrics 1996-2006	5584
Firms last throughout the sample period	3508
Firms exit the sample due to mergers	1613
Firms exit the sample for other reasons	463
Number of firms with valid cross-matched firm identifiers	5452
Number of firms with available data in stock/option trading and accounting variables	3868
Firms last throughout the sample period	2346
Firms exit the sample due to mergers	1295
Firms exit the sample for other reasons	227

Table 3.2 Cumulative Average Abnormal Trading Volume

This table presents the cumulative average abnormal trading volume 30 days leading up to the announcement date. Option volume, separated by calls and puts, are conditioned on option moneyness and maturities as well as on underlying stock trading liquidity. For each conditioning variable, option volume is computed from three samples: the whole sample, the sub sample where there is no media expectation about the merger and the sub sample where there are no acquiror's toeholds in target firms. Panel A and Panel B provide the cumulative abnormal trading volume for calls and puts respectively, whereas Panel a and Panel b in both panels are conditional on option characteristics and stock trading liquidity respectively. All numbers reported are statistically significant at one percent level.

Panel A. Call Options					
Panel a. Conditional on Moneyness and Maturity					
	By Moneyness			By Maturities	
	ITM	ATM	OTM	Short-Term	Long-Term
All Sample	9.953	13.720	9.880	16.111	9.585
No Media	8.637	12.559	8.806	14.666	9.307
No Toe-Hold	10.212	14.218	10.365	16.745	10.350
Panel b. Conditional on Stock Trading Liquidity					
	Lowest	Quintile 2	Quintile 3	Quintile 4	Highest
All Sample	22.967	20.823	14.735	13.332	7.018
No Media	22.702	17.481	13.543	11.057	5.758
No Toe-Hold	24.169	22.160	15.276	13.725	7.016
Panel B. Put Options					
Panel a. Conditional on Moneyness and Maturity					
	By Moneyness			By Maturities	
	ITM	ATM	OTM	Short-Term	Long-Term
All Sample	1.451	5.350	5.941	7.211	6.205
No Media	0.276	6.039	7.010	10.350	6.983
No Toe-Hold	4.730	3.579	6.324	8.490	1.560
Panel b. Conditional on Stock Trading Liquidity					
	Lowest	Quintile 2	Quintile 3	Quintile 4	Highest
All Sample	8.412	10.019	6.881	7.526	5.903
No Media	7.792	8.550	6.563	5.598	6.455
No Toe-Hold	8.815	9.756	7.347	7.946	5.055

Table 3.3 Leverage and Liquidity of Different Option Contracts

This table provides the cross-sectional average of proxies for liquidity and leverage for options with different maturities and moneyness. Option trading liquidity is proxied by natural log of trading volume over [t-240, t-60]. Leverage is proxied by option delta. Panel A and Panel B provides the liquidity and leverage characteristics for calls and puts respectively.

Panel A. Call Options					
	By Moneyness			By Maturities	
	ITM	ATM	OTM	Short-Term	Long-Term
Liquidity (Log Volume)	1.903	2.565	1.103	2.480	2.178
Leverage (Delta)	0.302	0.541	0.822	0.493	0.514
Panel B. Put Options					
	By Moneyness			By Maturities	
	ITM	ATM	OTM	Short-Term	Long-Term
Liquidity (Log Volume)	0.950	1.557	0.643	1.487	1.201
Leverage (Delta)	-0.316	-0.759	-1.068	-0.815	-0.734

Table 3.4 Determinants of Abnormal Option Volume

This table examines the determinants of the abnormal trading volume in the options market prior to takeover announcements. The regression specification is as follows:

$$CumAbvol_{opt} = \alpha + \beta \cdot Media + \gamma \cdot Toehold + \eta \cdot StkLiq + \omega \cdot OrderFlow_{stk} + \upsilon \cdot Volspread + \varepsilon$$

Where the dependent variable is the cumulative abnormal call option trading volume 30 days before the announcement date; Media is an indicator variable that equals to one if there is public news report about the merger deal one year prior to the announcement dates. Toehold is acquiror's toeholding in the target company prior to merger announcement. StkLiq is stock trading liquidity defined as the average of stock trading volume over the benchmark period ([t-240, t-60]). OrderFlow is the stock market order imbalance defined as buyer-initiated volume minus seller-initiated volume over the event period ([t-30, t-1]). Volspread variables in model 1 - 6 are cumulative implied volatility spread computed from the whole sample, ITM, ATM, OTM, short-term options and long-term options respectively. P-values are presented in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level respectively.

