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Option Implied Information for Quantitative Asset Management

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Chapter 1

1. Introduction

1.1 Informational Content of Option Markets

Derivatives play an indispensable role in financial markets nowadays. Their current size of \$700 trillion in outstanding notional value is more than 350 times greater than thirty years ago [Stulz (2004), BIS (2010)]. Along with this growing popularity, derivatives and especially option contracts have attracted the attention of financial researchers. While a lot of effort was put into research concerning the properties of derivatives and their correct valuation, the relationship between stock and option market has also attracted the financial researchers' attention in recent decades [e.g. Black (1975), Easley et al. (1998a)]. The main motivation of studies in this field of research is that option contracts are forward-looking contracts, since their payoffs depend on the future value of the underlying security. Hence, option markets are expected to incorporate the views of market participants about the potential future behaviour of the underlying assets. This information could be used for stock and portfolio selection, as well as in risk management. Especially in the asset management industry this additional information on potential future stock price movements and risk dynamics could help in investment decisions, portfolio optimisation and risk estimations.

Although numerous empirical studies investigate the informational linkage between stock and option markets, the evidence on market interrelationships between these two markets is still unclear. One large strand of literature examines the informational content

of option data for stock return predictability. While some authors argue that option prices and implied volatilities can predict future stock returns [e.g. Xing et al. (2008)], other researchers use the information content of option trading volume as a stock selection factor [e.g. Easley et al. (1998a), Pan and Poteshman. (2006)]. Another new strand of literature assesses the risk of underlying securities using option data. For example, Goyal and Saretto (2009) analyse the risk of securities using option implied volatility and develop volatility trading strategies based on this information.

Given these two strands of literature the objective of my thesis is to search for potential benefits and useful insights of option implied information. This is of particular interest for both academics and the asset management industry. This dissertation addresses the economic question of how information from option markets gets incorporated into asset prices and thus contributes to the literature that examines the linkage between the options market and the stock market.

1.2 Structure

This study is comprised of three essays which aim to improve the understanding of the informational content of option implied information. The first and second essays of the dissertation (chapter 2 and 3) focus on the predictability and informational content of option prices for future stock price movements. The third essay (chapter 4) is primarily concerned with the risk assessment of securities using option data. Chapter 5 gives a short summary of the main findings of all three essays.

1.2.1 Essay 1: The Informational Content of Put-Call Parity Deviations¹

The first essay (chapter 2) studies the informational content of put-call parity deviations. Previous studies show that deviations from put-call parity predict future stock returns. For example, Cremers and Weinbaum (2010) find that stocks with relatively expensive calls outperform stocks with relatively expensive puts at short-term horizons. They argue that this predictability reflects informed trading, with informed investors trading first in the options market. We extend their study and argue that only investors with short-term information trade in the option market and thus use short term options for their insider trading activities. We show that deviations from put-call parity in short-term options predict short-term returns, but not long-term returns. Furthermore, we find no evidence on insider trading in option markets of investors with long-term information. Our results indicate that long-term options are purchased primarily for investment purposes such as hedging.

1.2.2 Essay 2: Executive Compensation and Insider Trading around Mergers²

The second essay (chapter 3) studies option implied information in acquiring firms through mergers to detect informed trading activity. In the first part of the essay we

¹ The original essay, entitled "Informational Content of Put-Call Parity Deviations of Short- and Long Term Options" is joint research work of Lutz Johanning, Umut Ordu and Denis Schweizer. We thank Timo Gebken and Gaston Michel for helpful contribution to an early version of this essay.

² The original essay, entitled "Executive Compensation and Informed Insider Trading around Mergers and Acquisitions" is joint research work of Umut Ordu and Denis Schweizer.

Chapter 1. Introduction

show that abnormal option volume, which is a common indicator of informed trading, strongly increases prior to the announcement of a merger. Furthermore we show that the direction of option trades prior to an announcement can predict post merger returns. These results indicate informed trading activity prior to merger announcement and that option implied information can be used to predict the direction of post merger returns.

In the second part of this essay we try to explain that one part of abnormal option market activity prior to announcements is related to unreported trading of executives with a high stock price sensitivity. Our argument is as follows: executives with high wealth sensitivity to stock price changes have high incentives for insider trading in put option markets. A stock price decrease following an M&A-announcement would lead to large losses for the high sensitivity executive (e.g. employer options will get out of the money, lower bonuses etc.). To avoid the possible losses the executive has an incentive to hedge himself with put options. We expect that some of these highly sensitive executives will follow their incentives and trade illegally in option markets (or assign somebody else to do so). Thus we expect that the probability of insider trading in put options prior to an M&A-event is higher for those firms with high-sensitivity executives. We analyse the economic significance of post merger returns using portfolio trading strategies, quantile dummy regressions and test for several alternative explanations (e.g. weak governance and reported insider trades). Overall our results support the hypothesis that executives with high sensitivities might use option markets to hedge themselves against price decreases.

1.2.3 Essay 3: Option Implied Risk Dynamics around SEOs³

The third essay (chapter 4) examines the relationship between stock and option markets for the analysis of risk dynamics around SEO-events. We compare implied volatility from option markets and realized volatility from stock markets to show that option markets do not fully predict risk dynamics following extreme informational events as it is the case around equity issues. This is consistent with the findings of Stein (1989), Goyal and Saretto (2009) and Poteshman (2001) who observed misreaction in option markets as well. Our results support the hypothesis that option markets overestimate future volatility following seasoned equity offerings.

Moreover, we use volatility trading strategies to measure the extent of divergence between historical realized and implied volatility [see also Goyal and Saretto (2009)]. We find that straddle portfolios lead to risk adjusted positive returns of around five percent per month following SEO issuance. A first analysis indicates that the abnormal portfolio return of the volatility trading strategy could be interpreted as a risk premium for a compensation for writing options in a situation of a high uncertainty level around the SEO-event, where long options are more valuable.

³ The original essay, entitled "Do markets anticipate changes in risks after major corporate events? – Evidence from SEOs" is joint research work of Lutz Johanning, Umut Ordu and Denis Schweizer. We thank Timo Gebken and Gaston Michel for helpful comments and contribution to an early version of this essay.

Chapter 2

2. The Informational Content of Put-Call Parity Deviations⁴

2.1 Introduction

The financial literature features many controversial discussions about the informational content of put-call parity deviations. For example, Ofek et al. (2004) argue that deviations from put-call parity can arise in the presence of short sales constraints on the underlying stock; Bali and Hovakimian (2009) and Cremers and Weinbaum (2010), on the other hand, argue that put-call parity deviations contain information about future stock price behaviour. They argue that “high” positive differences between call and put implied volatilities indicate that call option prices exceed the levels implied by put option prices, and can thus predict positive stock price returns. Similarly, large negative differences between call and put implied volatilities would indicate that put option prices exceed the levels implied by put option prices, thus predicting negative stock price returns.

The innovative thrust of our paper is that it illustrates how the informational content of deviations from put-call parity depend on the time to maturity of the purchased option contracts – deviations in short-term contracts indicate informed trading; deviations in

⁴ The original essay, entitled "Informational Content of Put-Call Parity Deviations – Differences in Short- and Long-Term Options" is joint research work of Lutz Johanning, Umut Ordu and Denis Schweizer. We thank Timo Gebken and Gaston Michel for helpful contribution to an early version of this essay.

long-term contracts indicate hedging motives. In this sense, we posit that only deviations in short-term options will reflect informed trading activity and can predict future underlying equity returns. Our hypothesis is based on the theoretical equilibrium model of Easley et al. (1998b), who argue that informed traders may choose to trade in option markets because of the distinct characteristics of these markets. Hence, information is likely to be incorporated into asset prices in these markets first. If other markets fail to quickly incorporate the new information, a lead-lag relationship between asset prices may occur among different markets.

This informed trading activity should be reflected as deviations from put-call parity, because large differences between call and put implied volatilities may indicate price pressure in the option market from informed trading activity (Cremers and Weinbaum, 2010). However, deviations in long-term options are unlikely to be driven by informed trading, for several reasons.

First, it is unlikely that market participants would have credible information about events that are a year or more away. And if such information were available, investors would be unlikely to choose long-term options, because waiting until “closer” to the event is likely to save option time value and reduce the likelihood that confounding events in the meantime will undermine the strategy. Therefore, we argue that deviations from put-call parity for option contracts with long-term maturities are driven by hedging motives instead of by any superior informational content.

To test our hypothesis, we construct quantile portfolios based on put-call parity deviations, and analyse their subsequent returns. We observe that deviations in short-term option contracts predict short-term, but not long-term, future returns. This result is consistent with Cremers and Weinbaum’s (2010) observations, as well as with Easley

et al.'s (1998b) theoretical prediction that informed traders with short-term information (e.g., merger events, earnings announcements, etc.) will prefer short-term options for their trading activities.

Ultimately, we find no evidence of informed trading activity from put-call parity deviations in long-term option contracts. Our observation is consistent with the idea that informed traders with long-term information (e.g., information on the general prospects of a company) are exposed to a higher degree of uncertainty regarding the fulfilment of this information, and will thus rarely decide to trade in option markets. For example, unfavourable market conditions could outweigh any expected gains from the inside information, rendering the options unprofitable.

For long-term options, we observe that a portfolio consisting of firms with large negative put-call parity deviations (e.g., relatively more expensive puts than calls) has high and positive long-term (one-year) returns. We posit that this is because long-term put options are more likely to be used by mutual fund investors and insurance companies for investment purposes such as hedging, and not for exploiting inside information. Large negative put-call parity deviations could then indicate price pressure in the option markets, where more put options are demanded for hedging as the market anticipates higher risk in these positions. Following this idea, we could then interpret the reported higher positive portfolio returns as a risk premium to compensate for the higher (future) level of risk in these positions.

Under this assumption, we expect that firms with large negative put-call parity deviations in long-term options will be comparatively riskier. We show that asset beta as a proxy for risk level is higher in these firms than in those with small put-call parity deviations. Furthermore, we find that put-call parity deviations coincide with higher

volume when compared to options with lower deviations. We interpret this as support for the hypothesized price pressure in options markets.

This paper contributes to literature on the links between the options market and the stock market at a firm level. In particular, it is related to a recent strand of literature that examines the informational content of option markets for stock return predictability. Much recent attention has focused on factors that use the informational content of option prices and implied volatilities (e.g., Xing et al., 2010), and the informational content of option trading volume (e.g., Pan and Poteshman, 2006), as stock selection factors. We use a factor that combines both information sources by weighting put-call parity deviations with open interest.

Second, we extend and challenge the ongoing discussion of the informational content of put-call parity deviations. To the best of our knowledge, this is the first paper that analyses the informational content of put-call parity deviations of options with different times to maturity. This more refined classification enables us to conduct detailed analyses of short- and long-term informed trading activities, while avoiding oversimplification of the results by averaging through different maturities, as in Cremers and Weinbaum (2010).

Furthermore, we are the first to contribute empirically to discussions of the market segmentation theory (see Johnson et al., 2004, and Van Horne, 1980) for option markets, and to show strong evidence of the clientele effect for buying short- and long-term options. Informed investors (who have short-term information) are more likely to purchase short-term options, while investors buying long-term options are more likely to be uninformed and to base their investment decisions on hedging or speculation. Our

results show distinct differences in investor motives when buying options with different maturities.

The remainder of this paper is organized as follows. Section 2.2 gives an overview of the literature on the informational content of put-call parity deviations. In section 2.3, we describe our data sources, matching procedures, and the construction of the volatility spread measure. Section 2.4 presents our main results on the predictability of returns due to put-call parity deviations, while section 2.5 provides a possible explanation for the observed pattern of deviations in long-term options. Section 2.6 concludes.

2.2 Literature Review

The informational content of options markets has been widely studied in the finance literature. Black (1975) was among the first to predict that informed investors would choose to trade derivatives. He suggested that the higher leverage available in options markets might lead informed traders to choose them over stocks. And if the stock market is then slow to incorporate the information embedded in options markets, future stock returns should become predictable.

Subsequently, a large body of academic research has examined lead-lag relationships in general between the underlying stock market and the options market. For example, Chakravarty et al. (2004) use Hasbrouck's (1995) econometric model to analyse how options markets contribute to price discovery. They find that the call option market contributes an average of 17%, while the percentage varies across stocks.

Chan et al. (2002) analyse the informational content of option and stock quote revisions (returns), and option and stock net trade volume (buyer-initiated volume minus seller-

initiated volume) for future stock return predictability. Using intraday data, they show that option net trade volume has no predictive ability.⁵

Another strand of literature uses option implied information to detect informed trading activity prior to some specific events. Cao et al. (2005) show evidence of informed trading in takeover targets prior to merger announcements. Poteshman (2006) analysed option market activity prior to the September 11 terrorist attacks, and observed an unusually high level of put option buying on American Airlines and United Airlines, the two companies whose planes were hijacked that day.

More generally, Chesney et al. (2011a, 2011b) develop option implied indicators that can identify informed trading activities around mergers, earning announcements, the September 11 terrorist attacks, and the subprime financial crisis. Although numerous empirical studies have examined the informational links between the stock and options markets, evidence of market interrelationships remains somewhat unclear.

Easley et al. (1998b) provide a theoretical model of how information is incorporated into asset prices. They allow the participation of informed traders in the option market to be decided endogenously in a sequential equilibrium model. In this formal framework, informed investors choose to trade in the option market when 1) the leverage effect of options is large, 2) liquidity in the stock market is low, or 3) there are a large number of informed traders. According to this sequential trade model, option prices can convey information that is predictive of future stock price movements if at least some informed investors choose to trade in options before trading in the underlying stocks.

⁵ See Giamouridis and Skiadopoulos (2010) for an overview of the literature on the informational content of option markets.

Pan and Poteshman (2006) provide empirical evidence of this equilibrium model by analysing put-call ratios. Their research suggests that, overall, signed option volumes impact future underlying asset price dynamics. Moreover, Finucane (1991) analyses put-call parity deviations in S&P 100 Index options, and provides support for the notion that option markets can contain information on future stock price returns. In a similar fashion, Cremers and Weinbaum (2010) find that stocks with relatively expensive calls tend to outperform stocks with relatively expensive puts. Consistent with the Easley et al. (1998b) sequential trade model, they argue that this predictability reflects informed trading, with investors trading first in the options market.

However, Ofek et al. (2004), in contrast, argue that put-call parity deviations can arise in the presence of short sales constraints on the underlying stocks, and not because of informed trading. They show that deviations are asymmetric in the direction of short sales constraints, and are more likely to be observed in options written on stocks that are difficult or expensive to short. Battalio and Schultz (2006) question these findings, and criticize the use of non-synchronous prices. They argue that short sales constraints have little impact, and that using intraday options data, rather than closing quotes, could resolve most of the apparent put-call parity violations.

2.3 Data

To conduct our empirical analysis, we use daily stock and option data for the January 1996-December 2008 sample period. The data come from various sources: The option data come from OptionMetrics; the stock data come from the Center for Research in Security Prices (CRSP). The comprehensive option data cover all exchange-listed call and put options on U.S. equities, with approximately 7 million option price quotations per month.

OptionMetrics also reports the implied volatility on each option. The implied volatilities on options on the individual stocks, which are American, are calculated using a Cox-Ross-Rubinstein (1979) binomial tree, which takes into account discrete dividend payments and the potential for early exercise. The CRSP database includes monthly and daily price quotations for stocks on the New York and American stock exchanges, as well as on the NASDAQ.

Following Duarte et al.'s (2005) approach, we merge the option data with CRSP by requiring that the current CUSIP of the OptionMetrics security be in the historical record of CRSP CUSIPs. We thus eliminate options for which either the call or put has zero open interest, zero volume, or a bid price of zero.

2.3.1 Constructing the Volatility Spread Measure

To construct the volatility spread measure, our first step is to form pairs of call and put options on the same underlying equity, with the same expiration date and strike price. For every day and every pair, we determine deviations from put-call parity by taking the difference in implied volatility, or the “volatility spread,” between the call and put options. Several recent papers have followed a similar approach, such as Amin et al. (2004), Figlewski and Webb (1993), Bali and Hovakimian (2009), and Cremers and Weinbaum (2010).

In our second step, we divide the sample of option pairs into three time to maturity groups: short-term options with a time to maturity of less than one month, medium-term options with more than one month but less than one year, and long-term options with more than one year. Firms with both short- and long-term options on a given day are represented in both maturity groups on that day.

Finally, because firms may have several call and put option pairs on a given day and for a given maturity group, we measure the daily average deviation from put-call parity for a security in a time to maturity group by weighting the volatility spreads with the average open interest of the calls and puts. Such an open interest-weighted volatility spread enables us to combine the option pricing effects (deviations from put-call parity) with the option volume effects (weighting with open interest). A similar procedure is used by Cremers and Weinbaum (2010) and Wang (2008).⁶ The weighting ensures that firms will have only one measure of put-call parity deviation on a given day and for a given maturity group.

To summarize our calculation procedure, on every day t , we compute the put-call parity deviation of firm n as follows:

$$PC_{t,n} = \sum_{i=1}^z w^{i,t,n} \cdot (\sigma_{call}^{i,t,n} - \sigma_{put}^{i,t,n}), \quad (2.1)$$

$$w^{i,t,n} = \frac{OI_{call}^{i,t,n} + OI_{call}^{i,t,n}}{OI_{call}^{i,t,n} + OI_{put}^{i,t,n}}, \quad (2.2)$$

$$OI_{call}^{t,n} = \sum_{i=1}^z OI_{call}^{i,t,n}, \quad (2.3)$$

$$OI_{put}^{t,n} = \sum_{i=1}^z OI_{put}^{i,t,n}, \quad (2.4)$$

where $\sigma_{call}^{i,t,n} - \sigma_{put}^{i,t,n}$ is the implied volatility spread for option pair i on date t for underlying n , $w^{i,t,n}$ is the weighting of the volatility spread of option pair i with the

⁶ Easley et. al. (1998b), Chakravarty et. al. (2004), and Pan and Poteshman (2006), among others, document that option volume conveys information about future stock price movements. In addition, Wang (2008) shows that, during periods of informed trading activity, abnormal option trading volume is positively correlated with implied volatility spreads.

average open interest of this option pair, $OI_{call(put)}^{i,t,n}$ is the open interest of the call (put), and $\sigma_{call(put)}^{i,t,n}$ is the call (put) implied volatility. An option pair i consists of a call and a put option with the same underlying, maturity date, and strike price.

Table 2.1 gives the descriptive statistics for the resulting matched data sample over the January 1996-December 2008 period. For each time to maturity group, we report the time series average of daily firm data. A firm in a time to maturity group on a given day has valid option data when at least one call and put option pair is available on that date. Panel A shows that approximately 1.7 million firm observations have short-term maturities, more than half the firm observations (2.4 million) have medium-term maturities, and only 457,073 firm observations have long-term options data for the sample period.⁷ Furthermore, the average market value of firms in the long-term maturity group tends to be higher than that of firms in the short- and medium-term groups. This is intuitive, because long-term options are primarily traded for large-capitalization companies.

Panel B of Table 2.1 gives descriptive statistics for the time series-averaged daily volatility spreads of the firms. Consistent with Cremers and Weinbaum (2010) and Ofek et al. (2004), we note that the mean and median average volatility spread is small and negative, on the order of -1% for all time to maturity groups (i.e., put implied volatility slightly exceeds call implied volatility for our sample period).⁸

⁷ One firm observation consists of a pair of call and put options with the same strike, underlying, and maturity date.

⁸ This could be attributable to the presence of short sales constraints (as argued by Ofek et al., 2004), or to conditioning on the Black-Scholes (1973) model when computing volatility spreads (as argued by Cremers and Weinbaum, 2010).

We note further that the standard deviation of the volatility spread tends to be high for the short-term maturity group and low for the long-term maturity group. The lower variation is also reflected in the 10% and 90% deciles of the respective maturity groups, i.e., 7% and 4% for the volatility spread of the short-term options, and -3% and 2% for the volatility spread of long-term options.

Table 2.1: Summary Statistics

This table provides summary statistics for the January 1996-December 2008 sample period. We divide the sample into three time to maturity groups: firms with short-term options with a time to maturity of less than one month, firms with medium-term options with more than one month but less than one year, and firms with long-term options with more than one year. Panel A reports the total number of analyzed option pairs for the entire sample period (“Option observation total”), average number of option pair observations per day (“Option observation per day”), number of unique firms (“Unique number of firms”), and average firm size (“Size”). Panel B reports the summary statistics of the implied volatility spread, a security computed as the open interest-weighted difference of implied volatilities of call and put options with the same strike prices and maturities. Summary statistics are based on time series averages across the sample period.

	Option Maturities		
	Short-Term	Medium-Term	Long-Term
Panel A: Descriptive firm statistics			
Option observation total	1,791,045	2,442,295	457,073
Option observation per day	597	767	144
Unique number of firms	5,593	5,926	1,687
Size (Mio \$)	14,740	12,808	38,187
Panel B: Summary statistics of the implied volatility spread			
Mean	-0.01	-0.01	-0.01
Median	-0.01	-0.01	0.00
Stdv	0.07	0.06	0.05
Skew	-2.75	-6.02	-5.01
10% Decile Breakpoint	-0.07	-0.05	-0.03
90% Decile Breakpoint	0.04	0.02	0.02

2.4 Empirical Analyses of Deviations from Put-Call Parity

In section 2.4.1, we test whether put-call parity deviations can predict stock price returns (as a result of informed trading), and whether information type determines the preferred time to maturity of the purchased option contract. More precisely, we test whether investors with short- (long-) term information trade in short- (long-) term options. If they do, we should observe that put-call parity deviations in short-term option contracts will predict short-term, but not long-term, future returns. Similarly, deviations from put-call parity in long-term option contracts should predict long-term, but not necessarily short-term, future returns.

