ERASMUS UNIVERSITY ROTTERDAM
Erasmus School of Economics

Option strike effects on stock returns and volatilities

Msc. Econometrics and Management Science
Quantitative Finance

August 16, 2013

Author	:	L.H.E.T. Knops
Student nr.	:	363624
Supervisor	:	Dr. M. van der Wel
Co-reader	:	Dr. E. Kole

Abstract

Derivative markets have become so large that they sometimes overshadow the market for underlying securities, causing the so-called 'tail wags the dog' effect. In this thesis I present a new perspective on stock price behavior around option strike prices. The standard CAPM factor model for stock returns is extended with additional terms for detecting effects of strike price proximity. To disentangle a strike price effect from round-number effects, the study also uses variables taking option open interest and option gammas into account. The main factor model is extended with ARCH volatility effects, considered in a panel set-up, and estimated using maximum likelihood. I find that strike nearness in combination with a large option open interest affects the returns and market following behavior of the underlying negatively when taking the average daily trading volume in the underlying into account. The negative effect on the market following behavior is confirmed when taking additionally also the net gamma of the option open interest into account. Furthermore the size of the unexpected returns declines consistently if the underlying nears a strike. These results cannot be explained by the human bias for round numbers and are in accordance with existing theory on option pinning effects.

Keywords: Option trading; Strike prices; CAPM factors; Derivatives market

Contents

1 Introduction

Trading volumes and financial interest in derivatives have increased relative to those in the underlying securities in financial markets. Roll et al. (2010) estimate that trading volumes in derivatives on a single stock level have reached a level of approximately a quarter of the trading volumes in the underlying stock over the period between 1996 and 2007. Derivatives derive their value from the price level of the underlying securities. If trading volumes in the derivatives are high enough, a situation in which "the tail wags the dog" can develop. Trading activity in the derivative will then affect the activity in the underlying security such that its price is influenced.

I investigate the presence of this "tail wags the dog" effect in situations when the price of a stock is near the strike price of derivatives with this stock as the underlying security. In this vicinity additional effects related to option hedging come into play. These additional effects can potentially change the price behavior and returns of the underlying security. According to classical finance theory returns should be the same on these occasions as on any other trading day. I look for different behavior on these specific days by incorporating additional regression variables indicating nearness to a strike in a factor model for the stocks' daily returns.

The relevance of this study lies in both the academic and practical field. In the academic field this study follows to the wide array of anomalies that were researched following the work by Fama and French (1992). This study can potentially result in an additional anomaly for the returns of optionable securities. The discovery of anomalies also has a practical relevance as it (if the anomaly is strong enough) can serve as the base of a profitable trading strategy. This strategy exploits the effects forecasted with the anomaly which are not priced into the market.

In this study, I use data on 27 constituents of the Dow Jones 30 Index. The data consists of daily closing prices and returns on one side. On the other side I use daily option data on these same stocks, which consists of available strike prices and maturities, closing prices and open interests.

For the different underlyings I pose a CAPM formulation for returns. I construct these models in a similar fashion as Driessen et al. (2013), who study effects of the 52-week high and low on return and volatilities. I expand the basic factor model with additional variables indicating option strike nearness and option activity on the nearest option strike. I formulate three different return models in this study and carry out the parameter estimations for these models with a maximum likelihood method.

In a simple model I add only a dummy variable for nearness to strike to the factor model to allow for different alpha and market beta if the dummy takes value 1. I allow for conditional variance in this model which depends in different formulations on the nearness to strike dummy variable and additional AR terms.

Two more elaborate models incorporate the formulation with a nearness to strike dummy but add to this with an extra variable indicating the economic importance of the nearest strike. This step bans any potential effects that round numbers may have from the parameter estimates. In one model this importance is assessed on the base of the total option open interest on that strike. The other model applies the option gammas of the options that are outstanding. I derive these gammas first from available bid and offer prices for matched call and put options, risk free rates and the price of the underlying. These two models allow for conditional error variance conditional on the nearness to strike dummy variable combined with the open interest (gamma) and additional AR terms.

As a final step I apply a panel model setup to assess the nearness to strike effects for the entire panel in the formulation incorporating the dummy together with the additional open interest variable. This formulation results in estimates for the relevant parameters that are founded on the entire dataset in one regression. It distills the relevant parameter estimates from the single stock setups into one set of parameter estimates. At the same time the formulation leaves room for stock-specific parameters that are unrelated to strike nearness in the factor model.