	All Sample	ITM Options	ATM Options	OTM Options	Short Options	Long Options
Intercept	58.200*** (<.001)	6.058 (.262)	4.398*** (<.001)	0.792*** (<.001)	44.640*** (<.001)	17.998*** (<.001)
Media	3.458*** (.016)	2.344** (.030)	2.782** (.015)	2.552** (.018)	3.503*** (<.001)	0.861 (.402)
Toehold	-0.088* (.097)	-0.038 (.343)	-0.061 (.142)	-0.034 (.383)	-0.091* (.052)	-0.066* (.091)
StkLiq	-3.938*** ((<.001))	-0.159 (.713)	-2.327*** (<.001)	-1.385*** (.001)	-3.023*** (<.001)	-1.087*** (<.001)
$OrderFlow_{stk}$	0.290*** (<.001)	.253*** (<.001)	0.213*** (<.001)	0.146*** (<.001)	0.292*** (<.001)	0.151*** (.004)
Volspread	1.880** (.047)	0.848 (.349)	2.309* (.056)	2.353*** (<.001)	2.871*** (<.001)	1.403* (.010)
No.of obs	841	782	786	800	808	833
Adj R_2 (%)	7.4	2.98	5.45	3.04	8.26	1.90

Table 3.5 Lead-lag Relationship between Stock Market Order Flow and Relative Option Trading Volume

This table presents the test results of the lead-lag relationship between stock market order flow and relative option trading volume; Stock market order flow is defined as the buyer-initiated stock volume minus seller-initiated stock volume, where buy/sell initiation is classified using the standard Lee and Ready (1991) algorithm. Relative option trading volume is computed both by option maturity and option moneyness. For options with different maturities, relative option trading volume is defined as short-term volume minus long-term volume. For option moneyness, relative option trading volumes are either ATM volume minus ITM volume or ATM volume minus OTM volume. Both stock market order flow series and relative option trading series are standardized using the mean and standard deviation in the benchmark window ([t-150, t-30]). The following pooling regression is then estimated:

$$StkVol_t = \alpha + \beta_1 \cdot StkVol_{t-1} + \beta_2 \cdot OptVol_{t-1} + \varepsilon, t \in [t-30, t-1]$$

where StkVol and OptVol are the stock market order flow and relative option trading volume respectively. Panel A provides the regression results for the whole sample whereas Panel B and C provides the results for the sub sample where the cumulative implied volatility spread is negative and positive respectively. P-values are included in the parentheses.

Panel A. All Sample			
	Short - Long	ATM – ITM	ATM-OTM
α	0.065(<.001)	0.067(<.001)	0.044 (<.001)
β_1	0.089 (<.001)	0.094 (<.001)	0.109 (<.001)
β_2	0.011 (.009)	0.021 (<.001)	0.014 (<.001)
Panel B. No Cumulation of Implied Volatility Spread			
	Short - Long	ATM – ITM	ATM-OTM
α	0.095 (<.001)	0.105 (<.001)	0.069 (.002)
β_1	0.143 (<.001)	0.135 (<.001)	0.118((<.001)
β_2	0.007 (.244)	0.007 (.189)	0.012 (.013)
Panel C. Cumulation of Implied Volatility Spread			
	Short - Long	ATM – ITM	ATM-OTM
α	0.034 (.088)	0.033 (.118)	0.024 (.175)
β_1	0.077 (<.001)	0.081 (<.001)	0.110 (<.001)
β_2	0.014 (.011)	0.029 (<.001)	0.021 (.002)