In section 2.4.2, we examine the source of the predictability observed in section 2.4.1. In particular, we need to analyse whether predictability comes from the informed trading activity in option markets. We thus compare the widely used probability of informed trading estimate (PIN) and the abnormal option volume measures among different quantile portfolios. When the predictability of the put-call parity deviations is due to informed trading, we expect that the PIN estimates and abnormal option volumes will be higher for quantile portfolios that contain options with high put-call parity deviations.

In section 2.4.3, we follow Johnson et al. (2004) and Van Horne (1980), and explore whether there is a clientele effect in investors' motivation to buy option contracts with different times to maturity.⁹ In this sense, we analyse whether deviations from put-call parity in long-term option contracts are driven by hedging or by speculative purposes.

⁹ Johnson et al. (2004) and Van Horne (1980) are among those who have studied clientele effects in fixed-income markets (often referred to as the “market segmentation theory”). They find no direct relationships among the interest rates that prevail within short- and long-term markets. Investors and borrowers have

2.4.1 The Return Predictability of Put-Call Parity Deviations

To analyse return predictability, we construct quantile portfolios based on put-call parity deviations and analyse their subsequent returns. In particular, for each time to maturity group, we divide all firms into quantiles based on their levels of volatility spreads, and consider the subsequent returns on those portfolios over horizons of one week to twelve months. Portfolio selection is repeated every Wednesday.¹⁰

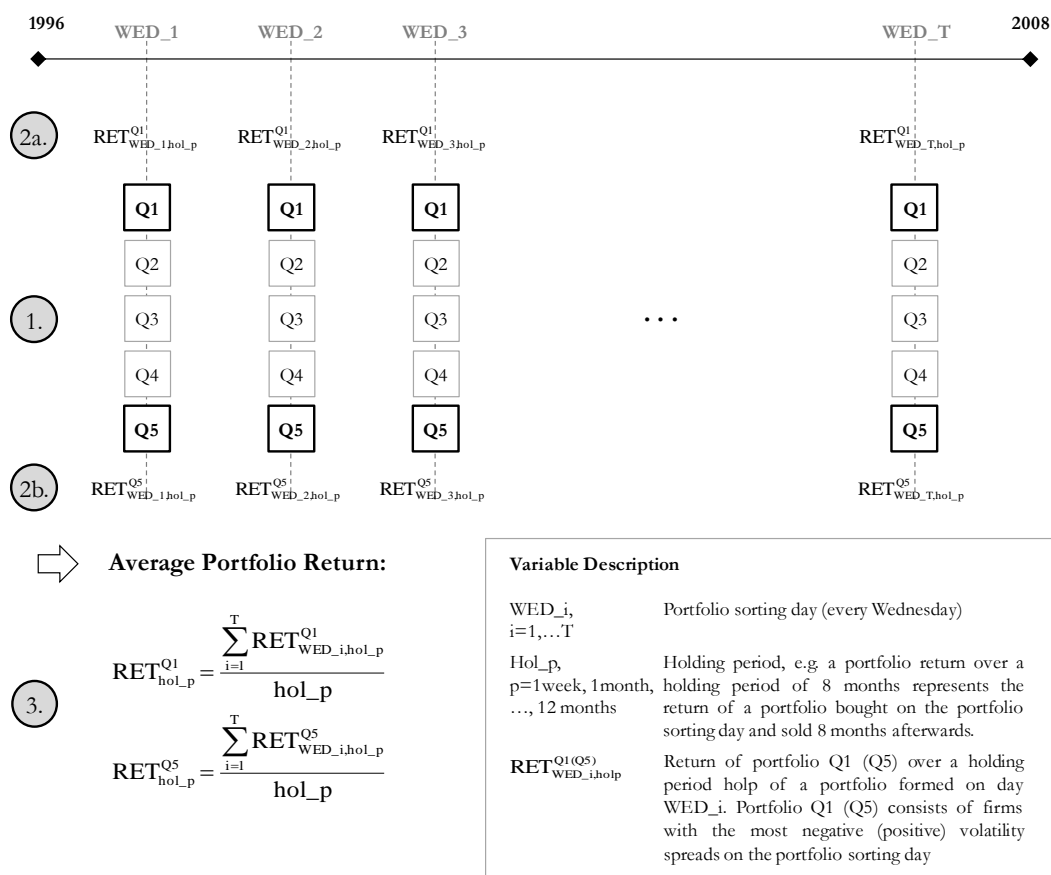
Figure 2.1 illustrates the return calculation procedure for a given time to maturity group. On every Wednesday (WED_i, $i=1, \dots, T$), we sort the firms in each group into quantile portfolios based on level of volatility spread (Q1, Q2, Q3, Q4, and Q5). For the two quantile portfolios with the largest put-call parity deviations (Q1 and Q5), we calculate returns (RET_{WED_i, hol_p}^{Q1} for portfolio Q1 and RET_{WED_i, hol_p}^{Q5} for portfolio Q5) over horizons of one week to twelve months (hol_p, $p=1 \text{ week}, \dots, 12 \text{ months}$). Finally, we compute the average returns over different holding periods for the quantile portfolios with the largest put-call parity deviations.

strong maturity preferences that they will try to attain when investing in or issuing fixed-income securities. As a result, the financial markets are segmented into several smaller markets, and the supply and demand forces unique to each segment determine the equilibrium yields.

¹⁰ For the sake of comparison, we follow Cremers and Weinbaum (2010) and also use Wednesday for the portfolio sorting. The authors find that the results are not sensitive when using option signals on different days.

Figure 2.1: Portfolio Sorting Procedure

This figure shows the sorting procedure used to obtain returns of quantile portfolios sorted on deviations from put-call parity. On every Wednesday (portfolio sorting date WED_i) from 1996 to 2008, we divide all firms into quantiles based on their levels of volatility spreads, i.e., portfolio Q1 has the lowest (most negative) volatility spread, portfolio Q2 has the second lowest volatility spread, etc. (“1.”). On all of these dates, we calculate the subsequent returns on the Q1 (“2a.”) and Q5 (“2b.”) quantile portfolios over horizons of one week to twelve months (hol_p=1 week,..., 12 months). In our final step, we take the average return over all portfolio sorting dates (“3.”).



Note that small deviations from put-call parity are often commonly observable because differences between call and put implied volatilities can be interpreted as deviations from model values for American options. Thus, we do not claim that put-call parity deviations represent arbitrage opportunities. Instead, we interpret large deviations

(quantile portfolios with the largest put-call parity deviations) as indicative of price pressures in the option market (Cremers and Weinbaum, 2010).

Battalio and Schultz (2006) illustrate the problems that can arise from the non-synchronicity of the option and stock markets. The option markets close at 4:02pm EST, while stock exchanges close at 4:00pm EST. To manage this problem, we follow Cremers and Weinbaum (2010), and form portfolios based on the 4:02pm EST volatility spreads. However, the returns only begin to accrue with the first trade when the stock market opens on the following day.

To ensure that our results are not driven by differences in risk or firm characteristics, we next follow previous work in financial economics and calculate risk-adjusted returns using the three factors of Fama and French (1993), Carhart's (1997) momentum factor, and a systematic coskewness factor as in Harvey and Siddique (2000).¹¹ We compute t-statistics using the Newey and West (1987) autocorrelation correction, because the holding period returns are autocorrelated up to the degree of the overlap, i.e., the returns for the four-week horizon are autocorrelated up to three lags.¹²

$$RET_T^{+PC} = \alpha + \beta_1 \cdot MKT_T + \beta_2 \cdot SMB_T + \beta_3 \cdot HML_T + \beta_4 \cdot MOM_T + \beta_5 \cdot SKEW_T + \epsilon_T, \quad (2.5)$$

$$RET_T^{-PC} = \alpha + \beta_1 \cdot MKT_T + \beta_2 \cdot SMB_T + \beta_3 \cdot HML_T + \beta_4 \cdot MOM_T + \beta_5 \cdot SKEW_T + \epsilon_T, \quad (2.6)$$

where RET_T is the return of the portfolio sorted by put-call parity deviations, MKT_T , SMB_T , and HML_T are the three Fama and French (1993) factors, MOM_T is the

¹¹ We obtain the three Fama-French factors and the momentum factor from Kenneth R. French's website.

¹² The regression specifications and variable names are the same as in Cremers and Weinbaum (2010).

Carhart (1997) momentum factor, and $SKEW_T$ is the Harvey and Siddique (2000) skewness factor.

Table 2.2: Return Predictability Due to Put-Call Parity Deviations

This table shows the returns of quantile portfolios sorted by put-call parity deviations. On every Wednesday, we divide all firms into quantiles based on their levels of volatility spreads of short-term (Panel A) and long-term options (Panel B). We then consider the subsequent returns on those portfolios over horizons of one week to twelve months. The first column indicates the holding period for the return calculation, e.g., the line “2 Month” shows the average annualized return of equity portfolios (portfolio “Q1,” “Q5,” and “Q5-Q1”) within the two months after the portfolio forming day (Wednesday). The first column (“Q1”) reports the annualized average portfolio returns of the quantile portfolio with the lowest (most negative) volatility spreads, the second column (“Q5”) reports the average return of firms with the highest volatility spreads, and the third column (“Q5-Q1”) gives the average return of the long-short equity portfolio. The “Alpha” column shows the risk-adjusted returns of the long-short portfolio using the three Fama and French (1993) factors, the Carhart (1997) momentum factor, and the systematic coskewness factor as in Harvey and Siddique (2000). We compute the t-statistics (column T-Stat) for the risk-adjusted long-short portfolio returns by using the Newey and West (1987) autocorrelation correction.

Panel A: Predictability with short-term options

in % p.a.	Long-Short Portfolio				
	Q1	Q5	Q5-Q1	Alpha	T-Stat
1 Week	-5.92	11.50	18.49	19.83	5.80
1 Month	1.88	6.75	4.79	6.68	4.31
2 Month	1.86	4.71	2.81	4.85	4.10
3 Month	2.23	4.82	2.54	4.20	4.00
4 Month	3.55	5.28	1.69	3.42	3.72
5 Month	3.65	5.61	1.92	2.06	2.39
6 Month	3.97	5.13	1.13	1.82	2.35
7 Month	4.26	5.55	1.26	1.52	1.99
8 Month	5.21	5.95	0.72	1.02	1.39
9 Month	6.09	6.84	0.74	1.96	1.75
10 Month	6.69	7.09	0.39	0.94	1.11
11 Month	7.12	7.60	0.47	-0.76	-0.78
12 Month	8.55	8.50	-0.05	-0.40	-0.43

Panel B: Predictability with long-term options

in % p.a.	Long-Short Portfolio				
	Q1	Q5	Q5-Q1	Alpha	T-Stat
1 Week	-0.80	4.62	5.47	9.52	1.69
1 Month	4.34	6.37	1.96	5.21	1.35
2 Month	5.24	6.40	1.12	4.05	1.58
3 Month	8.26	7.20	-1.01	1.77	0.78
4 Month	9.30	7.48	-1.72	0.77	0.40
5 Month	9.87	7.27	-2.46	-1.00	-0.52
6 Month	10.67	7.45	-3.06	-0.81	-0.39
7 Month	11.51	8.47	-2.90	-1.78	-0.84
8 Month	12.66	9.52	-3.02	-2.77	-1.25
9 Month	14.17	10.86	-3.20	-3.33	-1.50
10 Month	15.57	11.80	-3.68	-6.25	-2.72
11 Month	16.01	12.32	-3.64	-6.60	-2.91
12 Month	17.31	13.48	-3.82	-5.99	-2.47

Table 2.2 summarizes our results. In Panel A, we observe that the long-short portfolio consisting of short-term options with large put-call parity deviations has significantly positive short-term returns, while the longer-term returns are lower and gradually become insignificant. The long-short portfolio generates a raw return of approximately 18.5% p.a., and a significant risk-adjusted return of 19.8% p.a. for a one-week return period. The risk-adjusted returns gradually decrease over time, with significant values for the first half of the year after the sorting, and insignificant values afterward¹³. This is consistent with our hypothesis that short-term investors with insider information prefer to trade in short-term options, and that these options will have predictive power for subsequent stock returns only at short-term horizons.

¹³ Throughout this chapter, the term significance is related to the significance of the Newey and West (1987) T-statistic at a 10% level.

In Panel B of Table 2.2, we find no evidence of informed trading activities for long-term options at short-term horizons. The short-term horizon returns are low, t-statistics are insignificant, and long-term returns are high. However, the long-short portfolio, which consists of long positions in firms with high positive differences between call and put implied volatilities (which should predict positive stock price returns), and short positions in firms with high negative differences (which should predict negative stock price returns), is negative, indicating no predictability from put-call parity deviations.

There are several potential explanations for this observation. For example, our methodology may not be able to identify traders with long-term insider information. We also perform portfolio sorting on only a weekly basis. To identify any abnormalities, we would need a minimum number of informed trades. However, it is also likely that more traders possess short-term insider information (e.g., M&As, earnings announcements, dividend payments, SEOs, etc.) than long-term insider information. Thus, traders with long-term information face higher uncertainty levels about the fulfilment of the information. For example, if market conditions change dramatically, the options could become unprofitable. These investors may thus be less likely to trade (illegally) in option markets.

Furthermore, our long-term option dataset has many fewer observations than our short-term option dataset (597 daily observations on average for short-term options, versus 144 for long-term options). We thus tested for predictability using an alternative methodology that can detect informed trading. We constructed “extreme” portfolios

based on the largest changes in open interest on a given day, and then considered the subsequent returns.¹⁴

Table 2.3: Predictability using Open Interest

This table shows annualized returns for the portfolios with the largest changes (highest 20) in open interest in calls (column “Call”) and puts (column (“Put”) on a given day. The “Alpha” column shows the risk-adjusted return of these extreme portfolios using the three Fama and French (1993) factors, the Carhart (1997) momentum factor, and the systematic coskewness factor as in Harvey and Siddique (2000). We compute the t-statistics (column T-Stat) for the risk-adjusted portfolio returns by using the Newey and West (1987) autocorrelation correction. ** indicates a significance at the 5% level and * indicates a significance at the 10% level

in % p.a.	Return		Excess Return		Alpha		T-Stat (of Alpha)	
	Call	Put	Call	Put	Call	Put	Call	Put
1 Week	55.27	14.88	48.54	9.98	18.48	-0.94	0.67	-0.03
1 Month	18.83	28.58	14.47	23.94	4.37	-0.88	0.38	-0.08
2 Month	8.51	18.71	4.62	14.56	-6.76	-9.39	-0.65	-0.85
3 Month	20.09	12.19	15.95	8.27	3.28	-0.05	0.33	-0.01
4 Month	22.11	20.59	17.99	16.49	5.98	9.41	0.64	1.02
5 Month	17.47	20.34	13.52	16.32	5.14	8.07	0.53	0.98
6 Month	11.34	21.70	7.57	17.72	-3.28	12.20	-0.34	1.14
7 Month	12.04	18.82	8.28	14.92	0.70	6.96	0.08	0.89
8 Month	12.83	17.79	9.11	13.95	7.64	8.99	0.94	1.24
9 Month	11.73	14.40	8.07	10.64	11.04	-4.56	1.51	-0.70
10 Month	12.68	9.22	9.04	5.52	17.33	-5.26	2.15 **	-0.63
11 Month	13.06	8.29	9.46	4.62	13.35	-4.68	1.65 *	-0.50
12 Month	10.61	6.54	7.06	2.90	12.96	-3.73	1.69 *	-0.48

In this analysis summarized in Table 2.3 we observe that the long-term returns generated from the portfolio with high open interest in call options are slightly significant at a 10% significance level but the returns generated from the portfolio with

¹⁴ To account for firm characteristics, we weight the open interest measure by the number of outstanding shares of the given firm. See, for example, Jayaraman et al. (2001) and Donders et al. (2000), who use open interest as an indicator of informed trading activity.

high open interest in put options are highly insignificant. This is consistent with our previous results, which indicate that long-term options are not used by long-term investors for the purposes of informed trading.

Overall, our analysis indicates that investors with short-term information tend to trade in short-term but not long-term options. Furthermore, we find no evidence that investors with long-term information engage in informed trading.

2.4.2 Can Put-Call Parity Deviations be Explained by Informed Trading?

In this subsection, we analyze the source of the deviations from put-call parity in short- and long-term options. We need to determine whether the predictability of short-term options observed in Panel A of Table 2.2 is attributable to informed trading activity in options markets.

In a first analysis, we estimate the widely used probability of informed trading (PIN) for the quantile portfolios.¹⁵ The PIN signifies the probability that a particular stock trade is information-based. It is commonly used in the financial literature to detect informed trades in stock markets (see, e.g., Easley et al., 1997, 1998a; Cremers and Weinbaum, 2010; and Vega, 2006). The PIN measure is also positively correlated with the probability of informed trading. Thus, when observed abnormal returns of the quantile portfolios with the highest and lowest put-call parity deviations are a result of informed trading, these portfolios should have higher PIN measures than those that are not

¹⁵ To the best of our knowledge, Easley and O'Hara (1987) were the first to develop a measure of the probability of information-based trading.

within the top quantile. We posit that the average PIN in Portfolios Q1 and Q5 will be higher than in the other quantile portfolios (for example, Q3).

We obtain PIN data from two sources. From 1995 to 2001, we use Easley et al.'s (2002, 2004) PIN estimate; from 2003 to 2008, we use a slightly different measure developed by Venter and DeJongh (2004).¹⁶ Because we do not compare PIN measures over time, but only on a given date for different firms, the use of different PIN measures should not bias our results.

For short-term options, we observe higher PIN measures for both time periods in the top quantile portfolios (Q1 and Q5) than in the other portfolios (Q2, Q3, and Q4) – see Panel A in Table 2.3. This finding is consistent with the idea that market participants place informed investment decisions in the top quantile portfolios.

In addition to the PIN measures, we also analyse abnormal option volume within the quantile portfolios. This is another commonly used indicator of informed trading activity in option markets¹⁷ (see, for example, Easley et al., 1998b, and Pan and Poteshman, 2006).

Every Wednesday, we apply the quantile portfolio selection based on put-call parity deviations. We then construct abnormal option volume measures for every firm in our sample for calls (AVOL_C), puts (AVOL_P), and total options (AVOL), as follows:

¹⁶ We obtain PIN data for 1995 to 2001 from Soeren Hvidkjaer's website, and extended PIN data for 2003 to 2008 from Stephen Brown's website. The main difference between the two models is that Easley et al.'s (2004) model assumes that the daily numbers of uninformed buys and sells are uncorrelated, while Venter and DeJongh (2004) relax this assumption. For a description of the extended model and a discussion of why these PINs are considered superior, see Brown and Hillegeist (2007).

¹⁷ Several studies argue that option trading volume conveys information about future stock price movements. See, e.g., Easley et al. (1998b), Cao et al. (2005), Chakravarty et al. (2004), Schlag and Stoll (2005), Pan and Poteshman (2006), and Wang (2008).

$$AVOL_C_i = VOL_i^{call} - VOLB_i^{call} \quad (2.7)$$

$$AVOL_P_i = VOL_i^{put} - VOLB_i^{put} \quad (2.8)$$

$$AVOL_i = AVOL_C_i + AVOL_P_i \quad (2.9)$$

where $VOL_i^{call (put)}$ is the call (put) option volume, and $VOLB_i^{call (put)}$ is the daily long-term average trading volume of firm i .¹⁸

Under normal market conditions, the average AVOL for calls and puts is expected to be close to zero. When our intuition is correct and there is informed trading in option markets, we expect that the quantile portfolios with the largest put-call parity deviations (Q1 and Q5) will have higher abnormal option volumes than the other quantile portfolios (Q2 to Q4). We also expect that abnormal call option volume for the quantile portfolios with positive deviations from put-call parity should be higher than abnormal put option volume, and vice versa for the quantile portfolios with negative deviations. In Panel B of Table 2.4, we report average abnormal option volumes for the quantile portfolios based on differences in put-call parity deviations.

Consistent with the hypotheses developed in Easley et al. (1998b), we observe that quantile portfolio Q5 has higher abnormal put and call option volume than portfolio Q1. Thus, both the PIN measure and the abnormal option volume measure strongly

¹⁸ This is a representation of the fixed mean model commonly used in event studies. See MacKinlay (1997), Campbell et al. (1997), and Lyon et al. (1999).

indicate that abnormal returns for short-term options for the top quantile portfolios are attributable to informed trading.

To compare the results to the deviations from long-term options, we conducted the same analyses. In Panel C of Table 2.4 we observe that the PIN measures between the Q1 and Q5 and the other quantile portfolios (Q2, Q3, and Q4) are similar to the ones observed for the short term portfolio, however the difference in the Easley et al. (2002, 2004) PIN measure is statistically not significant. Furthermore, the results for the abnormal option volumes are inconclusive (Table 2.4, Panel D).

In summary, we find no evidence that put-call parity deviations from long-term options can be explained by informed trading activity. This indicates that the rationale for entering into long-term option contracts is likely to be different from that for entering into short-term options, as predicted by the clientele effect described in Johnson et al. (2004) and Van Horne (1980).

Table 2.4: Testing for Informed Trading Activities

This table shows the factors that indicate informed trading activities for quantile portfolios based on put-call parity deviations. The first column (“Q1”) reports the statistics of the quantile portfolio with the lowest (most negative) volatility spreads, the second column (“Q3”) reports the statistics of firms with average volatility spreads (benchmark), and the third column (“Q5”) gives the portfolio statistics of firms with the highest (most positive) volatility spreads. Panel A reports PIN measures as developed by Easley et al. (2002, 2004) for the 1995-2001 period (row (1)), and PIN measures as developed by Venter and DeJongh (2004) for the 2003-2008 period (row (2)). Higher PIN measures indicate a higher probability of informed trading. Panel B reports abnormal call (AVOL_C), abnormal put (AVOL_P), and total abnormal option volume (AVOL). Higher abnormal option volume indicates higher informed trading activity. The abnormal option volume is constructed using a fixed mean model as in MacKinlay (1997).