Key findings from this study are as follows. Nearness to strike alone has significant effects for some individual stocks under consideration on both the alpha and beta, but no common direction across all stocks. When taking additionally the option open interest on the nearest strike into account again significant effects are visible for individual stocks with also a common factor, namely a negative influence to the CAPM beta. Stocks that close near an existing strike with a high open interest become less sensitive to the market return and show more idiosyncratic behavior. Taking additionally also the gamma of the open interest into account proves not to be an addition to the model as it results in individual significant effects but no common direction across the different stocks. A decrease in the variance of the unexpected returns in the case of strike nearness is observable as a common effect on all stocks and across all model formulations. Hence idiosyncratic errors in the returns of the underlying decrease in the vicinity of an option strike.

The remainder of this report is structured such that Chapter 2 will provide an overview of the existing theoretical framework. Chapter 3 introduces the data employed for the research. Chapter 4 contains the methods applied and results obtained from the analysis. In Chapter 5 the obtained results are tested for their robustness to changes in the methods that are applied. Chapter 6 contains the conclusions of this research and in Chapter 7 areas for further research are suggested.

2 Theoretical framework

In this study, I devote research to the effect of option strike nearness to the price behavior of underlying stocks. Obviously the price behavior of traded securities has been subject of multiple academic research papers in the past. Also the behavior of underlyings in relation to effects of several types of derivatives has been examined in various studies.

Futures market effects

The market for the most basic type of widely traded derivatives is that for futures. Note that futures are virtually never constructed based on individual stocks as underlying, but rather on baskets of stocks or indices. This makes however no fundamental difference for the market situation. Several researchers put effort in deriving effects of the presence of a futures market on the market for the underlying. Gulen and Mayhew (1999) find that the introduction of a futures market has an increasing effect on the volatility of the market in the underlying for US and Japanese indices. Chan (1992) finds strong evidence that the futures market leads the cash market for the Amex Major Market Index (MMI) and only weak evidence of the cash market leading the futures market. This proves that there are at least periods in which the "tail wags the dog".

One-time effect of option introductions

For most single stocks, options are the only derivatives that are widely traded on an open market or exchange. A substantial amount of research is performed on the relation between single stock returns and options on these stocks. First there are researches that focus on one-time changes in the underlying's price level. Sorescu (2002) finds that the introduction of stock options increases returns on the underlyings in the first years and documents a reverse effect in later years. Lundstrum and Walker (2006) research the influence of the introductions of LEAPS, or stock options with a time to maturity of several years. They find that these introductions result in short term declines in the prices of underlyings, resulting from option activity replacing activity in the underlying stock.

Option pinning

Not only the introduction of options on a stock has an effect on the pricing of the underlying stock. Also the option expirations which take place on regular intervals have effects on the underlying. The effects around expiration are predominantly related to so called option pinning. Option pinning is the effect caused by market parties hedging their option position's delta by means of trading the underlying. The pinning process in stocks is modeled by Avellaneda and Lipkin (2003) whose work is later extended by Jeannin et al. (2008). Both studies find that returns in underlying stocks are partially induced by existing option positions on option expiration dates. Their models are based on the theory that a delta neutral position requires trading not only at the initiation of a position. Trading in the underlying is a continuous process of adjusting the hedge of the option position's delta as the delta changes with time and the price of the underlying. When approaching expiration the volumes of these re-hedging trades increase as can be derived from the option pricing model originally posed by Black and Scholes (1973). In their model option prices become increasingly sensitive for price changes in the underlying at the approach of the options' expiration date.

Ni et al. (2005) apply the option pricing and pinning models and find the presence of significant price clustering of optionable stocks around option strikes. They find that trades initiated by delta-hedging market participants are a major driver for this, especially in the last days leading up to expiration. This adds to existing work by proving that the effects are already present in the week leading up to expiration. In a more general study into the effect of option trading on stock returns, Pearson et al. (2007) show that the clustering effect of option hedging is not only confined to the expiration week, but is observable in the absolute return of the underlying in earlier periods as well. This is a confirmation of effects suggested by Willmot and Schönbucher (2000) who pose a theoretical model for the effects of delta-hedging activities on the market for the underlying away from expiration.