Table 3.6 Option Trading and Pre-Takeover Stock Price Runup

This table examines the informational content of abnormal trading volume in the options market prior to takeover announcements. The regression specification is as follows:

$$PriorRet = \alpha + \beta \cdot Media + \gamma \cdot OrderFlow_{stk} + \eta \cdot Cumabvol_{opt} + \varepsilon$$

Where the dependent variable is the cumulative abnormal return 30 days before the announcement date for each merger deal; Media is an indicator variable that equals to one if there is public news report about the merger deal one year prior to the announcement dates. $OrderFlow_{\_stk}$ is the Stock market order flow defined as the buy-initiated volume minus seller-initiated volume, where buy/seller initiation is classified using the standard Lee and Ready (1991) algorithm. $Cumabvol_{\_opt}$ are the cumulative abnormal option trading volume 30 days prior to the announcement dates. $Cumabvol_{\_opt}$ variables in model 1 - 6 are cumulative abnormal call option trading volume computed from the whole sample, ITM, ATM, OTM, short-term options and long-term options respectively. P-values are presented in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level respectively. All parameter estimates are multiplied by 100.

	All Sample	ITM Options	ATM Options	OTM Options	Short Options	Long Options
Intercept	2.642*** (<.001)	2.949*** (<.001)	2.707*** (<.001)	3.923*** (<.001)	2.719*** (<.001)	3.189*** (<.001)
Media	1.814 (.155)	1.932 (.127)	1.638 ((.197)	2.148* (.099)	1.848 (.148)	2.395* (.064)
$OrderFlow_{stk}$	0.484*** (<.001)	0.463*** (<.001)	0.458*** (<.001)	0.517*** (<.001)	0.491*** (<.001)	0.507*** (<.001)
$CumAbvol_{opt}$	0.163*** (<.001)	0.302*** (<.001)	0.230*** (<.001)	0.033 (.438)	0.188*** (<.001)	0.160*** (<.001)
No.of obs	852	845	809	846	848	839
Adj. R^2 (%)	10.02	11.40	10.25	6.94	10.34	8.70

Table 3.7 Forecasting Takeover Targets Using Option Trading Volume

This table presents the parameter estimates for the hazard model that forecasts takeover targets with a set of time-varying predictors. Sample period is from Jan 1996 to Dec 2006. Volume and Openint are the natural logs of the monthly option trading volume and open interest respectively computed from OptionMetrics database; Mktcap is the natural log of the price multiplied by shares outstanding. Ret is the monthly excess return computed from CRSP; Stkvol is the monthly stock trading volume scaled by shares outstanding; Btm is the quarterly book-to-market ratio computed from Compustat. Model 1 use the aggregate option trading volume whereas in Model 2 to Model 6, trading volume computed from ITM, ATM and OTM, short-term and long-term options are used respectively. P-values for the Chi-square test statistics are presented in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level respectively.

	All Sample	ITM Options	ATM Options	OTM Options	Short Options	Long Options
Volume	0.926*** (<.001)	0.641*** (<.001)	0.971*** (<.001)	0.290*** (<.001)	0.916*** (<.001)	0.720*** (<.001)
Openint	-0.668*** (<.001)	-0.492*** (<.001)	-0.652*** (<.001)	-0.206*** (<.001)	-0.526*** (<.001)	-0.637*** (<.001)
Mktcap	-0.203*** (<.001)	-0.034 (0.293)	-0.284*** (<.001)	-0.033 (.305)	-0.164*** (<.001)	-0.157*** (<.001)
Ret	1.299*** (<.001)	1.314*** (<.001)	1.531*** (<.001)	1.653*** (<.001)	1.435*** (<.001)	1.406*** (<.001)
Btm	0.427*** (<.001)	0.357*** (<.001)	0.660*** (<.001)	0.234*** (<.001)	0.504*** (<.001)	0.267*** (<.001)
Stkvol	0.011** (0.031)	0.014*** (<.001)	0.013*** (<.001)	0.019*** (<.001)	0.012*** (<.001)	0.018*** (<.001)

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