Panel A: Short Term Options - PIN estimates for different quantile portfolios

	Q1	Q3	Q5
(1) 1995-2001 Easley et al. (2002, 2004)	0.13	0.11	0.12
(2) 2003-2008 Venter and DeJongh (2004)	0.10	0.09	0.10

Panel B: Short Term Options - Abnormal option volume for different quantile portfolios

	Q1	Q3	Q5
AVOL_C	579	-339	612
AVOL_P	473	-297	393
AVOL	1,052	-636	1,006

Panel C: Long Term Options - PIN estimates for different quantile portfolios

	Q1	Q3	Q5
(1) 1995-2001 Easley et al. (2002, 2004)	0.11	0.10	0.11
(2) 2003-2008 Venter and DeJongh (2004)	0.10	0.07	0.08

Panel D: Long Term Options - Abnormal option volume for different quantile portfolios

	Q1	Q3	Q5
AVOL_C	969	222	2300
AVOL_P	1303	206	1429
AVOL	2272	428	3729

2.4.3 Can Put-Call Parity Deviations be Explained by Investment Purpose?

In section 2.4.2, we failed to find empirical evidence that deviations from put-call parity for long-term options can be explained by informed trading activity. We thus need to examine the other potential reasons for these deviations. Another motive for investors to purchase long-term options may be hedging or speculation. In this case, it would be rational to assume that investors willing to speculate on an upward-trending equity market would choose “high beta stocks” for their call option trades in order to obtain higher leverage. However, on the other hand, if investors want to hedge positions due to the expectation of a downward-trending equity market, the positions hedged first are likely to be the “high beta stocks.”

Therefore, we expect that the betas for the top quantiles (Q1 and Q5) will be higher than those of, e.g., Q3. Table 2.5 provides an illustration: The beta of quantile portfolio Q1 (Q5) is 1.44 (1.36), which is higher than that of quantile portfolio Q3 (1.25). This supports our hypothesis that investors use long-term options for different investment purposes than short-term options, where we do not see such clear sorting.

To further verify our hypothesis, we assume that put-call parity deviations for long-term options are triggered by the demand side, due to strong hedging or speculative demand. Consequently, we also expect that we can detect demand-side price pressures by comparing the option volumes in the quantiles for put and call options. In the top quantile, Q5, we expect the call option volume to be higher than in the other quantiles. And, indeed, call option volume in portfolio Q5 is 3,382, much higher than Q3 (2,810) and Q1 (2,714) (see Table 2.5). We note the same for put option volume, where the highest volume is found in the Q1 portfolio (2,488), again much higher than in the Q3 or Q5 portfolios. We conducted the same analyses for the short-term options, and again do not find consistent results.

In summary, we find distinct differences between the investment purposes of short- and long-term options. Short-term options are more likely to be used for their information content; long-term options are more likely to be used for investment purposes such as hedging.

Table 2.5: Statistics for Put-Call parity Deviations in Long-Term Options

This table shows portfolio statistics of quantile portfolios sorted by put-call parity deviations in long-term options. On every Wednesday, we divide all firms into quantiles based on their levels of volatility spreads of long-term options. We then report 1) the average beta on the portfolio sorting date where put-call parity deviations are measured (t), and use as proxy the beta coefficient from an ordinary least squares regression for the 250 trading days before the event, 2) call option volume at t , and 3) put option volume at t . The first column (“Q1”) reports the statistics of the quantile portfolio with the lowest (most negative)

volatility spreads, the second column (“Q3”) reports the statistics of firms with average volatility spreads (benchmark), and the third column (“Q5”) gives the portfolio statistics of firms with the highest (most positive) volatility spreads.

	Long-Term Options		
	Q1	Q3	Q5
Beta at t	1.44	1.25	1.36
Call Option Volume	2,714	2,810	3,382
Put Option Volume	2,488	1,980	2,267

2.5 Conclusions

This study has analysed the informational content and investment purposes of large put-call parity deviations for options with different time to maturities. We show that large deviations from put-call parity in short-term options can predict short-, but not long-term, returns. Quantile portfolios with large positive differences between call and put implied volatilities have an average 12% p.a. return within the first week after the observation, while those with large negative differences have an average -6% p.a. return in the first week after the observation. Furthermore, portfolios with high put-call parity deviations also exhibit higher probabilities of informed trading and higher abnormal option volume. These results indicate the predictability of the returns due to put-call parity deviations (Cremers and Weinbaum, 2010; Bali and Hovakimian, 2009) and informed trading of short-term investors in short-term options, which is consistent with Easley et al.’s (1998b) theoretical model.

We found no evidence of informed trading in long-term options by investors with long-term insider information. We interpret this result as evidence that there are few investors possessing long-term insider information who trade in option markets with long-term options, probably because they are exposed to higher uncertainty about the fulfilment of the insider information (e.g., market conditions could change and the

options could become unprofitable). Admittedly, we find strong support that long-term options are bought primarily for investment purposes, such as hedging or speculation.

Taken together, our short- and long-term option results provide strong empirical support for the view that options with differences in maturities tend to be purchased by different investor clienteles.

Chapter 3

3. Executive Compensation and Insider Trading around Mergers¹⁹

3.1 Introduction

Mergers and acquisitions (M&As) are important events in corporate finance associated with the creation, destruction, and redistribution of acquirer shareholder wealth. Extensive research has shown that shareholders in target firms gain significantly and that wealth is created at the announcement of takeovers. However, we know much less about the effects of takeovers on the shareholders of acquiring firms. Evidence suggests that, these shareholders earn about an average negative abnormal return at the announcement of acquisitions, though there is tremendous variation in returns, e.g. public versus private targets [Andrade et al. (2001)], cash versus stock payments [Moeller et al. (2004)], time periods [Bradley et al. (1988)], small versus large acquirer firms [Andrade et al. (2001)].

Researchers have been unable to successfully explain much of this variation, partially because the announcement of a takeover reveals information about numerous things. For example, Grinblatt and Titman (2002) state that the bidder stock return at the time of the bid cannot be completely attributed to the expected effect of the acquisition on profitability, and might tell more about how the market is reassessing the bidder's

¹⁹ The original essay, entitled "Executive Compensation and Informed Insider Trading around Mergers and Acquisitions" is joint research work of Umut Ordu and Denis Schweizer.

business than it does about the value of the acquisition. In the same line of argumentation Hietala et al. (2003) note that the announcement of a takeover reveals information about the potential synergies in the combination, the stand-alone values of the acquirer(s) and target(s), and the bidder overpayment.

The managers of the acquiring firm, rewarded for short-term performance, might have an incentive for a “signalling bias” by deliberately timing the “good news” of the bid announcement to coincide with the release of bad news such as unmet earnings targets [see Bhagat et al. (2005)]. With this practice acquirers’ management confounds the information about an acquisition’s value into the bidders’ stock price on the acquisition announcement, and results in a downward revaluation of an acquirer’s stand-alone value. This intended intransparent information policy probably creates higher uncertainty levels, unwanted by acquirer’s shareholders, and is therefore likely to negatively affect the stock price [Epstein and Schneider (2008)]. On the contrary the bid itself typically releases bad news about an acquirer, even when there is no motive to distort the markets perception of company value. For example, it may reveal serious empire-building tendencies of incumbent management, or that acquirer’s management has run out of profitable internal growth opportunities [see Fuller et al. (2002), and Hietala et al. (2003)]. Furthermore, acquirer’s management might engage in market timing and place stock bids when the stock is relatively overvalued [see, for instance, Shleifer and Vishny (2003) and Dong et al. (2006)].

In all of the above mentioned cases it is likely that acquirer’s management, who is in charge of the mergers’ decision-making process, destroy wealth of its own shareholders [see Betton et al. (2008), Chapter 15 for a summary]. These findings are in contrast to the neoclassical theory of M&A which asserts the profit motive of the acquirer will

naturally drive the ownership of assets to their highest value use. It follows from this motivation that the initiator (acquirer's management and its shareholders) will benefit from such wealth-enhancing transactions, rather than suffer losses. In addition acquirer's management compensation is linked to the performance via e.g. stock options, shares resulting at least in a short-term loss even if it can be overcompensated with "better" employment contracts for the merged company. This synchronization of management compensation with company performance should in theory reduce management's willingness to engage in negative-NPV investments, because (at least short-term) monetary losses could outbalance the utility from "ruling" a bigger empire and the discounted expected future remuneration increase in employment contracts.

This penalty of monetary losses from empire building is going to increase with a higher variable compensation (managerial pay to performance sensitivity) and should consequently reduce the incentive in pursuing value destroying mergers from acquirer's management and shareholders perspective. One way of uncoupling the alignment of interests between bidder's management and its shareholders is to hedge against losses in share price before the merger announcement. In this case bidder's management would reduce losses from their variable compensation (or even benefit) and at the same time maintaining the benefits. Interestingly, prior research on insider trading and compensation argues that insider trading is an efficient form of variable compensation as it allows insiders to profit from their innovation and effort [see among others Dye (1984), Carlton and Fischel (1983) and Manne (1966)] and is negatively correlated with managerial pay to performance sensitivity [see e.g. Zhang et al. (2005)]. In case of an "empire building" merger we would expect the opposite, since managers with the highest pay to performance sensitivity have the highest incentives to trade on insider information, because e.g. employer options will get out of the money, lower bonus, etc.

Chapter 3. Executive Compensation and Insider Trading around Mergers

One way of hedging against possible losses is to buy put options before the merger announcement. Given this rationale we expect to find higher put option volumes prior to an M&A-event for those bidders with high managerial pay to performance sensitivity.

To test our hypothesis that executive managers might trade with put options we conduct several analyses: In a first step we analyze abnormal trading activity in option markets for acquiring firms prior to merger announcements. Consistent with prior literature [e.g. Cao et al. (2005), Wang (2008)] we identify large abnormal call and put option volumes prior to a mergers. Furthermore we observe that abnormal call and put option volume is higher for stock- mergers than for cash-mergers.

In a second analysis we use abnormal option volume to test for predictability of post merger returns. When our intuition is correct and the abnormal trading activity observed in the first step indicates informed trading then we should be able to predict post M&A returns. We show that this is the case and that portfolios consisting of positions where the abnormal call volume is higher than the abnormal put volume generates positive abnormal post M&A returns whereas portfolios where the abnormal put volume is higher than the abnormal call volume generates negative abnormal post M&A returns.

Finally, we evaluate whether the observed abnormal option behaviour is linked to executive pay and performance sensitivity. We observe that a portfolio consisting of positions where the abnormal put volume is higher than the abnormal call volume as well as firms where executives have high wealth to performance sensitivities generates significant negative abnormal post merger returns. The portfolio consisting of more call than put option volumes has no significant abnormal post merger returns.

Overall our results support the hypothesis of informed trading activity prior to mergers and that top executives use option markets to protect themselves against short term

losses following mergers. Our results are of particular interest for existing literature analyzing the relationship between informed trading activity and executive compensation.

The remainder of this paper is organized as follows. In Section 3.2 we describe our data sources. In Section 3.3 we analyze option market trading activity prior to merger announcements. Section 3.4 investigates the predictability of post merger returns using option implied information prior to merger announcements. Section 3.5 presents our main results on informed trading of executives with high variable compensation. In Section 3.6 we show the results of additional robustness checks and Section 3.7 forms the conclusion of this study.

3.2 Data

The empirical analysis was conducted using daily M&A data for the sample period from January 1996 to December 2008. Our data comes from different sources:

- **Stock Price Data:** The stock price data comes from the Center for Research in Security Prices (CRSP). The CRSP database includes monthly and daily price quotations for stocks on the New York and American stock exchanges and NASDAQ. We use daily stock price data from 1995 to 2009. Data from 2009 is used to calculate post returns for mergers at the end of 2008. Data from 1995 is used to estimate abnormal returns using the market return model of Campbell et al. (1997)²⁰.

²⁰ In this model return data prior to the calculation period is needed in order to estimate historical benchmark returns.

- **M&A Data:** The M&A sample comes from the Thompson Reuters Securities Data Company's (SDC) Mergers and Acquisition Database. SDC covers corporate transactions involving at least 5% of the ownership of a company where the transaction was valued at a minimum of one million dollar or was undisclosed. We include all acquirer firms from the United States with a minimum rank value of fifty million dollars²¹. While most prior event study has analyzed target companies from the US we decided to analyze acquiring firms with no restrictions on the target firms' nationality. Compared to previous literature on insider trading around merger events, this enables us to analyze a much larger dataset²². When a firm has several deals within seven months we include only the event with the earliest announcement date. The other deals are excluded to ensure that the data in the estimation window (seven month prior to announcement – one month prior to announcement) and the event window (one month prior to announcement – announcement date) is not biased due to announcement effects.
- **Option Data:** For the analysis of informed trading in option markets we follow standard financial literature and take daily call and put option volume data from OptionMetrics²³. The database covers all exchange listed call and put options on US equities with approximately seven million options per month. OptionMetrics

²¹ Rank value is calculated by subtracting the value of any liabilities assumed in a transaction from the transaction value and by adding the target's net debt. Net debt is straight debt plus short-term debt plus preferred equity minus cash and marketable securities as of the date of the most current financial information prior to the announcement of the transaction.

²² Cao et al. (2005) analyze 78 takeover targets from 1986 to 1994; Jayaraman et al. (2001) analyze 33 acquisitions from 1986 to 1996; Arnold et al. (2006) analyze 45 targets from 1993 to 2002; Wang (2008) analyze insider trading from 1996 to 2006 using a sample of 1919 merger announcements with target stocks.

²³ Other studies arguing that option trading volume conveys information about future stock price movements are, Easley et al. (1998), Cao et al.(2005), Chakravarty et al. (2004), Schlag and Stoll (2005), Pan and Poteshman (2006), Wang (2008).

provides trading volume information for each option contract, which allows us to compute the trading volume for options classified by maturities and moneyness. We take only options contracts which are OTM or ATM with a maximum time to maturity of three months and an implied volatility larger than zero. We take only short term options since informed traders' private information is short-lived and they will choose to trade short-term options before their private information becomes public. We include OTM options as they provide the highest leverage for an insider trader and ATM options as these are the most liquid positions [see Black (1975), Easley et al. (1998), Wang (2008)].

- **Data on Executive Sensitivities:** In prior literature several authors proposed methods to estimate sensitivity measures of executive compensation. The most prominent one is the pay-for-performance sensitivity (PPS) described in Core and Guay (1999, 2002). PPS reflects the change of an executive's wealth from his stock and option holdings, given a 1% increase in stock price. Another commonly used sensitivity is the Jensen and Murphy (1990) measure (JM) which estimates the change in the total wealth of an executive for a dollar change in shareholder wealth. In a more recent study Edmans et al. (2009) compare different measures of executive sensitivity and proposed a new measure which they call scaled wealth to performance sensitivity (WPS). It is the dollar change in an executive's wealth for a 100 percentage point change in firm value, divided by annual flow compensation²⁴. We decided to use the measure of Edmans et al. (2009) in our analysis as the key advantage of this incentive measure is that, different to PPS and JM, it is independent of firm size and thus comparable across firms and over time.

²⁴ This incentive measure is a variant of the incentive measure used or advocated in Murphy (1985), Gibbons and Murphy (1992), and Rosen (1992).

Theoretically, it is generated by a model where effort has a multiplicative effect on both firm value and executive utility²⁵. In our analysis we use two representations of the WPS measure: The first one is the CEOs wealth to performance sensitivity (CEO-WPS) and the second measure is the average wealth to performance sensitivity of the top executives of a firm (EX-WPS). Both measures are calculated using data from the Execucomp and Compustat database. Details of the variable construction are provided in the Appendix (Section 3.8).

Every dataset is first matched with the CRSP dataset to have PERMNO as the key identifier. SDC M&A and OptionMetrics are matched with CRSP through six-digit- and nine-digit- CUSIPs. Execucomp and Compustat are matched with CRSP through the CCM-linking table available in WRDS²⁶. To ensure that option trading prior to an announcement is not due to a reported change in an executives ownership position we obtain information on the change in an insider's ownership position due to open market derivative transactions (SEC's Form 4) from the Thompson Reuters Insider Filings Database. We identify and exclude thirty merger events where option transactions from insiders were reported to SEC in the three months prior to the merger announcement.

Table 3.1 shows a summary of statistics for our sample. Our final sample consists of 5,986 M&A deals executed by 2,599 acquiring firms in the period between 1996 and 2008. 2,539 deals were paid by cash (cash-M&A), 1,830 by stocks (stock-M&A) and 1,617 were mixed transactions. Out of the 5,986 transactions we have valid CEO-WPS

²⁵ Recent papers using the scaled wealth to performance sensitivity of Edmans et al. (2009) are Frydman and Jenter (2010), Kim and Lu (2011), Hagendorff and Vallascas (2011)

²⁶ <https://wrds-web.wharton.upenn.edu/wrds/>

data for 3,714 positions. This smaller sample is only used in Sections 3.5 and 3.6 when we analyze the WPS measures.

Table 3.1: Sample statistics

The table reports portfolio statistics on acquiring stocks for three samples: the whole sample (column “All”), the subsample consisting of mergers where more than 50% of the merger was financed by stocks (column “Stock”) and the subsample consisting of mergers where more than 50% of the merger was financed by cash (column “Cash”). “EX-WPS” denotes the average wealth to performance sensitivity of top executives from acquiring firms. “CEO-WPS” denotes average wealth to performance sensitivities for CEOs of acquiring firms.

	All	Stock	Cash
Panel A: Size			
Total	5,986	1,830	2,539
US targets	5,059	1,692	2,088
Nr. of acquiring companies	2,599	1,240	1,511
WPS Data available	3,714	975	1,674
Panel B: Volume Measures (\$ Mil)			
Market Cap	9,240	7,665	9,504
M&A Rank Value	863	1,602	594
Panel C: Post M&A returns (%)			
First week	0.7	-0.6	1.4
First month	1.3	0.1	1.9
First three months	2.0	0.7	2.3

In Panel B of Table 3.1 we can observe that stock-M&A have lower market capitalizations but higher rank values than cash-M&A. The mean rank value is almost

twice as large as the mean for the whole sample. One possible explanation is that smaller firms with smaller market capitalization want to catch up to larger firms and are therefore involved in large mergers.

In Panel C we can observe that for the first week following the announcement date cash-M&A have positive returns and stock-M&A have negative returns. This is consistent with empirical literature which reports negative returns for stock mergers and positive returns for cash mergers²⁷

3.3 Abnormal option trading dynamics prior to merger announcements

Hypothesis 1: Prior literature shows evidence of insider trading in option markets for target firms. We hypothesize that there is also informed trading for acquiring firms in option markets prior to M&A-announcements.

In this section we want to analyze whether abnormal trading patterns in option markets can be observed prior to merger announcements. For this purpose we follow standard event methodology and employ a constant mean model to compute abnormal option volume²⁸. We define the estimation window from 240 to 31 calendar days prior to M&A-announcement (a six month period) and the event window from 30 to 1 calendar day prior to the announcement date. Then we compute normal trading volume by taking the average of the raw trading volume in the estimation window and daily abnormal trading volume by subtracting the normal trading volume from the daily

²⁷ Savor (2006) and Moeller et al. (2007) report positive post-merger returns for cash mergers and negative returns for stock mergers. Eckbo et al.(1990) and Eckbo and Thorburn (2000) analyze Canadian mergers and find that abnormal announcement returns are highest for cash mergers and lowest for stock mergers with mixed offers in between. See Betton et al. (2008) for an overview of empirical research on post merger returns.

²⁸ See MacKinlay (1997), Campbell et al. (1997) and Lyon et al. (1999)

trading volume in the event window. Finally we compute cumulative abnormal trading volume (CAVOL) by collating the daily abnormal trading volume over the thirty days leading up to the announcement date. CAVOL is estimated separately for calls and puts. Equation (3.1) and (3.2) summaries the calculation procedure of the CAVOL measure for calls and puts respectively:

$$CAVOL_C = \sum_{i=-1}^T VOL_i^{call} - VOLB^{call}. \quad (3.1)$$

$$CAVOL_P = \sum_{i=-1}^T VOL_i^{put} - VOLB^{put} \quad (3.2)$$

where $VOL_i^{call (put)}$ is the call- (put-) option volume of an M&A firm on date i and $VOLB^{call(put)}$ is the normal trading volume estimated in the estimation window. In regular market time CAVOL for calls and puts is supposed to be close to zero. When our intuition is correct and there is informed trading in option markets we expect to see a very high CAVOL for calls and puts in the lead up to an M&A-announcement. Table 3.2 shows volume statistics for daily option volume and for the CAVOL measures prior to mergers. Related to this, Figure 3.1 shows CAVOL dynamics for cash- and stock-M&A in the run up period.

Table 3.2: Option volume statistics

This table shows daily call and put option volume statistics in the lead up to an M&A-announcement for acquiring firms. Options included in the sample are OTM- or ATM with a maximum time to maturity of three months. The column "Stock" shows volume statistics for those mergers where more than 50% of the merger was financed by stocks. The column "Cash" shows volume statistics for those mergers where more than 50% of the merger was financed by cash. The numbers in brackets show the period length in calendar days relative to the M&A-announcement, e.g. [-30,-1] is the period between thirty days and one day prior to the M&A-announcement date.