The aforementioned research studies prove that option markets indeed influence the market in the underlying stocks. Now that we have established this, it remains the question which role the actual option strike prices play in this.

Round number preference

Option strikes are (except for post introduction contract adjustments) always equal to round numbers. This is an important realization. Round numbers in relation to investors' perception and irrational behavior is a combination which has attracted research with remarkable results in the past. Back in the time when stocks were traded in discrete price fractions Harris (1991) argued that traders have a preference for trading on quarters, halves or whole numbers rather than on odd eights. He showed this by categorizing a huge dataset of trades on the base of the execution price. At that time, this clustering could be regarded as a rational market response to trading impediments. Ikenberry and Weston (2008) provide evidence that also after decimalization of stock trading, prices cluster at increments of five and ten cents. They contribute this effect to the fundamental human bias for prominent (round) numbers as the effect is also prominently observable in times when order execution prices are no longer bound by fractions.

Knowing that we are dealing with the influence of the option strike itself on the market in the underlying on one side and on the other side the effect of the round number on which the option strike is pinned down will be of influence in this research. Our interest lies in providing insight in the actual strike effects without contaminating our results with separate effects of round numbers.

3 Data Description

The data used in this study consists of three parts. First, there is return and price data on underlying securities. Secondly data on options on these underlyings and finally risk-free rates and market wide returns are of use in the formulations that are presented in Chapter 4. Daily data on these sets are used over a sample period from 1 January 2000 to 31 December 2012 (3269 trading days). The following paragraphs provide a description of the data.

3.1 Underlying securities

In this study I analyze constituents of the Dow Jones 30 Index. These stocks are chosen as there is a very liquid market in options on these stocks ensuring availability of reliable option data. The companies of which the stock is included in the Dow Jones Index have an average market capitalization in excess of $ 130 billion and qualify as large caps. Among the constituents are Bank of America, ExxonMobil, Home Depot, Intel, McDonald's, Merck, Microsoft and Verizon Communications, all leading US companies in the sectors in which they operate.

In the first steps of the analysis we use daily closing prices and returns for the sampled companies. In a later stadium also the daily trading volumes in the stocks are used. These data series are sourced from Wharton Research Data Services (WRDS) Center for Research in Securities Pricing (CRSP) database. Because of issues with missing values and clear presence of noise in the data series for three of the Dow Jones 30 stocks, data for only 27 stocks is used in the remainder of this study. Statistics of the returns on these 27 stocks over the sample period are listed in Table 1.

Mean and median annualized returns vary a lot across the list of 27 stocks. Alcoa (AA) is the only company that shows a negative mean return over the sample period, though it is only slightly negative on an annualized base. United Health (UNH) is the top performer over the 13 year sample with an average annualized return in excess of 22 %. The volatilities of the different stocks differ significantly. We find an annualized 21 % as the lowest standard deviations of the annualized returns for Johnson & Johnson (JNJ), a pharmaceutical company (this sector is known as a very stable non cyclical one). A 53% standard deviation is listed for

Bank of America (BAC) operating in a sector of which we all know that especially the years 2007 until 2009 have seen very high volatility. Both negative and positive skewness are observed with Procter and Gamble (PG) standing out with a skewness of -3, caused by several very large negative returns (mostly after earnings announcements) in combination with rather low overall volatility. All stocks show excess-kurtosis and Jarque-Bera tests convincingly reject normality for all of the 27 underlyings.

Table 1: Descriptive statistics on the returns of the underlying stocks over the timeframe 2000 – 2012. Stock tickers are listed in the first column. Mean and median annualized returns (in percents) are reported in the second and third with the annualized standard deviation of the daily returns in column four. Skewness and Kurtosis figures are listed in columns five and six. Column 7 contains Jarque-Bera test statistics on normality.