	Call			Put		
	All	Stock	Cash	All	Stock	Cash
Size	5,986	1,830	2,539	5,986	1,830	2,539

Panel A: Average daily volume

Benchmark period	[-240,-31]	671	652	723	462	445	492
Event period	[-30,-1]	700	753	689	492	530	497
Immediate event period	[-7,-1]	759	781	770	518	544	522
Announcement date	[0]	1,100	1,559	953	723	862	715

Panel B: Cumulated abnormal volume (CAVOL)

Event period	[-30,-1]	574	2,032	-684	604	1,704	92
Immediate Event period	[-7,-1]	441	645	238	279	495	152

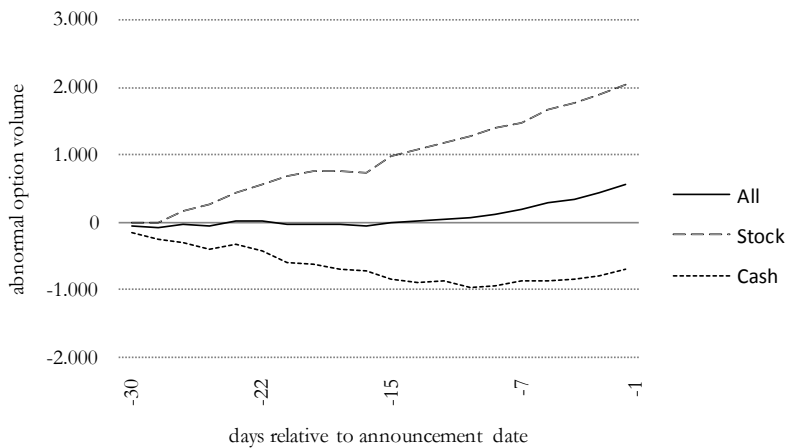
Panel C: Cumulated abnormal volume relative to benchmark volume (CAVOL/VOLB)

Event period	[-30,-1]	86%	312%	-95%	131%	383%	19%
Immediate Event period	[-7,-1]	66%	99%	33%	60%	111%	31%

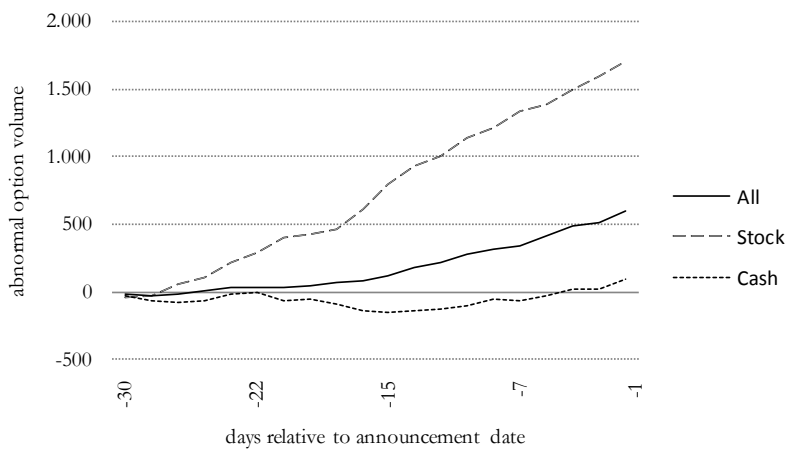
Figure 3.1: Cumulative abnormal call and put option volume dynamics for cash- and stock-M&A

Panel A shows cumulative abnormal call option volume dynamics (CAVOL_C) for all M&A firms, for cash-M&A and for stock-M&A in the lead up to an M&A-announcement. Similarly Panel B shows cumulative abnormal put option volume dynamics (CAVOL_P). The vertical axes shows the cumulative abnormal option volumes, calculated using equation (3.1) for calls and equation (3.2) for puts. The horizontal axes shows the trading days prior to the M&A-announcement.

Panel A: CAVOL_C dynamics



Panel B: CAVOL_B dynamics



In Table 3.2 we can observe large abnormal call and put option volumes in the month prior to M&A-announcements. Total CAVOL increases to 574 for calls and to 604 for puts. When we differentiate between cash and stock-M&A we observe that the increase

in abnormal call and put option volume only holds for stock mergers, e.g. the CAVOL_C for stock-M&A increases to 312% of the benchmark volume in the month prior to an announcement whereas the CAVOL_C for cash-M&A is negative (-95%). This can be observed also in Panel A of Figure 3.1: CAVOL_C for stock-M&A increase gradually in the event period whereas CAVOL_C for cash mergers becomes negative. The same relation holds for abnormal put option volume and can be also observed in Panel B of Figure 3.1. Stock-M&A have a CAVOL above the average of the total sample and cash-M&A have a CAVOL below the average of the total sample.

The results in Table 2 and Figure 3.1 support our hypothesis of informed trading in option markets prior to mergers. In addition they indicate that informed trading takes place only for stock-M&A and not for cash-M&A.

3.4 Predictability of post M&A returns

Hypothesis 2: Abnormal option volume indicates informed trading and thus can predict post M&A returns. Therefore high positive post M&A returns should coincide with high abnormal call option volumes and high negative post M&A returns should coincide with high abnormal put option volumes.

Based on our observation that abnormal option volume strongly increases before M&A-announcements, we want to investigate whether the direction of abnormal option volume (abnormal call versus abnormal put option volume) prior to an announcement has predictive power for post M&A returns. If the abnormal option volume mainly stems from informed traders then the option markets should contain information on future stock price dynamics and thus should be able to predict stock returns. To test this hypothesis we conduct two different analyses.

In a first indicative analysis we sort our sample of acquiring firms in two quantile portfolios: The Q20-quantile-portfolio (“Q20”) consisting of those 20% of the mergers with the most negative stock returns in the three months following the M&A-announcement and the Q80-quantile-portfolio (“Q80”) consisting of those 20% of the mergers with the most positive stock returns in the three months following the M&A-announcement. Then we compare the abnormal call and put option volumes between the Q20- and Q80-quantile-portfolios. If the level of option volume is related to insider trading we expect that the quantile portfolio with very high positive post M&A returns will have high abnormal call and low abnormal put option volumes and the quantile portfolio with highly negative post M&A returns will have high abnormal put and low abnormal call option volumes. The result of this analysis is presented in Table 3.3.

Table 3.3: Volume statistics for firms with high post M&A returns

The table shows daily volume statistics in the lead up to an M&A-announcement for acquiring firms. Options included in the sample are OTM or ATM with a maximum time to maturity of three months. The column "Q20" shows volume statistics for those 20% of the mergers with the most negative stock returns in the three months following the M&A-announcement. The column "Q80" shows volume statistics for those 20% of the mergers with the most positive stock returns in the three months following the M&A-announcement. The numbers in brackets show the period length in trading days relative to the M&A-announcement, e.g. [-30,-1] is the period between thirty days and one day prior to the M&A-announcement date.

	Call		Put	
	Q20	Q80	Q20	Q80
Size	1,198	1,198	1,198	1,198

Panel A: Average daily volume

Benchmark period	[-240,-31]	906	339	589	241
Event period	[-30,-1]	867	384	620	237
Immediate event period	[-7,-1]	935	393	635	246
Announcement date	[0]	1,531	510	908	321

Panel B: Cumulated abnormal volume (CAVOL)

Event period	[-30,-1]	-773	904	619	-80
Immediate event period	[-7,-1]	144	271	229	24

Panel C: Cumulated abnormal volume relative to benchmark volume (CAVOL/VOLB)

Event period	[-30,-1]	-89%	235%	100%	-34%
Immediate event period	[-7,-1]	16%	80%	39%	10%

In line with our expectations we can observe that assets with very high positive post returns (Q80-quantile-portfolio) have high abnormal call option volumes prior to a M&A-announcement (relative CAVOL of 235% for calls versus -34% for puts) and assets with very negative post returns (Q20-quantile-portfolio) have high put option volumes prior to M&A-announcement (relative CAVOL of 100% for puts versus -89% for calls)²⁹. The results of this preliminary analysis indicate a relationship between the direction of abnormal call and put option volume and post M&A returns.

In our second analysis we follow standard financial literature and test predictability through the analysis of trading strategy returns. We construct portfolios based on abnormal option volumes and analyze the economic significance of the returns generated by this strategy. The main purpose of this analysis is not to focus on trading profits but rather on the relationship between abnormal option volume and post M&A returns. As advocated by Cao et al. (2005) trading profits indicate the economic significance of each predictive variable. Thus the risk adjusted returns of a trading strategy can be used as a measure of a given signal's economic significance. The trading

²⁹ We can also observe that the when we differentiate between cash- and stock-M&A the effect only holds for stock-M&A. This is consistent with our observations in Table 3 2 where we showed abnormal trading is more common for stock mergers.

strategy to analyze predictability is specified as follows: first we calculate the cumulative abnormal call and put option volume for every stock-M&A-event in the month prior to an announcement using equation (3.1) and (3.2). Then we sort firms into two portfolios: Portfolio P1 consists of acquiring firms where the difference between CAVOL_C and CAVOL_P prior to the M&A-event was highly positive (33% with the highest positive difference). Similarly, portfolio P2 consists of acquiring firms where the difference between CAVOL_C and CAVOL_P prior to the M&A-event was highly negative (33% with the highest negative difference)³⁰. Firms in portfolio P1 have much higher abnormal call volumes than abnormal put volumes prior to announcement, thus we expect that the average post M&A return is positive for this portfolio. Similarly firms in portfolio P2 have higher abnormal put volume than abnormal call volume prior to an announcement and we expect that the average post M&A return is negative. In a last step we calculate different measures of weekly, monthly and three monthly returns of portfolio P1 and P2 following the announcement date. Table 3.4 summaries the result of the portfolio trading strategy.

³⁰ We analyze the 33% percentile due to small sample size. The main results stay the same when we reduce our sample size and analyze the highest 20% quintile.

Table 3.4: Predictability of post M&A returns

This table shows monthly returns of two different portfolios formed with stock-M&A on the day following the announcement date: Portfolio P1 consists of acquiring firms where the difference between abnormal call and put option volume prior to the M&A-event was highly positive (33% with the highest positive difference). Similarly portfolio P2 consists of acquiring firms where the difference between abnormal call and put option volume prior to the M&A-event was highly negative (33% with the highest negative difference). Panel A shows the average stock return within the first week following M&A-announcement; Panel B the average stock return within the first month following M&A-announcement and Panel C the average stock return within the first three months following M&A-announcement. The post-returns are mean adjusted, i.e. the mean return of the stock-M&A portfolio is subtracted from the raw return³¹. The returns are then scaled to monthly returns, e.g. in the three month following announcement portfolio P1 made an average monthly return of 0.29%.

	Return (in % per month)			T-Stat		
	P1	P2	P1-P2	P1	P2	P1-P2
Panel A: Post one week return						
Return (RET)	3.10	-3.61	3.40	1.87	-1.67	2.46
Excess Market (RET-RETM)	1.66	-3.44	2.60	1.06	-1.73	2.01
Excess Risk Free Rate (RET-RF)	2.73	-3.99	3.42	1.65	-1.85	2.47
Panel B: Post one month return						
Return (RET)	0.36	-1.48	0.92	0.53	-1.41	1.47
Excess Market (RET-RETM)	-0.47	-1.86	0.70	-0.74	-1.98	1.23
Excess Risk Free Rate (RET-RF)	0.02	-1.84	0.93	0.03	-1.76	1.50
Panel C: Post three months return						
Return (RET)	0.29	-0.92	0.60	0.68	-1.63	1.71
Excess Market (RET-RETM)	-0.42	-1.34	0.45	-1.08	-2.59	1.40
Excess Risk Free Rate (RET-RF)	-0.04	-1.28	0.61	-0.08	-2.26	1.74

³¹ As shown in Table 3.1 the mean return for stock-M&A is negative. Thus when we exclude the mean adjustment the post returns for the put option portfolio P2 is slightly more negative.

The results in Table 3.4 support our hypothesis of the predictability of post M&A returns: Portfolio P1 generates positive abnormal post M&A returns and portfolio P2 generates negative abnormal post M&A returns. For the first week following the M&A-announcement we observe that the returns for P1 is positive (3.1% per month) and for P2 negative (-3.6% per month). We see that the predictability is very strong for the first week following announcement and decreases over time. The sign of the post M&A returns for the first month and the first three months is still as expected (positive for P1 and negative for P2). However the t-statistics are not significant when analyzing time periods longer than the first week following the announcement. Overall these results indicate that abnormal option volume is related to informed trading and thus can predict future stock price returns³².

3.5 Executive-Wealth-Sensitivity and Insider Trading around Mergers

Hypothesis 3: Executives with high wealth sensitivity to stock price changes have high incentives for insider trading in put option markets. A stock price decrease following an M&A-announcement would lead to large losses for the high sensitivity executive. Thus we hypothesize that the probability of insider trading in put option markets prior to an M&A-event is higher for those firms who have executives with high wealth to performance sensitivities.

In the previous section we tested our hypothesis of informed trading around mergers by analyzing the relation between abnormal option volume and post M&A returns. These results indicate that informed trading is performed prior to mergers and the effect is more dominant for stock mergers than for cash mergers. In this section we want to go

³² The predictability doesn't change significantly when we take abnormal volume relative to the benchmark volume as an indicator of insider trading, i.e. divide CAVOL_C and CAVOL_P by their respective benchmark volumes.

one step further and examine the source of informed trading. We want to test the hypothesis that one part of informed trading prior to merger announcements is due to illegal trading activity of executives with high wealth sensitivity to the acquirer's stock price. The idea behind this hypothesis is that a stock price decrease following an M&A-announcement would lead to large losses for those executives whose compensation strongly depends on stock performance (e.g. employer options will get out of the money, lower bonus, etc). To avoid these possible losses some of the strongly affected executives could hedge themselves with put options. Thus we expect that the probability of unreported insider trading in put options prior to an M&A-event is higher for those firms having executives with high wealth to performance sensitivities.

To test our hypothesis we compare the stock price sensitivity of executives in acquiring firms with abnormal option volumes and post M&A returns. The analysis is only applied to mergers where more than 50% of the deal was financed by stocks, as our previous analyses indicate that insider trading occurs mainly in stock-M&A. We have followed recent financial literature and measure stock price sensitivity of executives through the wealth to performance sensitivity (WPS) as proposed by Edmans et al. (2009). This is the dollar change in the executives' wealth for a 100 percentage point change in firm value, divided by annual flow compensation.

In a first indicative analysis we study the relationship between executive WPS and abnormal option volume. For this purpose we sort our stock-M&A portfolio in firms with high abnormal volumes (portfolio P1) and in firms with low abnormal volumes (portfolio P2)³³. Then we calculate the median WPS for CEOs (CEO-WPS) and top

³³ Abnormal volume in this analysis is defined as the total of abnormal call and abnormal put option volumes in the three month prior to announcement.

executives (EX-WPS) of acquiring firms in portfolio P1 and P2³⁴. The results are summarized in Table 3.5.

Table 3.5: Abnormal option volume versus WPS of executives

This table shows median wealth to performance sensitivities of CEOs (“CEO-WPS”) and executives on average (“EX-WPS”) for two different portfolios formed with stock-M&A on the day following the announcement date: Portfolio P1 (column “P1”) consists of acquiring firms with very high abnormal option volumes (Panel A: highest 33%, Panel B: highest 20%) and portfolio P2 (column “P2”) consists of acquiring firms with very low abnormal option volumes (Panel A: lowest 33%, Panel B: lowest 20%). The column “All” shows average executives wealth to performance sensitivities for the whole stock-M&A sample. Wealth to performance sensitivity (WPS) is defined as the dollar change in the executives’ stock and option portfolio for a 1% change in stock price, divided by the executive’s annual total compensation.

Panel A: Q33-Portfolios

	P1	P2	All
Sample Size	276	276	834
Median EX-WPS	8	6	7
Sample Size	219	219	663
Median CEO-WPS	10	8	9

Panel B: Q20-Portfolios

	P1	P2	All
Sample Size	167	167	834
Median EX-WPS	9	6	7
Sample Size	133	133	663
Median CEO-WPS	11	9	9

Consistent with our expectations we can observe that WPS for CEOs and average WPS for top executives are larger for the portfolio with high abnormal option volume than for the portfolio with low abnormal option volume. We also see that the median WPS

³⁴ See Section 3.2 and Section 3.8 (Appendix) for the definition of CEO-WPS and EX-WPS and for details on the calculation procedure.

for CEOs is slightly higher than the median for the average of top executives. This is due to the fact that some CEOs own a large portion of the assets outstanding and therefore have a very high wealth to performance sensitivity. When averaging across executives to get EX-WPS such outliers are smoothed³⁵.

In a second analysis we test predictability through the examination of trading strategy returns. On the day prior to the announcement date we construct portfolios based on abnormal option volumes and WPS and analyze the significance of the returns generated by this strategy. As already pointed out in the previous section the main purpose of this analysis is not the focus on trading profits but on the relation and economic significance of each predictive variable³⁶. While the first constructed portfolio P1 consists of acquiring firms with higher abnormal call volumes than abnormal put volumes, the second portfolio P2 is comprised of acquiring firms with higher abnormal put volumes than abnormal call volumes. In contrast to the analysis conducted in the previous section this time we chose only firms for P1 and P2 where the executives have high wealth to performance sensitivities (33% with the highest sensitivities). Table 3.6 summarizes the result of the portfolio trading strategy³⁷.

³⁵ To give an extreme example, Michael S. Dell, CEO of Dell Inc. had a WPS of 2,288 in 2007, whereas the WPS for the other reported executives was only around one. This is also the reason why we do not report the mean CEO-WPS and EX-WPS in Table 3.5 (a single large CEO-WPS outlier observation will have a large impact on the mean).

³⁶ Note that the term “significant return” does not imply that trading profits can be generated using the described approach. For this purpose one would have to consider additional factors (e.g. illiquidity, timing of the trade, trading costs, etc.). This hold also for the other chapters where we analyze the significance of trading strategies. Throughout the dissertation significance is related to the statistical significance of a t-test at 5%, 10% or 15% level (depending on the analysis).

³⁷ We also calculated abnormal returns using the market model following Campbell et al. (1997). For Portfolio P2 we get a significant abnormal return of -7.06% (Ex-WPS) and -8.08% (CEO-WPS). Portfolio P1 has insignificant returns around zero.

Table 3.6: Abnormal option volume versus WPS

This table shows monthly returns of two different portfolios formed with stock-M&A on the day following the announcement date: Portfolio P1 consists of acquiring firms where the difference between abnormal call and put option volume prior to the M&A-event was highly positive (33% with the highest positive difference) and the wealth to performance sensitivity of the executives are very high (33% with the highest sensitivities). Similarly portfolio P2 consists of acquiring firms where the difference between abnormal call and put option volume prior to the M&A-event was highly negative (33% with the highest negative difference) and the wealth to performance sensitivity of the executives are very high (33% with the highest sensitivities). The table reports the average monthly stock return within the first week following M&A-announcement. The post-returns are mean adjusted, i.e. the mean return of the stock-M&A portfolio is subtracted from the raw return. In Panel A the sorting is based on the average WPS of top executives (“EX-WPS”) and in Panel B the sorting is based on the WPS of CEOs (“CEO-WPS”). WPS is defined as the dollar change in the executives’ stock and option portfolio for a 1% change in stock price, divided by executives’ annual total compensation.

Panel A: Average WPS of top management across firms (EX-WPS)

	First week return (in % per month)			T-Stat		
	P1	P2	P1-P2	P1	P2	P1-P2
Return (RET)	1.40	-6.87	4.29	0.42	-1.57	1.51
Excess Market (RET-RET _M)	0.02	-5.19	2.68	0.01	-1.29	1.04
Excess Risk Free Rate (RET-RF)	1.03	-7.25	4.31	0.31	-1.65	1.52

Panel B: Average WPS of CEOs (CEO-WPS)

	P1	P2	P1-P2	P1	P2	P1-P2
Return(RET)	3.54	-7.76	5.87	1.26	-1.40	1.81
Excess Market (RET-RET _M)	1.56	-5.13	3.43	0.62	-1.00	1.18
Excess Risk Free Rate (RET-RF)	3.17	-8.13	5.89	1.13	-1.47	1.82

In Panel A we can observe that firms with high abnormal put option volume and high EX-WPS have an average post M&A return of around -7% per month. The average return of portfolio P1 (high WPS and high abnormal call option volume) is positive but

not abnormal when deducting average market return. This indicates that insider information is used for protecting purposes and not to profit from an asset price increase.

In Panel B we report the results of sorting by CEO-WPS. For this group of executives we observe a similar pattern with highly negative abnormal returns for portfolio P2 and a much lower number of abnormal returns for portfolio P1.

Overall our hypothesis of insider trading in companies with high wealth to performance sensitivity seems to hold, if we analyze the average wealth to performance sensitivity of top executives and CEOs. They hedge themselves against possible stock price falls with put options, but they do not abuse their insider information for purely profit reasons.

3.6 Robustness Check

In this section we employ additional robustness checks to ensure that our results - in particular abnormal trading activity in option markets prior to mergers and predictability of post merger returns - are not an artefact of the methodology used: In section 3.6.1 we aim to show that 1) abnormality in option markets prior to merger events is observable and 2) that this abnormality is related to the trading activity of executives with high wealth to performance sensitivity. For this purpose we use the MAX- and SUM-Measure of Acharya and Johnson (2010) as an alternative method to the CAVOL-Measure to flag abnormal trading activity in option markets.

Following the observation of suspicious trading prior to mergers we then go one step further and show that this abnormality can predict future stock price returns as it is related to informed trading activity. We therefore use a regression framework in section

3.6.2 as an alternative method to the portfolio sorting approach to test for predictability of post merger returns using abnormal option volume as a predictor.

3.6.1 Robustness check for abnormal option volume

In a first step, to capture unusual trading activity in option markets prior to merger events, we construct the MAX- and SUM-Measure introduced in Acharya and Johnson (2010) and also used in Gao and Huang (2011). The MAX-Measure aims to flag the occurrence of suspicious activity prior to merger announcement whereas the SUM-Measure gives an indication of the amount of such activity. As argued by Acharya and Johnson (2010) the measures are not meant to assess whether insider trading took place in any particular instances. Rather the goal is to analyze the variations in the likelihood of such trade across merger events. To construct the factors, we first estimate residuals from the following two regression specifications (conditional and unconditional) for every stock-M&A firm:

Unconditional variant:

$$VOL^{call} = \alpha + \varepsilon^{call}, \quad (3.3)$$

$$VOL^{put} = \alpha + \varepsilon^{put}, \quad (3.4)$$

Conditional variant:

$$VOL^{call} = \alpha + VOL_{market} + \beta_1 \cdot RET_{market} + \beta_2 \cdot LVOL_{stock} + \beta_3 \cdot LRET_{stock} + \beta_4 \cdot LVOL^{call} + \varepsilon^{call}, \quad (3.5)$$

$$VOL^{put} = \alpha + VOL_{market} + \beta_1 \cdot RET_{market} + \beta_2 \cdot LVOL_{stock} + \beta_3 \cdot LRET_{stock} + \beta_4 \cdot LVOL^{put} + \varepsilon^{put}, \quad (3.6)$$

where $VOL^{call(put)}$ is the standardized call- (put-) option volume of a given M&A firm, VOL_{market} and RET_{market} is the contemporaneous market volume and return, $LVOL_{stock}$ and $LRET_{stock}$ is the lagged volume and returns of the underlying stock, $LVOL^{call(put)}$ is the lagged dependent variable and $\varepsilon^{call(put)}$ are the regression residuals³⁸. We run the regressions using daily data for a three month period preceding the M&A announcement as the regression should describe “normal” (or expected) values for call and put option volumes prior to merger announcements. For every regression specification we then use the standardized regression residuals to construct the conditional and unconditional MAX- (SUM-) Measure, which is defined as the maximum (sum) of the daily standardized residuals during the five trading days prior to the merger announcement. In a last step we compute the MAX- (SUM-) Measure also from a 5-day window three months prior to the merger event (“Benchmark-Measure”). Figure 3.2 shows the histograms of the conditional MAX-Measure (Panel A for calls and Panel C for puts) and the conditional Benchmark-Measure (Panel B for calls and Panel D for puts). The comparison of the MAX-Measure with the Benchmark-Measure enables us to identify cross-sectional variation in our measures over our sample of stock merger events³⁹.

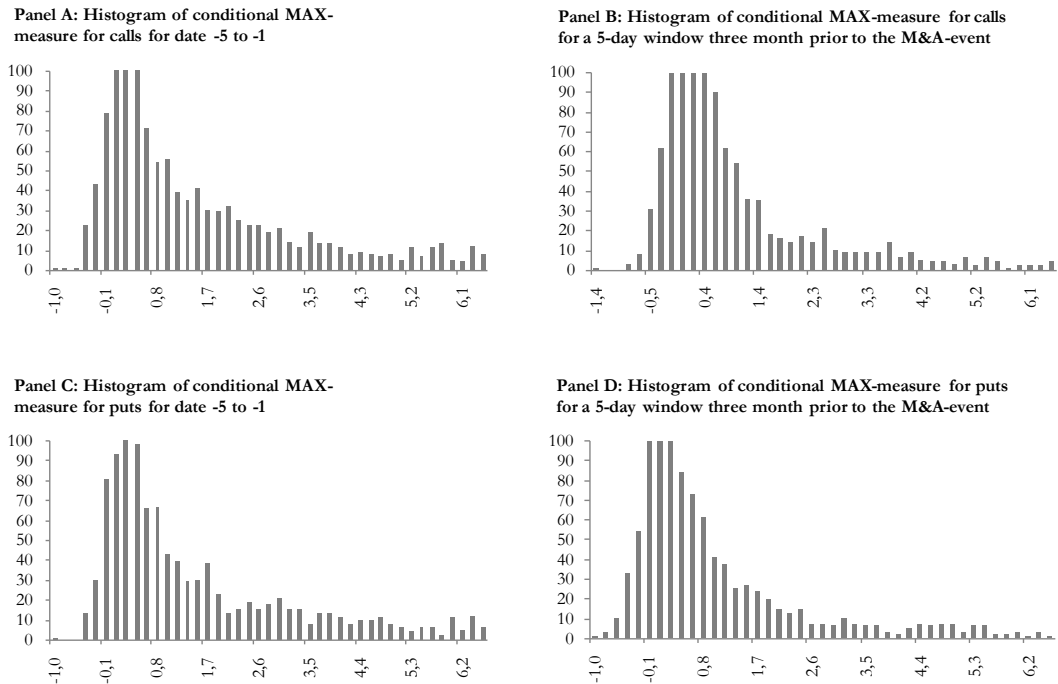
³⁸ Note that the normalization of option volume is necessary as there is a large number of zero-volume observations which makes the data non-normal and would lead to potentially biased OLS results. See, for instance, Acharya and Johnson (2010).

³⁹ We also built the histograms for the unconditional variant of the MAX-Measure which is computed using just a constant term to explain call and put option volume. The results are very similar and are omitted for brevity.

We observe that the histograms computed for the five day window immediately before the merger announcement (Panel A and Panel C) show fatter right tails than the histograms computed for normal periods (Panel B and Panel D). This is consistent with the observation of Acharya and Johnson (2010) and shows evidence that the cross-sectional variation in the MAX-Measure during the 5-day window prior to bid announcements appears to be informed trading activity related to the merger event (see Acharya and Johnson (2010) for a similar argumentation)..

Figure 3.2: Histogram of the conditional MAX-Measure

The figure shows the histograms of the conditional MAX-Measure for call and put option volume computed using the pre-bid window from date -5 to -1 (Panel A for calls and Panel C for puts) and computed over a 5-day window which starts three months prior to the merger event (Panel B for calls and Panel D for puts). Date 0 is the M&A announcement date.



In a second analysis we aim to show that high wealth to performance sensitivity of executives can explain one part of the observed abnormal option volume. For this purpose we regress the conditional and unconditional MAX- and SUM-Measure on

executive WPS values. Furthermore we use market size as a control factor, as larger deals will expand the universe of people privy to the negotiation process leading up to the launch of a merger event and thus increase the probability of informed trading activity [Acharya and Johnson (2010)]. Table 3.7 summarizes the results.

Table 3.7: Explaining unusual trading activity

The table shows regression results (coefficients and related t-statistics in parentheses) for different measures of abnormal trading activity in option markets prior to merger announcements. Panel A shows regression specifications for calls and Panel B for puts. For every stock M&A firm, the MAX- (SUM-) Measure is the maximum (sum) of the daily standardized residuals calculated during the five trading days prior to the merger announcement. The unconditional variant of the MAX- and SUM-Measure uses standardized residuals out of equation (3.3) and (3.4) and the conditional variant uses standardized residuals out of equation (3.5) and (3.6). Numbers in brackets show t-values.

Panel A: Regression specification for calls

	MAX				SUM			
	Uncond	uncond	cond	cond	Uncond	uncond	cond	cond
CEO-WPS	0.7 (2.8)		0.6 (3.0)		1.1 (2.9)		0.8 (3.1)	
EX-WPS		3.5 (4.9)		2.7 (5.0)		5.2 (4.9)		3.6 (5.1)
Size	0.0 (3.8)	0.0 (3.7)	0.0 (3.6)	0.0 (3.4)	0.0 (3.8)	0.0 (3.7)	0.0 (3.6)	0.0 (3.4)

Panel B: Regression specification for puts

	MAX				SUM			
	Uncond	uncond	cond	cond	Uncond	uncond	cond	cond
CEO-WPS	0.8 (3.6)		0.7 (4.1)		1.2 (3.6)		0.9 (4.1)	
EX-WPS		3.2 (5.0)		2.7 (5.1)		4.7 (5.0)		3.5 (5.2)
Size	0.0 (3.5)	0.0 (3.3)	0.0 (3.7)	0.0 (3.5)	0.0 (3.7)	0.0 (3.5)	0.0 (3.7)	0.0 (3.5)

The results show a clear picture: For every measure of abnormal trading activity in option markets (unconditional/conditional, MAX/SUM, calls/puts) we observe that high wealth to performance sensitivity of executives (CEOs as well as top executives in general) is positively related with the degree of unusual trading activity prior to merger announcements. The highly significant t-values, which are slightly higher for put option markets favours our view that one part of informed trading prior to announcements might be explained by executives with high wealth sensitivity to stock price changes who buy options to avoid possible short term losses.

Furthermore we observe a positive relationship between market size and abnormal option volume which is consistent with the hypothesis in Acharya and Johnson (2010) that market size can approximate for uncounted insiders.

3.6.2 Robustness check for predictability

In order to make sure that our results from the predictability analysis using a portfolio sorting approach are not an artefact of the method we used, we repeat the analysis for stock mergers using a regression method. Following standard literature and consistent with our earlier methodology, we construct dummy variables for the highest 33% of abnormal option volumes and dummy variables for the highest 33% of abnormal option volumes as well as highest wealth to performance sensitivities of executives. We then regress weekly excess returns to these dummy variables and controls⁴⁰. The results are reported in Table 3.8. In the following section we refer to firms with a dummy variable

⁴⁰ The intercept term in our dummy regressions represent the abnormal excess post merger returns of the omitted category with a dummy value of zero (“omitted firm”), e.g. firms with abnormal option volumes which are not within the highest 33% of the values. The slope coefficient of the dummy variable represents the change in the intercept for the firms with a dummy value of one, e.g. firms with abnormal option volumes within the highest 33% of the values. See for example Cremers et al. (2010) who test for robustness of their volatility trading strategy following the same methodology.

of zero as “omitted firms”. The odd numbered columns in Panel A and B include the three Fama French (1993) factors, the Harvey and Siddique (2000) skewness factor and market size as control factors⁴¹. Furthermore we also include a dummy variable to control for the public status of the target company as prior research showed evidence of variation in post merger returns between public and private targets⁴².

In Panel A we use as a dependent variable, the absolute of excess post merger returns to analyze whether there is a significant relation between high abnormal volume and high post M&A returns. The idea is that informed trading in option markets only occurs if the direction of the merger is clearly known (either a strongly positive or a strongly negative effect). For mergers with no clear effect on post M&A returns we do not expect informed trading. For this purpose we regress absolute values of weekly returns in excess of the risk free rate on a dummy variable whose value is one if the total abnormal call and put option volume is within the 33% with the highest abnormal option volume and zero else.

In column (1) and (2) we regress absolute excess returns following merger announcements using a dummy variable representing high abnormal option volume prior to announcement and control factors. We observe that high abnormal option volume has a positive and significant coefficient, which implies that the highest 33% of abnormal option volume have higher abnormal post merger returns than omitted firms (the remaining 67%). This observation is consistent with our results from Section 3.3 and 3.4, where we showed that abnormal option volume indicates informed trading prior to merger announcements.

⁴¹ We obtain the three Fama and French factors from Kenneth R. French’s homepage.

⁴² See for example Andrade et al. (2001), Fuller et al. (2002) and Chang (1998). Note that more than 60% of target firms in our sample are public.

In column (3) to (6) we regress a dummy variable representing high abnormal option volume as well as high executive WPS (column (3) to (4) for high EX-WPS and column (5) to (6) for high CEO-WPS) and control factors on absolute excess returns following the merger announcement⁴³. We observe that only the coefficient for the CEO-WPS dummy variable is positive and significant. This implies that firms with high abnormal option volumes and high CEO-WPS have higher abnormal post merger returns than omitted firms. This is consistent with our results from Section 3.5 and supports our hypothesis that abnormal volume is an indicator of informed trading in option markets.

Another possible explanation for the observed abnormal trading volume prior to mergers could be high incentives for insider trading due to existing governance structures within the merger company. In their pioneering work Gompers et al. (2003) introduce the G-Index to differentiate between two types of governance structures: Companies that reserve little power for management and allow shareholders to quickly and easily replace executives (low index value, referred to as a “democratic firm”) and companies which reserve extensive power for managers and place strong restrictions on shareholders’ ability to replace executives (high index value, referred to as a “dictatorship firm”)⁴⁴. Based on this differentiation an alternative explanation for insider trading could be the illegal actions of executives within dictatorial firms, as they might feel that they are weakly controlled by shareholders. To test for this hypothesis we construct the G-Index of Gompers et al. (2003) and regress a dummy variable representing high abnormal option volume as well as high values of G (column (7) to

⁴³ The dummy variable is one if the corresponding firm has abnormal option volumes within the 33% of highest values as well as wealth to performance sensitivities within the 33% of highest values. It is zero otherwise.

⁴⁴ Several other authors used the G-Index as a governance measure. See for example Duarte et al. (2008), Masulis et al. (2007) and Wang and Xie (2009).

(8))⁴⁵. We observe that the sign of this coefficient is negative and also insignificant. Therefore our results in Panel A reject this alternative hypothesis.

In Panel B of Table 3.8 we test whether the direction of abnormal option volume can predict the right direction of post merger returns, i.e. high abnormal call option volumes should predict higher post merger returns and high abnormal put option volumes should predict lower post merger returns.

In column (1) and (2) we show that the direction of post merger return (positive versus negative) is predicted correctly by abnormal call and put option volume. Firms with very high abnormal call option volumes have higher post merger returns than omitted firms. Similarly, firms with very high abnormal put option volumes have lower post merger returns than firms within the omitted category. Only the dummy variable for abnormal put option volume has a significant coefficient. This is in line with our main hypothesis that insider trading is done by executives for hedging purposes which is mainly done through put options.

In column (3) to (6) we regress WPS dummy variables and controls on excess post merger returns. The coefficients of the dummy variables which represent firms with high call volumes as well as high WPS are positive and the coefficients of the dummy variables which represent firms with high put option volumes as well as high WPS are negative. Positive coefficients indicate that the firms with a dummy variable of one have higher abnormal post returns than omitted firms with a dummy value of zero. Negative

⁴⁵ We obtain data for the governance index from the RiskMetrics Governance and Directors database, formerly known as the Investor Responsibility Research Center (IRRC) database. The database publishes detailed listings of corporate-governance provisions for individual firms. The matching of RiskMetrics with the CSRP database is done by ticker symbol and was supplemented by handchecking names and exchanges. Following Gompers et al. (2003) we exclude dual class stocks (less than 10% of the total). See Gompers et al. (2003) for details on the index construction.

coefficients can be interpreted respectively. We can observe that the coefficients of the dummy variables are in line with our hypotheses (positive for abnormal call option measures and negative for abnormal put option measures). As observed in Panel A the dummy variable representing high option volumes in combination with high governance index values has no significant effect on post merger returns (see column (7) and (8)).

For all regressions the coefficients of the dummy variable for abnormal put option volume has higher values than the coefficients of abnormal call option volume measures. This is in line with our hypothesis that insider trading is more severe in put option markets as they are the main market for hedging purposes. However, some of the coefficients are not statistically significant. One possible explanation is the relatively small number of firms having a dummy variable of one, i.e. high abnormal option volumes (within the highest 33% of the values) and high WPS (within the highest 33% of the values). There are only around 100 observations where a firm is within the 33% with the highest abnormal option volume measure and within the 33% with the highest WPS measure⁴⁶.

⁴⁶ Acharya and Johnson (2010) argue that option volume data can be non-normal distributed as there are several days where no options are traded (zero option volume). This could lead to misspecification problem with OLS results. However we are not significantly affected by this “zero option volume” problem as we only include dummy variables for firms with the highest abnormal option volumes. Firms with high abnormal option volume will be more likely firms without zero trades.

Table 3.8: Dummy Regressions

In this table we regress absolute (Panel A) and raw values (Panel B) of weekly excess returns (in excess to the risk free rate) on several dummy variables and controls. The odd numbered columns include the three Fama French (1993) factors, the Harvey and Siddique (2000) skewness factor and market size as control factors. The intercept term represent the abnormal excess post merger returns of the omitted category with a dummy value of zero, e.g. firms with abnormal option volumes which are not within the highest 33% of the values. The slope coefficient of the dummy variable represents the change in the intercept for the firms with a dummy value of one, e.g. firms with abnormal option volumes within the highest 33% of the values. The variables are described below. We use Newey and West (1987) t-statistics to account for autocorrelation and heteroskedasticity. ** indicates a significance at the 5% level and * indicates a significance at the 15% level. The sample size is 1830 and the average rsquare is around 7%

Variable description: **ABS(.)**: absolute values; **RET**: First week post return of acquiring firms in stock mergers following the announcement date in excess of the risk free rate; **D_AVOL**: Dummy variable for the 33th percentile with the highest total cumulative abnormal option volume (CAVOL_C as defined in equation (1)+ CAVOL_P as defined in equation (2)); **D_AVOL_C**: Dummy variable for the 33th percentile with the highest cumulative abnormal call option volumes; **D_AVOL_P**: Dummy variable for the 33th percentile with the highest cumulative abnormal put option volumes; **D_EX-WPS**: Dummy variable for the 33th percentile with the highest wealth to performance sensitivity of top executives; **D_CEO-WPS**: Dummy variable for the 33th percentile with the highest wealth to performance sensitivity of CEOs; **D_GOV**: Dummy variable for the 33th percentile with the lowest governance value measured by the governance index introduced by Gompers et al. (2003); **MKT-RF**: Fama French-Factor; **SMB**: Fama French-Factor; **HML**: Fama French-Factor, **SKEW**: Harvey and Siddique (2000) skewness factor; **STAT**: Dummy variable for the public status;

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Panel A: Absolute excess return as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha	7.25 **	6.66 **	7.41 **	6.76 **	7.39 **	6.75 **	7.47 **	6.78 **
D_AVOL	0.90 *	0.84 *						
D_AVOL*D_EX-WPS			0.68	0.72				
D_AVOL*D_CEO-WPS					1.35 *	1.55 *		
D_AVOL * D_GOV							-0.13	0.12
ABS(Mkt-RF)		0.48 **		0.48 **		0.47 **		0.48 **
ABS(SMB)		0.36 **		0.36 **		0.36 **		0.37 **
ABS(HML)		0.24 *		0.24 *		0.25 *		0.25 *
ABS(SKEW)		0.81 **		0.82 **		0.82 **		0.82 **
MCAP		0.00 **		0.00 **		0.00 **		0.00 **
STAT		-3.18 **		-3.19 **		-3.19 **		-3.19 **

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Panel B: Excess return as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha	-0.45	0.66	-0.56 *	0.57	-0.61 **	0.52 **	-0.65 **	0.50 **
D_AVOL_C	0.99	0.81						
D_AVOL_P	-1.89 **	-1.51 **						
D_AVOL_C * D_EX- WPS			1.46	1.24				
D_AVOL_P * D_EX- WPS			-2.83 **	-2.35 **				
D_AVOL_C * D_CEO- WPS					1.23	1.39		
D_AVOL_P * D_CEO- WPS					-2.00	-1.47		
D_AVOL_C * D_GOV							-0.16	-0.01
D_AVOL_P * D_GOV							-0.05	0.25
Mkt-RF		0.81 **		0.81 **		0.81 **		0.82 **
SMB		0.07		0.07		0.06		0.06
HML		-0.43 **		-0.44 **		-0.44 **		-0.44 **
SKEW		-0.55 **		-0.55 **		-0.56 **		-0.56 **
MCAP		0.00 **		0.00 **		0.00		0.00
STAT		-2.12 **		-2.10 **		-2.09 **		-2.08 **

It is possible that there are alternative explanations for our observation of abnormal post merger returns. One possible alternative explanation that high abnormal option volume in combination with high wealth to performance sensitivity seems to predict post merger returns could be the existence of a general relationship between mergers and executive compensation. It is possible that companies with high variable compensation perform better or worse than companies with low variable compensation. To test for this alternative explanation we calculate correlation coefficients between post merger returns and WPS. As a result we get values for the Pearson correlation coefficient, Kendall (1955) Tau and Spearman (1904) Rho very close to zero and the null hypothesis that post M&A returns and stock price sensitivity of executives are independent can't be rejected⁴⁷.

Another possible alternative explanation for our observations could be that the market anticipates the announcements. Jensen and Ruback (1983) and Jarrell and Poulsen (1989) argue that abnormal trading activity prior to merges could be due to speculation based on public information. However, in order to explain the observed abnormal option volume and predictability of post merger returns through a market anticipation theory, speculators who are not in possession of the terms of the merger would have to be able to predict several details of the merger event. They would have to 1) detect the company involved in the merger, 2) anticipate the direction of post merger returns in order to buy call or put option positions and 3) to predict the timing of the merger as the abnormal option trading activity is observable only in the month prior to the

⁴⁷ The correlation coefficient is -0.008 for EX-WPS and -0.05 for CEO-WPS, Kendall's Tau is -0.01 for EX-WPS and -0.003 for CEO-WPS, Spearman's Rho is -0.01 for EX-WPS and -0.004 for CEO-WPS. We also build quantile portfolios sorted on post M&A returns and analyzed WPS for the highest 20% and lowest 20% quantile. Consistent with the magnitude of the correlation coefficients this analysis shows no significant relation between post M&A returns and CEO-WPS or EX-WPS.

merger. It is possible that they might know possible candidates and also the direction of post merger return, e.g. they could use accounting and historical merger data to imply candidates and the direction of post merger return. However it would be crucial to predict also the exact timing of the merger, which in our opinion is not very likely⁴⁸. This precision of predictability would be necessary as abnormal option trading behaviour is only observed in the month prior to the merger announcements and not before. As a consequence uninformed speculators would tend to trade in longer term options as these contracts would offer the greatest possibility of payoff if a takeover attempt is expected at some unknown date [Arnold et al. (2000)]. Arnold et al. (2000) show that insiders who know the timing of the merger will choose shorter term options, since these contracts provide the greatest profit within a short period of time and are therefore more attractive for them. As we use only short term options in our analysis this supports the hypothesis that our observed option volume run up is more likely due to informed trading and not due to market anticipation⁴⁹. Furthermore Acharya and Johnson (2010) argue that if abnormal option volume is due to speculators aiming at identifying merger events this should be also reflected in a year dummy, as the precision and number of such traders should have been increased and perhaps even gotten better over time, i.e. more information can be generated about the likelihood of the event. For robustness we re-run our regression results in Table 3.8, [Panel B, column (2)] with year dummies to test for this possible relationship. We observe that the coefficients in the main regression are unaffected in size and statistical significance and the year dummy

⁴⁸ While there is a large strand of literature analyzing patterns of merger waves or assessing the probability of a merger for a given company (see Betton et al. (2008) for an overview) we found no study indicating the predictability of the month of a merger for a given company.