Ticker	Mean	Median	St. Dev.	Skewness	Kurtosis	JB-test
AA	-0.06	0.00	44.80	0.23	10.21	7,110
AXP	10.76	0.00	40.61	0.39	11.46	9,841
BA	11.86	10.03	32.49	-0.03	7.74	3,064
BAC	11.44	3.08	53.29	0.87	25.23	67,713
CAT	18.81	14.95	34.81	0.12	6.81	1,983
CSCO	2.53	10.18	44.68	0.55	11.13	9,179
CVX	13.98	23.93	27.23	0.42	15.93	22,857
DD	5.27	0.00	30.43	0.03	7.63	2,915
DIS	10.96	0.00	33.70	0.27	10.82	8,361
GE	1.70	0.00	33.57	0.33	11.02	8,816
HD	7.20	0.00	35.02	-0.37	15.35	20,856
IBM	9.59	6.25	28.28	0.27	10.52	7,753
INTC	5.23	0.00	41.75	-0.10	9.39	5,559
JNJ	7.64	3.63	20.60	-0.22	16.92	26,404
KO	6.69	7.58	22.88	0.31	11.37	9,600
MCD	11.49	17.40	25.67	-0.02	8.18	3,650
MMM	10.44	5.48	25.21	0.23	7.75	3,095
MRK	4.86	6.90	30.05	-0.87	21.33	46,150
MSFT	1.62	0.00	33.19	0.27	12.21	11,591
PFE	5.05	0.00	27.45	-0.10	7.53	2,795
PG	6.90	4.73	23.38	-3.01	70.56	626,724
TRV	13.89	5.95	33.08	0.82	18.44	32,857
UNH	22.56	15.18	35.25	1.01	28.25	87,411
UTX	13.42	9.88	29.69	-0.82	22.49	52,130
VZ	6.30	0.00	27.45	0.37	9.48	5,788
WMT	4.73	4.48	26.02	0.37	8.26	3,844
XOM	11.60	17.55	26.53	0.37	13.70	15,682

3.2 Options

Having chosen constituents of the Dow Jones 30 Index as the underlying securities, we use data on the associated options in further analysis. The entire dataset is sourced from WRDS' OptionMetrics database. The option data that is sampled with daily frequency consists in the first place of the option strikes that are available for trading. The exchange board is responsible for introducing options and setting strike prices. The intervals between strike prices and the maturities that should be available for trading vary according to the price, market capitalization and liquidity of the underlying. Generally a minimum interval of $ 1.00 between strikes is maintained for stocks with a price below $ 20. A maximum interval of $ 5.00 is observed for stocks of over $ 50. Note that these are only rough observations and that the actual intervals vary per stock. Additional strikes are introduced periodically and after large price changes of the underlying to ensure a wide enough variety of choice around the underlying's price. Maturities available for trading are generally the front three months and quarterly or semi-annually after that until (again depending on the underlying) up to three or even five years out in time.

For the stocks under consideration the amount of option strike price / maturity combinations available for trading is at any moment in the region of 80 to 100. Each of the strike / maturity combinations has both a put and a call option listed, such that for each trading day about 160 to 200 individual lines of option data are available for each underlying stock. Aggregating these lines provides a daily list of available strikes prices. This list determines together with daily closing prices of the underlying stock whether the underlying trades close to a strike or not.

In Figure 1, daily available strikes and closing prices in the stock are plotted against time for Alcoa (AA). The range of available option strikes changes over time as do the intervals between the strikes. It is adjusted regularly with the introduction of new strikes, based on the current stock price. Hence the range of strike prices shows co-movement with the stock price itself. There is however some lag in this co-movement as the introduction of options with long maturities results in strikes existing up until this maturity where the stock price may have moved far away from this strike in an early stage. For instance at the end of 2009, there are still options listed with strikes of up to $ 70, whereas the Alcoa stock price has not been above $ 20 for over a year. Note that the abrupt drop in share price visible in June of 2000 is caused by a 2-for-1 stock split.

In a later stage of the analysis also daily open interest in each option as well as maturity dates and closing bid and ask prices are used for calculating open interest at the nearest strike and option gammas. For both these calculations it is a first step to determine which option strike is nearest to the price of the underlying. The daily open interest at the nearest strike is obtained by summing all open interests of existing options with this particular strike. Option gammas are calculated for all options with this particular strike and various maturity dates, each with their own volatilities implied by their price on the option market. The results of the option gamma calculations are in accordance with a set of OptionMetrics listings. An elaborate derivation of the option gamma calculations is included in Appendix 1.

A plot of the daily development in the open interest and closing bid and ask prices for a given option on Alcoa is included in Figure 2. The option for which the plot is made is the AA Mar-2009 40 call option. It is introduced on 30 May 2006 and expires on 17 January 2009. In the beginning we see a buildup of open interest starting from zero at introduction with some sudden increases as well as decreases (though less often). The bid and ask prices move together closely. These movements can be (partially) related back to the development in the price of the underlying in Figure 1. An increasing price of the underlying results (roughly speaking) in an increase of the option price which is consistent with the properties of a call option.

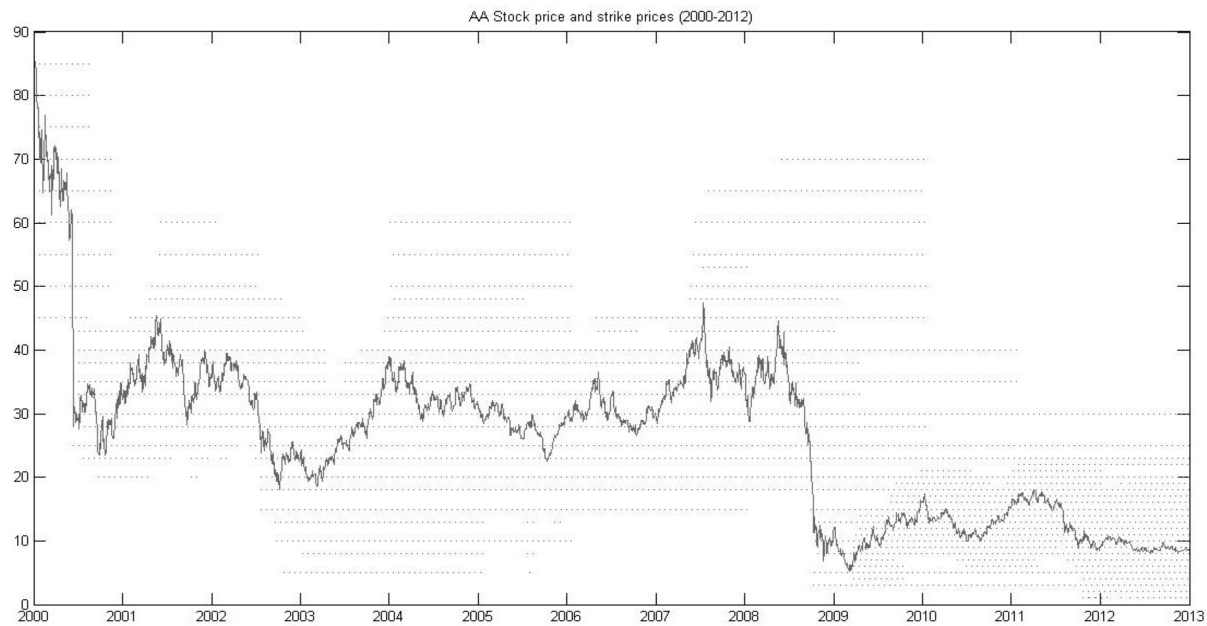

Figure 1: Alcoa (AA) share price and strike prices (Time Frame 2000 – 2012). A time series plot of the Alcoa share price development together with the existing option strikes (dotted) at each instance is provided in this figure.

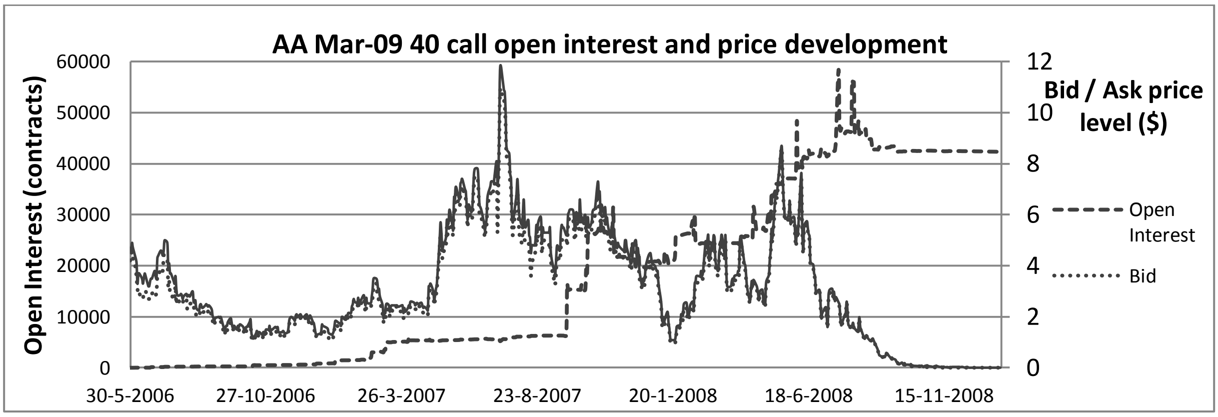

Figure 2: Alcoa (AA) March-2009 40 call option open interest and price development. A time series plot of the development of the open interest and bid and ask prices over the life of the option.