⁴⁹ This is also consistent with our results in section 3.2 where we observed that short term options predict future returns and indicate informed trading activity whereas long term options do not provide information on future stock price movements.

has no significant value [T-Value of 0.9 and p-value of 0.33)]. This further indicates that our results are not driven by a market anticipation hypothesis.

3.7 Conclusion

In this paper we have analyzed informed trading activity prior to merger announcements. We identify large abnormal call and put option volumes of acquiring firms prior to an announcement. Option volume prior to announcement is approx. 300% higher than the respective option volume in the benchmark period. We argue that the abnormal trading activity observed in option markets is related to informed trading activity prior to merger announcements. As an evidence for that we show that the direction of abnormal option volume (abnormal call versus abnormal put option volume) prior to an announcement can predict post merger returns. A portfolio consisting of firms with very high abnormal call option volume generates positive abnormal post M&A returns (3.1% per month) and a portfolio consisting of firms with very high abnormal put option volume prior to merger announcements generates negative abnormal post M&A returns (-3.6% per month). These results indicate that the observed abnormal trading activity stems from informed traders and thus contain information on future stock price dynamics.

In addition to that we show evidence that one part of informed trading prior to announcements can be explained by executives with high wealth sensitivity to stock price changes who buy put options to avoid possible short term losses. We observe that a portfolio consisting of positions where the abnormal put volume is higher than the abnormal call volume as well as firms where executives have high wealth to performance sensitivities generates significant negative abnormal post merger returns

around -5%. The portfolio consisting of more call than put option volumes has no significant abnormal post merger returns.

We used different measures of abnormality, quantile dummy regressions and control for several alternative factors which could possibly explain the abnormal trading activity in option markets and predictability of post merger returns. These robustness analyses are consistent with our prior findings and support the hypothesis of informed trading activity prior to mergers and that top executives use option markets to protect themselves against short term losses following mergers.

3.8 Appendix

Here we describe the methodology of calculating WPS as we did for the top executives of a firm (EX-WPS) and CEOs (CEO-WPS). The data comes from Execucomp and Compustat. The methodology is the same as in Edmans et al. (2009) to measure CEO-WPS values. In contrast to Edmans et al. (2009) who calculated the sensitivity only for CEO's we calculate the sensitivity also for all executives available for a given firm in Execucomp and take the average of it⁵⁰.

In a first step we calculate the delta of each option position held by the executives using the Black Scholes (1973) formula modified to account for dividend payouts by Merton (1973):

⁵⁰ Due to changes in the accounting treatment of stock-based compensation under Financial Accounting standards (FAS 123R), which took effect in December 2005, Execucomp changed their database structure and also some variable names from 2006 onwards. In this appendix we follow Edmans et al. (2009) and use the old variable names. See for example Hayes et al. (2012) who provide details about the calculation of each compensation variable under both the old and new formats.

$$e^{-dt} N \left[\frac{\ln\left(\frac{S}{X}\right) + \left(r - d + \frac{\sigma^2}{2}\right)}{\sigma\sqrt{T}} \right] \quad (3.7)$$

where

N is the cumulative probability function for the normal distribution

d is the expected dividend yield (Execucomp variable *bs_yield*)

σ is the stock return volatility (Execucomp variable *bs_volatility*)

r is the risk free interest rate (Execucomp variable *risk_free_rate*)

S is the closing stock price (Execucomp variable *prc*⁵¹)

X is the exercise price of the option. The calculation is different for different option categories (newly granted options, previously granted exercisable options and previously granted unexercisable options). If the option is a new grant (awarded during the current year) X is given by the Execucomp variable *expri*. For previously granted options the exercise price is approximated using the methodology recommended by Core and Guay (2002). First the number and realized values (excess of stock price over exercise price) of newly granted options are deducted from the number and realized values of unexercised options. Then the realizable values of the unexercisable and exercisable options are divided by the number of unexercisable and exercisable options to obtain an estimate of how far these options are “in the money.” Subtracting this from the firm’s stock price generates an estimate of the average exercise price of the executives’ unexercisable and exercisable options⁵². See Edmans et al. (2009) and Core and Guay (2002) for calculation details.

T is the time to maturity in years. As for the strike price, the calculation is different for different option categories. If it is a new grant T can be calculated using the maturity date (Execucomp variable *exdate*). For unexercisable options Core and Guay (2002) recommend a maturity of one year less than the maturity of newly granted options. The maturity of exercisable options is assumed to be three years less than for unexercisable options. In a last step the maturities exercisable and unexercisable options are multiplied by 70%. This is done to capture the fact that executives typically exercise options prior to maturity⁵³.

In a next step the total delta for each executive is calculated. The delta values for each type of option grant (current year option grants, previously granted unexercisable

⁵¹ If this is missing we take the identical Compustat variable *prc_f*

⁵² Core and Guay (2002) show that their approximation method explains about 99% of the variation in option portfolio values and sensitivities that one would obtain from having full proxy statement information on previously granted options. Other studies that use the Core and Guay (2002) approximation include Knopf et al (2002), Rajgopal and Shevlin (2002), Bergstresser and Philippon (2006), Cheung and Warfield (2005), Burns and Kedia (2006), Erickson et al. (2006), Edmans et al. (2009) and Shaw (2011).

⁵³ See also Core et al. (2003)

options, and previously granted exercisable options) are multiplied by the number of shares of each type of grant, and then summed. To this total option delta the delta of share holdings has to be added, which is equal to the numbers of share holdings by the executive (Execucomp variable *shrown*) multiplied by one (the delta of each share is one). The resulting total delta (“delta_total” in equation (3.8)) of the executive describes the dollar change in the executives’ wealth for a dollar change in the stock price.

In a last step the wealth to performance sensitivity for a given executive (e.g. executive i in company t) is calculated as follows:

$$WPS_{i,t} = \frac{\text{delta_total}_{i,t} \times S}{TDC1_{i,t}} \quad (3.8)$$

where $TDC1_{i,t}$ is a variable in Execucomp describing the total flow compensation from salary, bonus and new grants of stock and options for executive i in company t . For every acquiring firm t we calculate the WPS once for CEO’s as done by Edmans et al. (2009) (equation 3.9) and once for all executives of the firm ($i=1:n$) and take the average of it (equation 3.10)⁵⁴:

$$CEO\text{-}WPS_t = WPS_{CEO,t} \quad (3.9)$$

$$EX\text{-}WPS_t = \frac{\sum_{i=1}^n WPS_{i,t}}{n} \quad (3.10)$$

⁵⁴ We calculate the CEO-WPS to compare the results with Edmans et al. (2009). Our replicated CEO-WPS measure correlates to more than 99% with the measure calculated in their paper.

Chapter 3. Executive Compensation and Insider Trading around Mergers

The resulting sensitivity shows the dollar change in the executive's stock and option portfolio for 1% change in stock prices, divided by the executives annual compensation.

Chapter 4

4. Option Implied Risk Dynamics around SEOs⁵⁵

4.1 Introduction

The analysis of how investors react to new information has received a great deal of attention in recent financial literature. One body of literature finds that stock market investors overreact to information at very short horizons, e.g., less than one month (Lehmann, 1990). Furthermore, they tend to underreact to information over three- and twelve-month horizons (Jegadeesh and Titman, 1993), and overreact again to information over horizons of longer than one year (De Bondt and Thaler 1985, 1987, 1990).⁵⁶ Some authors have constructed theoretical models in an effort to explain that behaviour (see, for example, Barberis et al., 1998; Daniel et al., 1998; and Hong and Stein, 1999). These theoretical and empirical findings suggest that the information flow in financial markets may not always be processed efficiently.

Of the many studies on investor misreactions, the literature on option market anomalies is still somewhat limited. The extant literature has analysed option market misreactions by measuring the impact of new information on implied volatility. In an early article,

⁵⁵ The original essay, entitled "Do markets anticipate changes in risks after major corporate events? – Evidence from SEOs" is joint research work of Lutz Johanning, Umut Ordu and Denis Schweizer. We thank Timo Gebken and Gaston Michel for helpful comments and contribution to an early version of this essay.

⁵⁶ See Shleifer (2000) and Shefrin (2000) for a good summary of studies that support this interpretation.

Stein (1989) studied the term structure of the implied volatility of S&P 100 index options, and found that investors tend to overreact to current information. Poteshman (2001) analysed S&P 500 index options, and showed that option market investors overreact to periods of increasing or decreasing daily volatility changes. Cao et al. (2005) also examine S&P 500 index options, and find increasing misreactions after four consecutive daily variance shocks with the same sign.

In this paper, we aim to contribute to the current debate over investor misreactions by investigating whether option markets can anticipate expected changes in risk dynamics in the presence of extreme informational events. For this purpose, we analyse option market behaviour following seasoned equity offerings (SEOs). A recent study that investigated risk dynamics around SEO events observed large volatility fluctuations (Carlson et al., 2010). We believe these fluctuations can make it very difficult for option market investors to anticipate future volatility, which is a necessary component of option pricing. Thus, we use option market reactions to SEO events as our vehicle for determining whether option markets correctly anticipate and process changes in risk under extreme market conditions.⁵⁷

To be more precise, we test the hypothesis that, in the presence of extreme informational events such as equity issues, option markets are able to anticipate changes in risk dynamics. We compare realized stock volatility and option-implied volatility. Implied volatility from option markets, as a measure of capital market predictions of

⁵⁷ Other authors have also analysed risk dynamics around corporate events. Lewis et al. (2002), for example, analyses risk changes around convertible debt offerings and finds decreasing risk following issuance. Loughran and Ritter (1995) find that risk declines for three years subsequent to an IPO. Bharath and Wu (2005) have examined risk dynamics of acquirers up to five years following M&As, and document increases in risk prior to mergers. Healy and Palepu (1990), Denis and Kadlec (1994), and Carlson et al. (2010) are among other authors who have analysed risk dynamics around SEOs.

future risk, provides a rich source of information about investor expectations of future stock volatility.⁵⁸

In an efficient market, we would expect implied volatility to be a good predictor of future realized volatility. If investors formulate their expectations rationally, any changes in implied volatility should fully incorporate the set of new information accumulated to date. However, we find a strong divergence between option-implied and realized volatility following equity issuance, with realized volatility showing a strong decrease after issuance, while expected volatility implied from option markets remains constant and thus overestimates realized volatility. Our results support the hypothesis that option markets overestimate future volatility following SEOs. Our findings are also in line with those of Stein (1989), Goyal and Saretto (2009), and Poteshman (2001), who have found evidence of option market misreactions.

To measure the extent of divergence between historical realized and implied volatility, we analyse the risk-adjusted returns of volatility trading strategies following issuance. Goyal and Saretto (2009), among others, use volatility trading strategies to measure the extent of mispricing in option markets. In particular, they show the profitability of volatility trading strategies by constructing decile portfolios of straddles based on the difference between historical realized volatility and volatility implied from individual

⁵⁸ A number of authors have examined the informational role of option-implied information around corporate events. For example, Amin and Lee (1997) and Donders et al. (2000) analyse option-implied information around earnings announcements. Cao et al. (2005) analyse option markets around takeovers, while Arnold et al. (2006) analyse tender offers. For a theoretical analysis of how information gets incorporated into asset prices, see, e.g., Biais and Hillion (1994), Easley et al. (1998), and John et al. (2000).

stock options.⁵⁹ Their results suggest that investors overreact to current events in their estimation of future volatility.

Following the same methodology, we examined volatility trading strategies around SEO events using straddle portfolios. We observe a divergence between stock and option market expectations. We also find that straddle portfolios that explore the differences between option-implied and realized volatility lead to statistically significant risk-adjusted positive returns of around 5% per month for the one-month period after SEO issuance.

However, not all of our highly positive portfolio returns are abnormal; they are simply not related to commonly known risk factors. Epstein and Schneider (2008) offer one explanation for the overestimation of future volatility by option market participants. They examine investors' reactions to information signals that have uncertain implications. Based on Gilboa and Schmeidler's (1989) assumption that investors will attempt to maximize utility under the worst possible perceived outcome, Epstein and Schneider (2008) show that investors will want to be compensated for the risk of uncertainty.

Following this idea, the reported abnormal portfolio returns could be interpreted as a risk premium to compensate for the high level of uncertainty surrounding SEO events.⁶⁰

⁵⁹ In addition to Goyal and Saretto (2009), several other authors have used straddle portfolios to analyse risk dynamics. Coval and Shumway (2001), for example, study index option returns, and find that zero-cost at-the-money straddle positions (a combination of calls and puts with offsetting covariances) on the S&P 500 produce average losses of about 3% per week. Their results suggest that factors besides market risk, such as systematic risk, may be important for pricing option market risk. Following the same methodology, Arisoy et al. (2007) use zero-beta straddle returns to examine whether volatility risk is a priced risk factor in securities returns.

⁶⁰ It remains unclear how an SEO affects the future performance of the underlying equity. However, there is a large body of literature on the topic. Papers analysing the performance of SEO firms include, but are not limited to, Loughran and Ritter (1997), Spiess and Affleck-Graves (1995), Brav et al. (2000),

When uncertainty increases, stock options become more attractive (valuable), because of, e.g., an increase in expected value due to the asymmetric payoff profile. In those situations, market participants may have an aversion to writing options, and will thus likely require an additional risk premium as compensation for the uncertainty.

Under this assumption, we expect the option markets to overestimate future volatility. In our initial analysis, we use illiquidity (measured by abnormal trading volume and abnormal zero option trades) in options markets as a proxy for uncertainty, and find a positive correlation between profitability and illiquidity.

This paper contributes to the literature in several ways. First, it is related to a recent strand of literature that examines market efficiency through option-implied information. However, it differs in that we concentrate on stock market options for one specific corporate event. Most previous studies on option market misreactions have estimated the degree of overreaction for one general market index. Second, in contrast to the large volume of work on stock market misreactions around equity offerings, our paper uses option-implied information to analyse investor behaviour around corporate events.⁶¹ The benefits of examining option rather than stocks have been shown in Stein (1989). The only uncertain variable in option valuation is the volatility of the underlying asset, but equity or bond prices are affected by additional uncertainties such as changes in common risk premiums.

Eckbo et al. (2000), Jegadeesh (2000), Mitchell and Stafford (2000), Clarke et al. (2001), and Lyandres et al. (2008). See Ritter (2003) for a summary of the extant literature.

⁶¹ There is a large body of literature that analyses over- and underreactions in stock markets around SEOs. Loughran and Ritter (1995), Eckbo et al. (2000), and Lyandres et al. (2008) have all shown that new equity issuers underperform benchmark stocks over a five-year post-offering period. In addition, Purnanandam and Swaminathan (2006) show that overvalued SEOs experience a larger decline in market value over the next five years. They argue that investors underreact to SEO events when determining the valuation of SEO firms. These results suggest that equity offerings can affect stock values, and the information flow following an SEO event is not necessarily processed efficiently in financial markets.

Third, this paper is related to a new strand of literature that examines volatility trading strategies for the analysis of risk dynamics. Goyal and Saretto (2009), Coval and Shumway (2001), and Arisoy et al. (2007) are among those who have used straddle strategies to analyse volatility dynamics. Straddle portfolios neutralize the impact of movements in the underlying stocks, and can be useful in analysing risk dynamics.

To the best of our knowledge, however, ours is the first paper to analyse risk dynamics around SEOs using straddle returns. Most prior research has focused on stock market beta dynamics as a means to analyse risk around corporate events.⁶² Our paper contributes to the current debate on risk dynamics by identifying an innovative trading strategy that links information (processing) from option and stock markets and produces abnormal returns.

The remainder of this paper is organized as follows. Section 4.2 describes our data sources, filter criteria, and matching procedures. Section 4.3 then presents our main results on the cross-sectional analysis of risk dynamics in stock and option markets over time. Section 4.4 examines straddle strategies based on the difference between option-implied and realized volatility, and section 4.5 concludes.

4.2 Data

We conduct an empirical analysis using daily stock and option data for our sample period of January 1996-December 2005. The data come from several sources: The option data originate from OptionMetrics, the stock data from the Center for Research in Security Prices (CRSP), and the SEO data come from the Securities Data Company's

⁶² See, for example, Lewis et al. (2002), Carlson et al. (2010), and Loughran and Ritter (2005).

(SDC) Global New Issues Database. The option data cover all exchange-listed call and put options on U.S. equities, with approximately 7 million options per month.

OptionMetrics also reports implied volatility for each option. The implied volatilities on individual stock options, which are American, are calculated using a Cox-Ross-Rubinstein (1979) binomial tree model, taking into account discrete dividend payments and the possibility of early exercise. The CRSP database includes monthly and daily price quotes for stocks on the New York Stock Exchange (NYSE), the American stock exchange (the AMEX), and the NASDAQ. The SDC database contains traditional SEOs from the 1996-2005 time period.

Our first step is to filter the SEO data following Carlson et al.'s (2010) method. We exclude utilities and financials, taking only common stock issues traded on the NYSE, the AMEX, or the NASDAQ by U.S. companies that are not coded as IPOs, unit issues, ADRs, or ADSs. If a firm had more than one SEO, we treat the transactions as separate observations. Furthermore, we require the SEO securities to have valid stock price data in CRSP. We obtain a total of 4,232 SEO events that fulfil these criteria.⁶³

In our next step, we match the 4,232 SEO events with the standardised option dataset in OptionMetrics. For each firm and trading day, we take standardised equity-implied volatilities and premiums for ATM (at-the-money) call and put options, with a one-month time to maturity. In OptionMetrics, the implied volatilities of standardised ATM options are calculated by interpolating the volatility surface. The forward price of the underlying security is first calculated, using the zero curve and the projected distributions. Next, the volatility surface points are linearly interpolated to the forward

⁶³ We use “SEO event” or “event date” throughout this paper to refer to the issue date of the seasoned equity offering as reported in SDC.

price and the target expiration, in order to generate ATM-implied volatilities. A standardised option is included only if enough option price data exist on that date to accurately interpolate the required values.

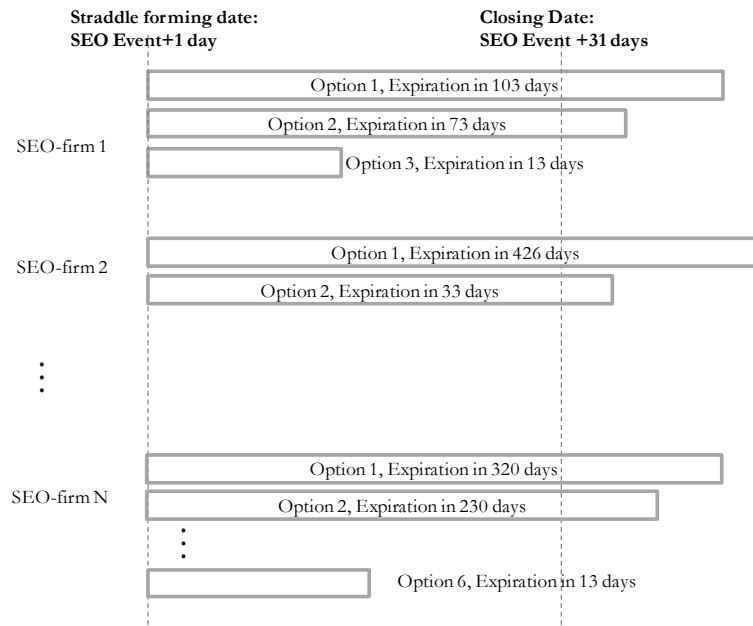
Berndt and Ostrovnaya (2008), Rogers et al. (2009), and Stein and Stone (2010) have all used OptionMetrics standardised option data for their analyses. Standardised options are generally believed to have two advantages over traded options. First, the data granularity is higher, because standardised options are constructed to be ATM. We obtain 1,753 observations with standardised option data, and only 290 observations with traded option data.

Second, standardised option data are more suitable for the accurate calculation of monthly straddle portfolio returns. As we note later, this return calculation is necessary in order to analyse volatility trading strategies. Moreover, because standardised option duration is held constant, the straddle returns are not affected by changes in option prices due to, e.g., variations in time to maturity.

Figure 4.1 illustrates the maturity mismatch problem of traded options, which is also described in Rogers et al. (2009) and Patell and Wolfson (1979, 1981). Traded options normally mature only on the third Friday of the month. However, obviously, not all SEO events take place on the same day, so options available on the straddle forming dates (the days following the SEO event) will have expiration dates that can differ up to approximately one month. This implies that, when we close a straddle position, after one calendar month, we would not expect the underlying options to expire on this date.

Figure 4.1: Option closing before expiration date

This figure illustrates the task of calculating monthly option returns for SEO securities on the day following the SEO event (the straddle formation date). Firms that undergo an SEO (SEO firm) have several options available to them on the date of issuance. Because options generally mature only on the third Friday of the month, the options on the straddle formation date usually have expiration dates different to one month.



We use standardised option data in an effort to avoid the biased returns that can result from the maturity-mismatch problem. Using traded options that do not expire at the straddle closing day, however, can lead to inappropriate and biased results. This is because the price of an option on the closing date reflects not only the development of the underlying asset up to that date, but also future market expectations up to the expiration date. Therefore, only options that expire at the closing date are ideal

measures of past underlying performance or risk dynamics.⁶⁴ Table 4.1 provides summary statistics for the matched sample.

Table 4.1: SEO distributions by year

The sample consists of common stock issues traded on the NYSE, AMEX, or NASDAQ that are not coded as IPOs, unit issues, ADRs, or ADSs. Regulated utilities (SIC = 481 and 491-494) and financial institutions (SIC = 600-699) are excluded. To be included, firms must have valid quotes as of the date of issuance in the OptionMetrics standardised option database. The options are constructed to be ATM, and have exactly one month to maturity.

Year	Aggregate gross proceeds (Mil. USD)	Market Cap (Mil. USD)	No. of offerings
1996	166	1,275	154
1997	177	1,631	161
1998	269	4,139	147
1999	302	4,004	218
2000	363	6,396	205
2001	232	2,494	183
2002	168	1,611	170
2003	141	1,626	174
2004	194	3,225	189
2005	209	2,782	152
Total	226	3,022	1,753

Table 4.1 shows that the number of SEOs fluctuates from year to year. Most of the offerings we consider here took place around the year 2000. This year also saw the highest amount of gross proceeds and the largest market capitalization.

⁶⁴ As a robustness check, we replicate our results in section 4.4 with the traded option data sample. Our results remain qualitatively the same.

4.3 Volatility Dynamics

Carlson et al. (2010) examined the realized volatility of stocks around SEO events and found a decrease, followed by an increase, in volatility around SEO issuance. Our next step is to replicate this result; we then determine whether option markets predict these strong volatility fluctuations in stock markets. We thus compare realized volatility calculated from stock market returns with volatility implied from option prices. Implied volatility from option markets as a measure of capital market prediction of future risk provides a rich source of information about investor expectations of future stock volatility.

For each SEO stock, we calculate annualized monthly realized and implied volatility from the five-month period prior to the SEO event to the five-month period afterward. We calculate monthly realized volatilities following the procedure in Schwert (1989). For each day, we calculate monthly historical variance by taking the sum of the squared daily returns (after subtracting the average daily return in the month) over the previous month's daily returns, as follows:

$$\sigma_{HV}^2 = \sum_{i=1}^{N_t} r_{it}^2 \quad (4.1)$$

where there are N_t daily returns r_{it} in month t . We then annualize the resulting monthly realized volatilities.⁶⁵

⁶⁵ Calculating monthly realized volatility on a daily basis leads to strongly autocorrelated volatility data. However, because we aim to compare the dynamics of volatility between two markets, this problem is irrelevant.

We obtain monthly implied volatilities from the standardised option dataset.⁶⁶ We take the implied volatility of linearly interpolated ATM call and put options with thirty-day expiration dates.⁶⁷ In a similar analysis, Goyal and Saretto (2009) use ATM options with thirty-day expiration dates, and compare monthly implied volatility with monthly realized volatility.

For robustness and to better understand volatility dynamics, we also calculate realized and option-implied volatilities of matched firms as well as market aggregates. Following the standard literature, we match by firm size and industry classification.⁶⁸ We calculate the realized and implied volatility of matched firms and of the market in a similar manner to our SEO firm calculations.

Figure 4.2 shows the cross-sectional average of calculated volatilities around the SEO event for SEO firms, matches, and the market.

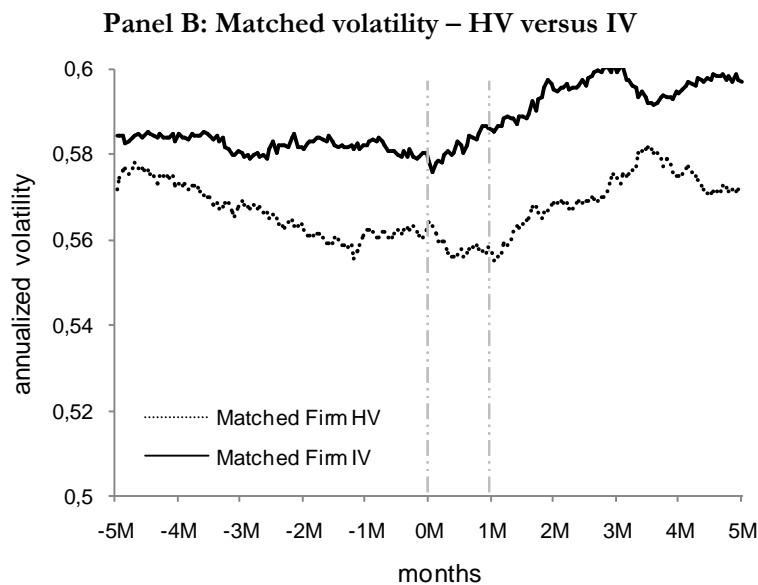
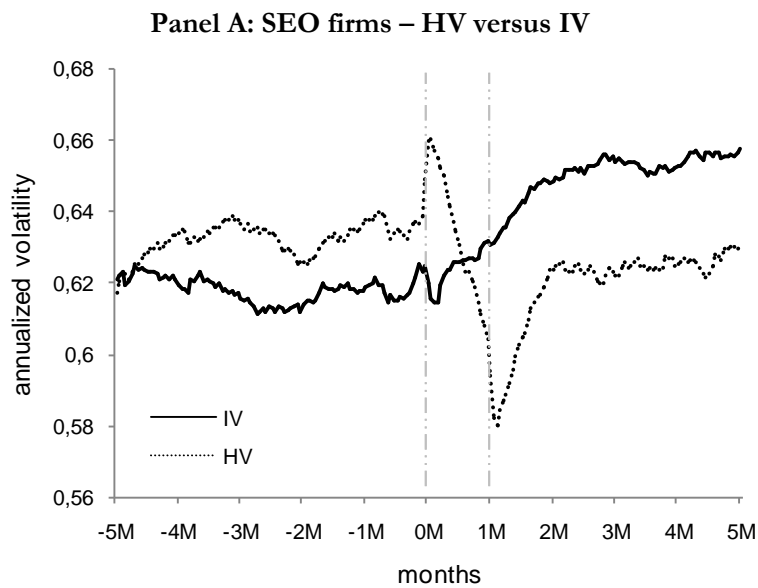
⁶⁶ We choose the standardised option sample for our volatility dynamics analysis because options usually expire on the third Friday of the month, so a daily volatility comparison of traded options would be biased by a declining time to maturity. This problem can become especially severe as the option approaches its maturity date (see Rogers et al., 2009, and Patell and Wolfson, 1979, 1981). In contrast, standardised options have an exact thirty-day time to maturity. See section 4.2 for other advantages of the standardised option dataset.

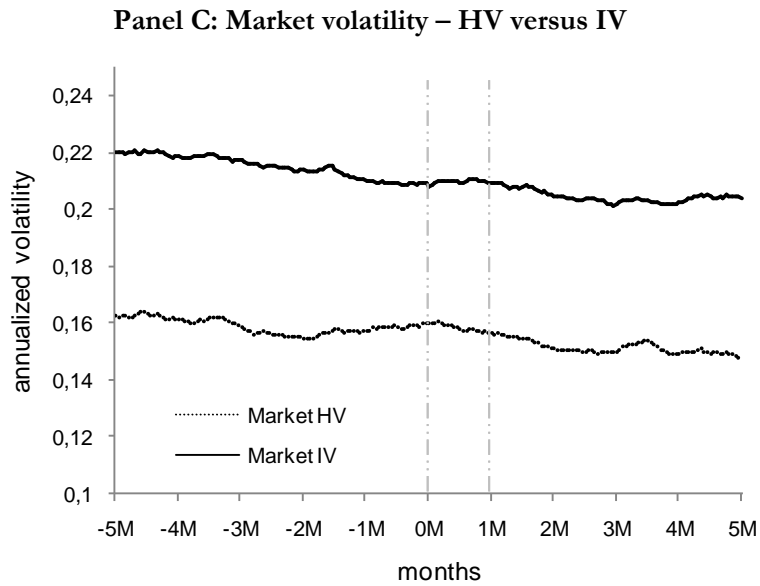
⁶⁷ Throughout this paper, “days” refers to calendar days, if not stated otherwise.

⁶⁸ See, for example, Ritter (1991), Michaely et al. (1995), and Spiess and Affleck-Graves (1995).

Figure 4.2: Comparison of realized and option-implied volatility around SEO events

This figure compares realized (HV) and option-implied (IV) volatility dynamics for the five months prior to the SEO event to the five months afterward. Panel A displays volatility dynamics for SEO firms, panel B shows those for matched firms, and panel C shows those for the market. The solid lines show the average option-implied volatility, representing an annualized volatility expectation for the following calendar month. The dashed line shows realized volatility dynamics around SEO events. Realized and option-implied volatilities are annualized. The dashed vertical grey lines are auxiliary lines that mark the SEO event date and the one month date after the SEO event. All positive numbers on the x-axes are months after issuance; all negative numbers on the x-axes are months prior to issuance.





Because implied volatilities reflect annualized volatility expectations for the following month, implied volatility lags realized volatility by one month. This means that the implied volatility shown in Figure 4.2 on month x must be interpreted as the market prediction of future realized risk on month $x + 1$ (e.g., the following month).

Consistent with Carlson et al.'s (2010) observations, realized volatility for SEO firms experiences strong fluctuations around equity issuance. As panel A of Figure 4.2 shows, realized volatility drops dramatically immediately after the SEO event (0M to 1M), and begins to increase strongly one month after issuance. Standard real option theory may provide an explanation for the decrease. According to a theoretical framework developed by Carlson et al. (2010), firm risk depends on the relative value of a growth option prior to the SEO event. Their model predicts a drop in risk on the SEO date proportional to the amount of proceeds from the issuance.⁶⁹

⁶⁹ For a more detailed discussion of theoretical approaches to analysing patterns in financial returns around SEO events through real option theories, see Lucas and McDonald (1990) and Carlson et al.

The strong increase in volatility one month after the SEO is more difficult to interpret, although Carlson et al. (2010) may also provide an explanation. They argue that post-SEO firms may have additional investment commitments, which could lead to the post-issuance increases in volatility. However, we note again that our focus is on the empirical relationship between capital market predictions of future risk and realized volatility, so we do not explore this idea any further here. We should simply bear in mind that Carlson et al.'s (2010) theoretical arguments underline our reasoning that the level of uncertainty surrounding SEO events can be rather high.

Interestingly, volatilities implied from option markets react differently than realized volatilities. Realized volatility shows strong fluctuations around the SEO event, but implied volatility increases smoothly during the event. This suggests that option markets do not fully anticipate the risk dynamics around these events.

To be more precise, at the SEO date, realized volatility increases, while implied volatility – the market's expectations about future stock volatility for the following month – decreases. The direction (decrease) in future volatility is supported by the data and realized volatility decreases, but it is much stronger than expected at the SEO date (see Figure 4.2). The option market thus estimates a higher volatility than the realized volatility one month after the event date.

This overestimation could stem from the incapability of the option markets to correctly anticipate how stock market participants will react (misreactions), or because of a high level of uncertainty surrounding the impact of the issuance on investors. At those times, the options will be valuable, due to their asymmetric pay-off profile, and they are likely

(2006, 2010). Please note that the observed decrease in realized volatility is also consistent with the financial leverage explanation of Hamada (1972). He argues that the nondiversifiable risk should be greater for a firm with higher debt-equity ratio than for a firm with a lower debt-equity ratio.

to be traded at a risk premium, which could lead to an overestimation of realized volatility.⁷⁰ One month after the SEO event, we observe that the market prediction of volatility for the following month (two months after the SEO event) is almost the same or slightly higher than the final realized volatility. This could be a sign that option markets have processed the new information, that the level of uncertainty is now lower, and the market is thus predicting future realized volatility more correctly.

Note also that, before issuance, the implied volatility is smaller than the realized volatility; afterward, the issuance increases and remains at a higher level. This suggests that option markets might add a risk premium to firms that increase capital through equity issuance.

In panels B and C of Figure 4.2, we see no decline for matched firms or market aggregates around issuance. This suggests that the sharp drop in volatility observed in panel A for SEO firms is not attributable to broad-based changes in volatility. Furthermore, we see that 1) the average volatility of SEO firms and matched firms is higher than the average volatility of market aggregates, and 2) the average volatility of SEO firms is much higher than average market volatility, which is consistent with observations made by Carlson et al. (2010).

⁷⁰ It is possible that the increased uncertainty around SEOs is attributable to the intended use of proceeds. In the majority of cases, the firms tend to be vague, and state only that the funds will be used for general corporate purposes. This may increase uncertainty. Autore et al. (2009) investigate the relationship between seasoned equity issuers' stated intended use of proceeds and their subsequent long-run stock and operating performance. They find that issuers that stated recapitalization or general corporate purposes tend to underperform in the subsequent three years, but issuers that provided explicit investment details exhibited little or no subsequent underperformance. We did not control for the use of proceeds within our analysis, however, because, in the majority of cases, SDC provides several or unclear statements on their use (this is true for more than 80% of our sample). When we follow Autore et al. (2009), who observed the same pattern in the SDC, and exclude these issuers from our analysis (to avoid ambiguity about the intended use of the proceeds), the resulting sample is too small to draw meaningful conclusions.

Finally, panels A, B, and C of Figure 4.2 show that option-implied volatility is higher than realized volatility for matched firms and market aggregates [see Poon and Granger (2003, 2005)]. This observation is consistent with Coval and Shumway (2001), who studied option returns on the S&P 500 with volatility trading strategies. Their results suggest that factors other than market risk, such as systematic risk, can lead to higher implied volatilities, and may be important for precisely pricing the risk in option markets. Thus, it is important to directly account for this kind of systematic risk in our empirical specifications. Furthermore, we observe that the average volatility of SEO firms is much higher than overall average market volatility.

4.4 Analysis of Economic Significance using Straddles Strategies

This section provides a more complete analysis of the observations from Figure 4.2. In particular, we test whether volatility strategies that trade on the differences between realized and implied volatility following SEO events are profitable.

4.4.1 Methodology

Goyal and Saretto (2009) and Arisoy et al. (2007) are among those who have analysed risk dynamics with volatility trading strategies. We follow Goyal and Saretto (2009) and use straddle returns for our analysis of volatility dynamics. Straddle portfolios neutralize the impact of movements in underlying stocks, and are commonly used in analyses of volatility behaviour. Long/short straddles are formed by combining one long/short ATM call with one long/short ATM put option, with the same underlying, strike price, and maturity date.

For our analysis, we examine the period beginning one day after the SEO event and ending one month after it.⁷¹ In Figure 4.2, this period is marked with two dashed vertical grey lines. At the beginning of this period, we see that realized volatility is higher than implied volatility. This suggests that implied volatility, which is a thirty-day forecast of realized volatility, ultimately anticipates a decrease in realized volatility. At the end of the period, we note that realized volatility has decreased, but more dramatically than the option markets expected. Thus, we predict that a volatility trading strategy speculating on a decrease in volatility for this time period could lead to positive returns.

Based on the observations in Figure 4.2, we test the hypothesis that a short straddle portfolio formed on the day after the SEO event (Date+1) and closed one month after it (Date+31) is profitable. This volatility trading strategy is illustrated in Figure 4.3.

⁷¹ As a robustness test, we analysed short straddle returns for the period beginning one month after the SEO date and ending two months after issuance. Consistent with our observations in Figure 4.2, this straddle strategy was not profitable, because the option markets have processed the new information and can thus predict future realized volatility almost correctly.

Figure 4.3: Payoff profile of a short straddle strategy

This figure sets the payoff chart of a straddle strategy (on the right-hand side of the chart) relative to possible stock price paths of SEO firms following issuance. The short straddle strategy becomes more profitable as the volatility of the SEO firm decreases.

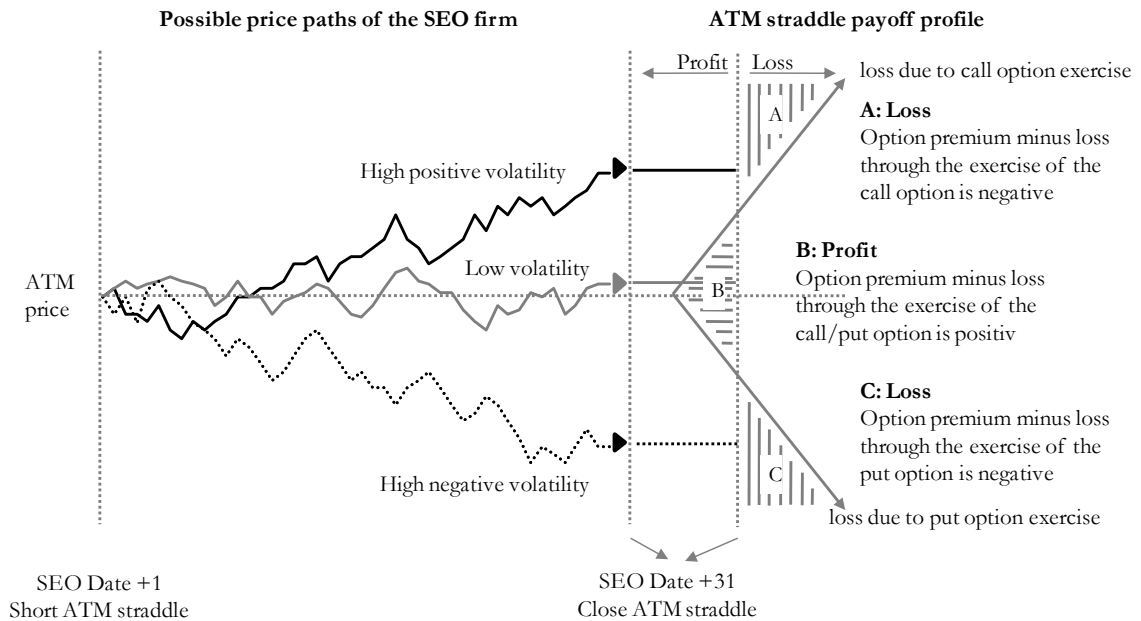


Figure 4.3 sets the payoff profile of a straddle in relation to possible stock price paths of SEO firms. On the left-hand side of the chart, the stock price is simulated for the thirty calendar days following the SEO announcement. We short an ATM straddle on the day following the announcement (Date+1), and close this position thirty-one calendar days afterward (Date+31). To obtain a short straddle position, we sell an ATM call and an ATM put with the same strike, underlying, and expiration date, and obtain an option premium from the option buyer as insurance against any price increases (call option) or decreases (put option) of the underlying equity (SEO firm). The straddle position is profitable when the option premium obtained at Date+1 is higher than the amount to be paid if the call or put option is exercised. The right-hand side of the chart illustrates this idea through the commonly known payoff profile of a straddle position.

Chapter 4. Option Implied Risk Dynamics around SEOs

If the price of the SEO firm increases (decreases) significantly (“high volatility”), the call (put) buyer will exercise the ITM position and the short straddle will have a negative payoff (see shaded areas A and C of Figure 4.3). If the price of the SEO firm remains principally unchanged (“low volatility”), the options will not be exercised or the exercise of the call (put) will not lead to high payments for the straddle seller. The option premium obtained at Date +1 is thus higher than the payouts obtained from the exercise of the call/put positions (shaded area B).

When option markets anticipate risks correctly, we expect the option premiums obtained for selling the call and put options at Date+1 to be generally the same as the cost to pay when these options are exercised at Date+31. When our hypothesis is supported, and option markets overestimate risks or price options at a risk premium following SEO announcements, we generally expect that the option premiums will be higher than the average option payouts, thus generating a trading profit. Therefore, by selling the “expensive” options, we expect the option premium obtained at Date+1 to be higher than the cost of exercising the options at Date+31. And the costs of exercising one of the two options will be low if the closing price of the SEO firm at Date+31 is close to its original price at Date+1 (“low volatility”).

Note that, in Figure 4.2, we observed an increase in implied volatility between Date+1 and Date+31. This observation may initially seem to contradict our hypothesis that a short volatility strategy for the same time period is profitable. However, this assumption is misleading, because, for straddle return calculations, we only need option market information at Date+1 when we are forming the portfolio, not at Date+31 when closing the position. The closing price is the terminal payoff of the options, and is determined by the stock price, not by option prices or by volatilities at Date+31.

Therefore, the implied volatility or the option prices on the closing date are actually irrelevant for the return calculation, because they would bias the results by reflecting market expectations for the following thirty days (Date+61), not the past thirty days.

As the reference beginning price, we take the price of the standardised ATM call and put options with expiration dates of exactly thirty days; as the reference closing price, we take the terminal payoff of these options.⁷² We follow Coval and Shumway (2001) and use raw net returns instead of logarithmic returns, because options held to maturity can have net returns of -100% (i.e., expire worthless), and the log transformation of -1 is not defined.

4.4.2 Raw returns

In this subsection we analyse the raw returns from the short straddle strategy for different industry groups. The results in Table 4.2 from the volatility trading strategy support our observations in Figure 4.2, that the volatility implied from option markets is too high compared to realized volatility. By selling straddles on the day after an SEO event, and closing one month after the announcement, the volatility trading strategy obtains positive raw returns of about 6.9% per month. When we differentiate among industry sectors, we observe that equity offerings in mineral industries exhibit the largest average straddle returns (11.5%), and those in the transportation/communications industries exhibit the lowest (2.6%). We also observe that the straddle returns are all positive across industry sectors, indicating qualitatively that our sample composition is homogeneous.

⁷² The terminal payoff for a call position is $\max(S-K; 0)$; for a put position, it is $\max(K-S; 0)$. S is the closing price of the underlying equity, and K is the strike price of the option. OptionMetrics sets the theoretical price of standardised options equal to the midpoint of the best closing bid price and best closing offer price for the option.

Moreover, we note that the raw straddle returns of matched firms are also positive. However, they are lower than those for SEO firms. As we see in the next subsection, this result can be almost fully explained by common risk factors.

As a first robustness check, we find a statistically significant 3.46% per month return for a long/short portfolio consisting of a long straddle portfolio of matched firms (3.42%) and a short straddle portfolio of SEO firms (6.88%) – see Table 4.2. Because the matched firms have virtually the same firm characteristics as the SEO firms, the long/short portfolio's return should not be driven by common market risk factors but by the equity offering.