3.3 Additional market data

Apart from data on options and underlying stocks, we use some additional data series in our analysis as will become clear in Chapter 4. These series are a daily market return series and a series of daily risk free rates. Both these series are part of the famous Fama French studies and are updated on French's personal website. Daily figures on the market wide return as well as daily risk free rates are therefore sourced from this website. Summary statistics of these series are reported in Table 2.

Table 2: Descriptive statistics on the market and risk-free returns over the timeframe 2000 – 2012.

	Mean	Median	St. Dev.	Skewness	Kurtosis	JB-test
Market	2.31	12.50	21.54	-0.01	6.48	1,649
Risk-free	2.10	1.50	0.13	0.62	-0.98	2,371

An average annualized market return of 2.31% is recorded over the sample period running from 2000 through to 2012. The average risk-free rate is approximately the same over this period. Both series are clearly not following a normal distribution with the market return showing excess kurtosis whereas the risk-free rate shows a platykurtic pattern.

3.4 Preliminary analysis

With the daily closing prices together with an overview of daily available option strikes it is possible to make a first split. By defining a range around the strike prices and checking daily whether the closing price of an underlying stock is within this range, the sample can be split in one part where the previous day's closing price is near a strike and a second where this is not the case. For these two samples we can draw up similar descriptive statistics as are reported for the entire sample in Table 1. This split is made taking a range of (an arbitrary) $ 0.30 into account around the strikes. Descriptive statistics for split samples are listed in Table 3.

Table 3: Descriptive statistics on Returns split for share price nearness to option strike on previous day. In this table, the same statistics are presented as presented in Table 3.1. In this case however, the sample of returns is split in two for each stock. This split is made based on the previous day's closing price in relation to the existing option strikes on that day. A reading is included in the 'Near' sample if the share price was within (an arbitrary) $ 0.30 distance of an existing option strike. If this was not the case, the reading is added to the 'Far' sample.