In the next subsection, we follow standard financial literature and calculate risk-adjusted straddle returns to determine whether the positive returns are “abnormal,” or the result of common risk factors.

Table 4.2: Returns of straddle portfolios following an SEO event

This table shows average monthly returns and the sample size of short straddle portfolios formed beginning one day after the SEO event (Date+1) to one month after the SEO event (Date+31). Average returns are reported for different industry groups and matched firms. We do not report average returns for the industry groups “Agriculture, Forestry, Fisheries” (SIC = 01xx-09xx) or “Public Administration” (SIC = 91xx-97xx) because of the small sample size. Matched firms are matched by firm size and industry classification.

	Monthly Raw Return	
	(%)	Sample Size
Total	6.88	1,753
Mineral Industries	11.54	133
Construction Industries	3.33	20
Manufacturing	6.81	821
Transportation, Communications	2.63	189
Wholesale Trade	6.62	72
Retail Trade	8.07	107
Service Industries	7.10	406
Others	-	5
Matched Firms	3.42	1,753

4.4.3 Risk-adjusted returns

This subsection describes our econometric framework, which involves estimating the excess returns of the straddle portfolios after correcting for common risk factors. As per previous work in financial economics, we calculate risk-adjusted returns using the three Fama and French (1993) factors, the Carhart (1997) momentum factor, and the Coval and Shumway (2001) volatility factor. The volatility factor is computed by taking the excess return on a zero-beta S&P 500 index ATM straddle. Zero-beta index straddles combine long positions in calls and puts that have offsetting covariances with the index.

Coval and Shumway (2001) define the return of a zero-beta index straddle as:

$$r_{straddle} = \frac{-c\beta_{call} + S}{p\beta_{call} - c\beta_{call} + S} r_{call} + \frac{p\beta_{call}}{p\beta_{call} - c\beta_{call} + S} r_{put} \quad (4.2)$$

where $r_{straddle}$ is the straddle return, r_{call} and r_{put} are the call and put option returns, c and p are the call and put option prices, and S is the level of the S&P 500 index. Furthermore, β_{call} is the call option delta, which is calculated by using the Black and Scholes (1973) beta, defined as:

$$\beta_{call} = \frac{S}{c} N \left[\frac{\ln\left(\frac{S}{K}\right) + \left(r - d + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \right] \beta_S \quad (4.3)$$

where $N[.]$ is the cumulative normal distribution, K is the exercise price of the call option, r is the risk-free short-term interest rate,⁷³ d is the dividend yield for S&P 500 assets, σ is the standard deviation of S&P 500 returns, and t is the option's time to maturity.

In addition to the common risk factors, we also control for firm characteristics. We adjust for skewness with the Harvey and Siddique (2000) skewness factor, and account for differences in the size of proceeds by constructing a variable, "prosize," which we define as:

⁷³ For the short-term interest rate, we use the BBA Libor one-month rate from Bloomberg.

$$\text{Prosize} = \frac{\text{Value of Proceeds}}{\text{Market Capitalization}} \quad (4.4)$$

Table 4.3 reports the estimated parameters from the regression analysis. Regression (1) shows that the variables that adjust for firm characteristics have very small and insignificant effects on the straddle portfolio return. Regression (2) shows the regression results for the common risk factors. The straddle portfolio has negative loading on the volatility factor, the momentum factor, and on two of the Fama and French (1993) factors (“Mkt-rf” and “SMB”). The loading on the HML factor is positive but not significant.

Even more interesting is the fact that alpha, which can be interpreted as the mispricing or risk premium to the factor model, remains positive and significant (5.6% per month). When we control for both risk factors and firm characteristics in Regression (3), the straddle return decreases slightly to 5.1% per month, which is still highly positive and significant.

Regression (4) reports loadings for the matched-firm straddle portfolio. The alpha here is almost zero. This indicates that the positive raw return for matched firms can be almost fully explained by common risk factors.

Table 4.3: Risk-adjusted return calculations

This table shows monthly returns of a short straddle portfolio adjusted with a five-factor model that uses the three Fama-French (1993) factors (“Mkt-RF,” “SMB,” and “HML”), the Carhart (1997) momentum factor (“Mom”), and the Coval and Shumway (2001) volatility factor (“Coval-RF”). In addition, the returns are controlled for different sizes of proceeds – we use the “prosize” variable to denote the value of proceeds divided by the market cap - and the Harvey and Siddique (2000) skewness factor (“skew”). Our return analysis is conducted for the period beginning one day after the SEO event and ending one month after it. The first row gives the coefficients, while the second row gives the t-statistics (Newey and West, 1987) in parentheses. The dependent variable is the return of interpolated options with expiration dates of exactly thirty days. Regression results for the industry groups “Agriculture, Forestry, Fisheries” (SIC = 01xx-09xx), “Construction Industries” (SIC = 15xx-17xx), “Wholesale Trade” (SIC = 50xx-51xx), and “Public Administration” (SIC = 91xx-97xx) are not reported due to small sample sizes (less than 100 observations). Regressions (1)-(3) show straddle returns of SEO firms, regression (4) shows straddle returns of matched firms (matched by firm size and industry classification).

	(1)	(2)	(3)	(4)
Sample Size	1,753	1,753	1,753	1,753
Alpha	5.92 (2.09)	5.60 (2.69)	5.10 (1.68)	-0.03 (-0.01)
Size	1.32 (0.94)		1.02 (0.73)	0.00 (0.63)
Skew	1.12 (1.81)		-1.13 (-1.23)	0.30 (0.30)
Coval-RF		-0.10 (-3.65)	-0.10 (-3.53)	-0.16 (-5.51)
Mkt-RF		-1.46 (-3.00)	-1.62 (-3.23)	-0.63 (-1.18)
SMB		-0.06 (-0.13)	-0.46 (-0.87)	0.78 (1.38)
HML		0.41 (0.62)	1.03 (1.27)	1.02 (1.17)
Mom		-0.02 (-0.04)	-0.18 (-0.45)	-0.50 (-1.16)

However, not all of our highly positive portfolio returns are abnormal. Our empirical analysis merely demonstrates that the returns cannot be explained by the usual sources of risk. It is possible that the observed positive returns represent a compensation for another type of risk. In the following subsection, we will explore one possible explanation for this.

4.4.4 Option market risk premiums

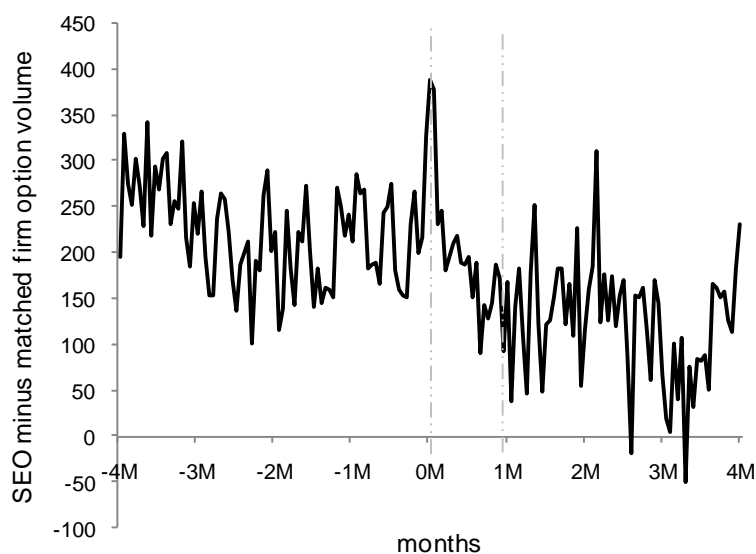
We use the findings of Epstein and Schneider (2008) as one possible explanation for why the option markets seem to overestimate future volatility. The authors argue that investors want to be compensated for uncertainty when they process news of unclear quality. Under this framework, we can interpret the excess returns (over common risk factors) for the straddle portfolio as compensation for option market investors' uncertainty about the implications of an SEO announcement. Thus, as uncertainty increases, stock options become more attractive (valuable) to, e.g., risk-averse investors, because they can protect against adverse price movements and because the asymmetric payoff profile may lead to an increase in expected value.

Under those conditions, market participants may have an aversion to writing options, and will thus need to be compensated with an additional premium. We should also observe higher option premiums and lower liquidity in option markets following the SEO event. The abnormal straddle returns already indicate the higher option premiums. To test this hypothesis, we follow Cao and Wei (2010) and use option volume to measure liquidity, which can be considered as a proxy for option market uncertainty.

Figure 4.4 shows daily abnormal option volume around the SEO event (by matched SEO firms).⁷⁴ From this first analysis, we note that option market liquidity in the first month after the SEO event decreases by approximately 15% compared to average liquidity over the four months prior to the SEO event.⁷⁵ This clearly supports our hypothesis that lower liquidity indicates higher uncertainty.

Figure 4.4: Liquidity around SEO events

This figure shows the change in option market liquidity for the four months prior to the SEO event to the four months afterward. We calculate option market liquidity by deducting matched-firm option volume from SEO option volume. Negative option market liquidity indicates that matched-firm option volume was higher than the SEO option volume. The dashed vertical grey lines are auxiliary lines that mark the SEO event date and the one month date after the SEO event. All positive numbers on the x-axes are months after issuance; all negative numbers on the x-axes are months prior to issuance.



⁷⁴ As in section 4.3, we match on firm size and industry classification.

⁷⁵ The decrease does not change when we use the five months prior to the SEO event as our benchmark.

Our second analysis investigates whether liquidity (measured by abnormal trading volume) can explain the abnormal returns of the straddle strategy. We calculate post-merger short straddle returns for different portfolios, as follows:

- Portfolio P1-AVOL consists of the SEO firms with the highest abnormal option volume in the month following the SEO event (highest quantile). Abnormal option volume (AVOL) is calculated as:

$$AVOL = \frac{\sum_{i=1}^{20} (VOL_i^{SEO \text{ firm}} - VOLB^{SEO \text{ firm}}) - (\sum_{i=1}^{20} (VOL_i^{\text{Matched-firm}} - VOLB^{\text{Matched-firm}}))}{20} \quad (4.5)$$

where $VOL_i^{SEO \text{ (Matched-) firm}}$ is the option volume of an SEO (matched-)firm on trading date i , and $VOLB^{SEO \text{ (Matched-) firm}}$ is the average daily trading volume estimated for the window (four months to one month prior to the SEO event).⁷⁶

The index variable i describes the trading days following the SEO event, e.g., date $i = 1$ is the first trading date after the SEO event.

- Portfolio P2-AVOL consists of the SEO firms with the lowest abnormal option volume in the month following the SEO event (lowest quantile).
- Portfolio P1-AZOT consists of the SEO firms with the highest abnormal zero option trades (AZOT) in the month following the SEO event (highest quantile). We calculate abnormal zero option trades (AZOT) using Lesmond et al.'s (1999) method:

⁷⁶ This is a form of the constant mean model used in standard event methodology. See MacKinlay (1997), Campbell et al. (1997), and Lyon et al. (1999).

$$AZOT = \frac{\sum_{i=1}^{20} n_{vol,i=0}}{20} - \frac{\sum_{i=-21}^{-80} n_{vol,i=0}}{60}, \quad (4.6)$$

where the first term describes the daily proportion of zero option volumes in the first month following the SEO event, and the second term describes the daily proportion of zero option volumes in our benchmark period (the four months to one month prior to the SEO event). The index variable i describes the trading days following the SEO event.

- Portfolio P2-AZOT' consists of the SEO firms with the lowest abnormal zero option trades in the month following the SEO event (lowest quantile).

We can see clearly from Table 4.4 that the SEO firms with lower option market liquidity (e.g., low AZOT and high AVOL measures) have higher short straddle returns than those with more liquid option markets (high AVOL and low AZOT).⁷⁷ Overall, these two analyses support the explanation that option market uncertainty (as approximated for by liquidity) can explain abnormal straddle returns.

⁷⁷ Our option market liquidity measures exhibit contrary properties: AVOL measures liquidity and AZOT measures illiquidity.

Table 4.4: Option markets liquidity following SEO events

This table shows short straddle returns for different quantile portfolios sorted by liquidity: Portfolio P1- (P2-) AVOL consists of the SEO firms with the highest (lowest) abnormal option volume in the month after the SEO event; portfolio P1- (P2-) AZOT consists of the SEO firms with the highest (lowest) abnormal zero option trades in the month after the SEO event. High AVOL (AZOT) indicates highly liquid (illiquid) option markets.

	P1 (highest quantile)	P2 (lowest quantile)
AVOL	-4.3%	7.4%
AZOT	5.0%	0.1%

4.4.5 Robustness check

As a robustness check, we recalculate the returns of the volatility trading strategy for the same period, but using traded option data instead of standardised option data.⁷⁸ For the return calculation, we use traded call and put options that expire the following month, and have expiration dates no longer than thirty calendar days. To avoid the maturity mismatch problem in Figure 4.1, we hold all options to maturity, which implies that the option returns for each SEO event will represent returns different to one month (i.e., the options of security X have twenty days to maturity; the options of security Y have twenty-eight days to maturity; and so on).

By averaging these returns, we obtain an average time to maturity of twenty-five calendar days, which is slightly less than one month. This methodology is different from

⁷⁸ For a detailed description of the matching procedure and filter criteria for the CRSP and OptionMetrics datasets, see Goyal and Saretto (2009) and Cremers and Weinbaum (2010). Consistent with Goyal and Saretto (2009) we use the mid-point price as a reference. For robustness we also used the bid price and find qualitatively stable results when controlling for common risk factors.

the analysis we used with the standardised dataset, where all options had thirty days to maturity. As a reference beginning price, we take the average of the closing bid and ask quotes of traded ATM call and put options with expirations in the following month; as a reference closing price, we use the terminal payoff of the options.

Coval and Shumway (2001) used a similar method to calculate option returns. They took options with between twenty and fifty days to expiration to analyse the behaviour of ATM options with one month to maturity. We chose to take average returns for a time period of no longer than one month, because we believe the results could otherwise be skewed.⁷⁹ Table 4.5 shows the raw and risk-adjusted returns for this alternative straddle return calculation methodology, and compares the results with those in Table 4.3.

Table 4.5 shows that the sample size is much smaller than that of the standardised option data (290 as opposed to 1,753).⁸⁰ This difference can be largely explained by two restrictive filter criteria. First, the traded option data consist of only traded options (with open interest larger than zero), while the standardised option data have no such restriction. Second, the traded options are required to be ATM at the portfolio formation date. This is not the case for all traded options. The standardised option data are created to be ATM, even though this option does not exist in the market.⁸¹

⁷⁹ In panel A of Figure 4.2, we note that, before the end of our trading period (illustrated by two vertical dashed grey lines), volatility drops sharply. After the end of the period, it begins to increase immediately. Using periods longer than thirty days could mean including the effects of the increase in volatility after thirty days, and thus skew our results. When we split the sample of straddles that expires before and after the thirty-day time period, we find that short straddle positions with options that expire before thirty days have a 6.88% average return (as reported in Table 4.5); those with options that expire between thirty and fifty days have a 0.8% average return (not tabulated).

⁸⁰ Due to this small sample size, we do not differentiate among different industry sectors.

⁸¹ At-the-money (ATM) options are defined as those with strike prices within 5% of the current stock price. See, for example, Chakravarty et al. (2004) and Battalio and Schultz (2006). Note that our traded option sample would not increase significantly if we eased the ATM criteria, because most of the options are filtered out due to zero open interest, which is the main criterion of traded options.

Despite the smaller sample size, the results in the first column of Table 4.5 (“Traded Option Data”) are consistent and similar to our standardised option data analysis. Straddle returns calculated using traded option data lead to a 6.88% average raw return over a twenty-five-day period, which is almost identical to that reported for the standardised option data. By considering common risk factors, we obtain an unexplained alpha of 3.89% for the twenty-five-day period, which is lower than the alpha reported for the standardised option dataset (5.60% for a thirty-day period), but is still high.

Table 4.5: Risk-adjusted return calculations with traded option data

This table shows monthly returns of a short straddle portfolio adjusted with a five-factor model that uses the three Fama-French (1993) factors (“Mkt-RF,” “SMB,” and “HML”), the Carhart (1997) momentum factor (“Mom”), and the Coval and Shumway (2001) volatility factor (“Coval-RF”). In addition, the returns are controlled for different sizes of proceeds – we use the “prosize” variable to denote the value of proceeds divided by the market cap - and the Harvey and Siddique (2000) skewness factor (“skew”). In the first column, we use traded option data to calculate straddle returns (“Traded Option Data”). Our return analysis is conducted for the period beginning one day after the SEO event and ending one month after it. The dependent variable is the return of straddle portfolios with average expiration dates of twenty-five days. The second column duplicates the results from Table 4.3, where standardised option data was used to calculate straddle returns (“Standardised Option Data”). The first row gives the coefficients; the second row gives the t-statistics (Newey and West, 1987) in parentheses.

	Traded Option Data	Standardized Option Data
Raw Return	6.883	6.877
Size	290	1,753
Alpha	6.85 (1.04)	5.10 (1.68)
Size	-2.84 (-1.08)	1.02 (0.73)
Skew	-3.78 (-1.87)	-1.13 (-1.23)
Coval-RF	-0.17 (-2.48)	-0.10 (-3.53)
Mkt-RF	-0.55 (-0.47)	-1.62 (-3.23)
SMB	-0.86 (-0.64)	-0.46 (-0.87)
HML	2.77 (1.47)	1.03 (1.27)
Mom	0.01 (0.01)	-0.18 (-0.45)

4.5. Conclusion

We analyse cross-sectional risk dynamics around SEOs, and show that short-term risk dynamics following SEO announcements are not fully reflected by option markets. In particular, we find that realized volatility exhibits a strong decrease following the announcement, while the expected volatility implied from option markets remains constant and thus overestimates realized volatility. This significant overestimation of future risk, however, only occurs for the first month following the announcement. Afterward, option markets begin to process the new information and estimate future volatility correctly, so expected volatility implied from option prices is approximately the same as realized volatility, plus some additional risk factors observed by other researchers.

In a further analysis, we examine the extent of investor misreactions by analysing volatility trading strategies based on the difference between option-implied and realized volatility. We use straddle portfolios to explore the differences between option-implied and realized volatility following SEO announcements, which led to significantly positive returns of around 5% for a one-month period. However, not all of our highly positive portfolio returns are abnormal. They are simply not related to commonly known risk factors. In a preliminary analysis, we show that an uncertainty premium in the option market could (partially) explain the abnormal returns.

Chapter 5

5. Summary

The objective of this study is to search for potential benefits and useful insights of option implied information. For this purpose three essays analyse the informational content of options under different circumstances.

The first essay in chapter 2 (“The Informational Content of Put-Call Parity Deviations”) empirically analyses put-call deviations for options with different times to maturity. We argue that investors actively choose the maturity of the options, and thus the informational content of put-call parity deviations will vary among maturity groups. Therefore, we expect to find different investor clienteles for short- and long-term options. For short-term options we argue that insider trading activity should be reflected in deviations from put-call parity as large differences between call and put implied volatilities can be interpreted as an indicator of price pressure in the option market due to insider trading activity. Consistent with previous literature [Cremers and Weinbaum (2010), Bali and Hovakimian (2009)] our results indicate that large deviations from put-call parity in short-term option contracts are due to insider trading activities and thus can predict short-term future returns. On the other hand we found no evidence of predictability in long-term option contracts. In comparison, we find that long-term options are purchased primarily for investment purposes such as hedging. Overall these results provide evidence that option markets provide information on future stock price movements and that the informational content of options varies for different types of option contracts.

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In the second essay in chapter 3 (“Executive Compensation and Insider Trading around Mergers”) we go one step further and analyse the informational content of short term options prior to a specific event, i.e. an M&A announcement. We observe high abnormal option volumes prior to merger events and show that the direction of these option trades can predict post merger returns. Our results indicate informed trading activity prior to merger announcement and that option implied information can be used to predict the direction of post merger returns. Furthermore, we provide evidence that one factor in abnormal option market activity prior to announcements (i.e. put options trading) is illegal insider trading of executives with high stock price sensitivity. This observation is consistent with the hypothesis that executives with high sensitivities use put option markets to hedge themselves against price decreases. A stock price decrease following an M&A-announcement would lead to large losses for the high sensitivity executive (e.g. employer options will get out of the money, lower bonuses etc.). To avoid the possible losses the executive should hedge themselves with put options.

Finally, the third essay in chapter 4 (“Option Implied Risk Dynamics around SEOs”) analyses option implied information on risk dynamics prior to SEO events. We aim to show that option markets are not able to fully predict future risk dynamics around extreme informational events like equity issues. For this purpose we compare realized stock volatility and option implied volatility and find strong divergence between these two measures following equity issuance. We observe that realized volatility shows a strong decrease following issuance, whereas expected volatility implied from option markets stays constant and thus overestimates realized volatility. This divergence between historical realized and implied volatility is economically significant when using volatility trading strategy, exploring the difference in volatility estimation in stock and option markets. We find that straddle portfolios lead to statistically significant risk

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adjusted returns of around five percent per month following SEO issuance. We do not claim that the positive portfolio returns are all abnormal, only that they are not related to commonly known risk factors. In a preliminary analysis we show evidence that an uncertainty premium in the option market could (partly) explain the abnormal returns. These results show that option implied information can provide additional insights not only on future stock volatility dynamics but also gives an indication of market uncertainty regarding the outcome of a new informational event like seasoned equity offerings.

To summarize, this dissertation shows evidence that option implied information, provides a rich source of information about investors' expectations about future stock price movements and risk dynamics. In three selected essays we show that option implied information can be used to analyse informed trading activities or to gain a better understanding on risk dynamics following unexpected events. This is of particular interest for both academics and the asset management industry to gain a better understanding on the cross-market relationship between stock and option markets.

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