Ticker	Sample size		Mean		Median		St. Dev.		Skewness		Kurtosis		JB-test	
	Near	Far	Near	Far	Near	Far	Near	Far	Near	Far	Near	Far	Near	Far
AA	1115	2153	2.58	-1.14	12.63	-7.98	44.34	45.05	-0.21	0.44	7.83	11.37	1094	6350
AXP	1076	2192	23.85	4.96	-1.98	0.00	42.52	39.61	1.08	-0.03	13.50	10.03	5157	4519
BA	689	2579	37.55	5.21	26.58	3.88	31.83	32.65	0.14	-0.07	5.30	8.33	154	3051
BAC	1006	2262	59.85	-9.69	0.00	5.24	67.03	45.83	1.67	-0.45	20.31	24.69	13028	44413
CAT	656	2612	46.68	11.50	35.64	9.99	35.17	34.71	0.69	-0.03	6.70	6.81	427	1580
CSCO	1233	2035	-9.32	9.61	0.00	11.93	45.16	44.40	0.73	0.44	12.48	10.27	4724	4551
CVX	413	2855	21.72	13.17	4.18	27.23	25.78	27.42	0.09	0.46	4.77	17.19	54	24070
DD	980	2288	-5.14	9.88	5.70	-5.26	29.64	30.77	-0.30	0.15	7.15	7.78	717	2183
DIS	1158	2110	40.49	-5.49	23.78	-14.16	31.71	34.71	0.80	0.07	10.32	10.88	2712	5455
GE	1239	2029	-7.97	7.99	0.00	0.00	34.71	32.85	0.04	0.55	8.27	13.05	1432	8644
HD	1053	2215	21.78	0.85	6.25	0.00	34.01	35.46	0.32	-0.65	8.16	18.23	1188	21565
IBM	406	2862	31.34	5.89	8.69	6.05	30.65	27.86	1.16	0.08	9.66	10.64	841	6964
INTC	1171	2097	26.65	-7.40	9.00	0.00	39.83	42.74	0.19	-0.23	6.07	10.73	465	5241
JNJ	560	2708	12.37	6.77	9.94	0.00	24.01	19.82	-2.34	0.56	30.72	10.23	18447	6041
KO	770	2498	11.05	5.67	7.09	7.88	19.96	23.69	0.54	0.27	7.00	11.85	550	8182
MCD	752	2516	-14.65	19.47	0.00	20.48	25.47	25.71	-0.32	0.07	7.77	8.28	726	2928
MMM	471	2797	0.57	12.43	-16.45	8.13	23.91	25.40	0.34	0.21	11.98	7.19	1591	2067
MRK	1018	2250	-6.48	9.92	-7.04	17.34	28.00	30.94	-3.35	-0.04	55.69	10.60	119672	5409
MSFT	1301	1967	-4.23	5.51	-9.23	0.00	29.78	35.28	-0.03	0.38	8.28	13.11	1510	8428
PFE	1170	2098	13.16	0.73	-7.68	0.00	26.56	27.93	0.16	-0.22	8.00	7.28	1224	1615
PG	637	2631	7.04	7.07	0.00	7.48	19.34	24.26	-0.09	-3.34	7.89	74.92	637	571933
TRV	429	2839	-0.72	16.28	-9.95	9.60	31.02	33.38	1.58	0.73	12.58	19.07	1817	30815
UNH	905	2363	-0.47	31.27	10.00	18.40	39.68	33.40	-0.83	2.19	11.97	39.15	3140	130561
UTX	495	2773	-5.57	17.16	-15.38	14.78	27.74	30.01	0.88	-1.06	12.48	23.84	1917	50711
VZ	1065	2203	-0.42	9.84	0.00	5.10	22.94	29.38	0.24	0.38	9.21	9.06	1720	3421
WMT	718	2550	12.44	2.88	5.50	4.11	26.94	25.75	0.72	0.26	10.15	7.61	1593	2288
XOM	653	2615	14.32	11.21	22.35	16.90	23.08	27.32	-0.32	0.47	5.84	14.50	230	14509

We cannot yet draw any definite conclusions on the base of the data contained in this table; there are however some observations to be made. The sizes of the "Near" and "Far" sample for instance vary across the different stocks. The "Near" sample ranges between 400 and 1300 observations per stock with the "Far" sample making up for the reminder of the 3268 observations (not 3269, as we include a split based on the one day lag of the nearness to a strike). For all stocks except Procter and Gamble (PG) there is a difference of at least a few percent between the mean annualized returns of the different samples. This difference reaches 45% for the Walt Disney Company (DIS) and almost 70 % for Bank of America (BAC). There is however no clear pattern of consistently higher returns for one of the two samples. The standard deviations of the two samples are mostly a lot closer to each other. An exception to this is Bank of America where the difference is as large as 20%. Also we find several names for which the standard deviations lay approximately 5% apart. Again there is no clear pattern of consistently smaller standard deviations in one of the two samples. The Jarque-Bera test statistics indicate that none of the samples are normally distributed. These are all mere observations and no definite points. The split samples provide however a starting point for further analysis which is performed in Chapter 4.

4 Results of modeling and analysis

In this chapter, we analyze in detail the data introduced in Chapter 3. I propose functional forms for the effects of trading near option strikes, similar to the ones used by Driessen et al. (2013) for detecting the effects of 52-week highs and lows. I start off with a functional form applying only a dummy variable as an indicator of strike nearness. In a next step, this functional form is expanded with a variable indicating the option open interest on the nearest strike. A third setup replaces the (simple) open interest with one taking the gammas of the different options into account. Furthermore I estimate a panel formulation and finally a formulation allowing asymmetric behavior.

4.1 CAPM type model with dummy variables

To assess the presence and size of the effects of trading near existing option strikes on the underlying, I use a framework within which I can separate the different components that together result in the returns of the underlying. The Capital Asset Pricing Model (CAPM), being the most widely used asset pricing model, offers a starting point. Its formulation is

$$Ra_{e,t} = \alpha + \beta(Rm_{e,t}), \tag{4.1}$$

with $Ra_{e,t} = Ra_t - Rf_t$ and $Rm_{e,t} = Rm_t - Rf_t$.

In this formulation, the estimated return on a certain asset over period t in excess of the risk-free return is equal to a constant plus a factor that depends linearly on the excess return of the market over this same period t. Hence, this formulation separates the observed excess returns already in two components: a constant and a time varying market-wide part. We would however like to see what role the nearness to an option strike plays in the return generating process rather than learning which part is constant and which is influenced by the market return. In Chapter 3, we made a start with exploring this role by splitting the return samples off all stocks under consideration in two subsamples, one for which the previous day's closing price was near a strike and one for which this was not the case. Parallel to that split, we can introduce a similar split in the CAPM model by making use of a dummy variable in addition to the original model. With this dummy we can allow for different α and β coefficients on days for which the previous day's closing price is near a strike versus the days where this is not the case. Specifically we consider

$$Ra_{e,t} = \alpha_0 + \alpha_1 D_{t-1}^{strike} + \left(\beta_0 + \beta_1 D_{t-1}^{strike}\right) Rm_{e,t}, \tag{4.2}$$

with D_t^{strike} a dummy variable with value 1 if the day's closing price of the underlying is near a strike and zero otherwise. Hence we get two different values for the constant term in the asset's return, α_0 in case the previous days' closing price is not near a strike and $\alpha_0 + \alpha_1$ if the previous days price is near a strike. The same holds for the β coefficient.

We can apply the formulation in equation 4.2 to our data set and estimate the different parameters for the 27 underlying stocks in the data sample. For the sake of making the parameter estimation extendable in the reminder of this study, this is done with a Maximum Likelihood Estimation (MLE) method. For this type of estimation, a distribution for the errors needs to be assumed for constructing the (log) likelihood function. I present different alternatives for the error distribution in paragraphs 4.1.1 and 4.1.2.

4.1.1 Constant error variance

As a starting point we assume that the errors are distributed according to a normal distribution with mean zero and standard deviation σ being constant over time. The standard deviation of the errors is estimated in the same step with the parameters of the return equation. The likelihood function that is to be maximized based on the assumption of normal errors with constant variance is derived in Appendix 2.

Taking the likelihood function together with equation (4.2) to the data we have on hand, we obtain parameter estimates for α_0, α_1, β_0, β_1 and σ for each of the 27 stocks under consideration as listed in Table 4. We calculate standard errors of the estimation based on the estimated information matrix. The diagonal of the inverse information matrix contains the squared standard errors for each of the parameter estimates. An estimate of the information matrix is obtained by taking the negative of the expected Hessian matrix.

We can relate the α_0 parameter estimates to the efficient market hypothesis. In an efficient market, the α_0 parameter should be centered around zero. The β_0 estimates should average around 1, as the returns on the list of stocks under consideration form an integral part of the market return. The parameter estimates confirm this is the case. Looking solely at these parameter estimates would lead to concluding that we are indeed dealing with an efficient market here. In our regression we however also include additional α_1 and β_1

parameters for assessing the effects of strike nearness. These parameters should both be centered around zero to be in accordance with an efficient market. We observe however a considerable amount of estimates significantly different from zero.

Table 4: Parameter estimates of CAPM model with dummy for nearness to strikes and constant error variance. This table shows the results of estimating a model as proposed in equation (4.2) with normal errors with standard deviation σ to 27 stocks. The D_t^{strike} dummy in this equation takes value 1 if the day's closing price of the underlying is within $ 0.30 of an existing option strike in the underlying. Significance levels of the parameters are 1 % for ** and 5 % for * all measured in difference to zero.

Ticker	α0		α1		β0		β1		σ	
MMM	0.0295		-0.0457		0.777	**	0.024		1.188	**
AA	-0.0247		0.0148		1.397	**	0.059		2.075	**
AXP	-0.0150		0.0874		1.399	**	0.048		1.696	**
BAC	-0.0366		0.1615		1.361	**	0.702	**	2.533	**
BA	0.0287		0.0108		0.933	**	-0.040		1.623	**
CAT	0.0574		-0.0109		1.096	**	0.107	*	1.587	**
CVX	0.0353		0.0360		0.806	**	0.044		1.319	**
CSCO	0.0001		-0.0366		1.535	**	-0.327	**	2.100	**
KO	0.0043		0.0011		0.467	**	0.043		1.293	**
DD	-0.0065		0.0373		0.934	**	0.177	**	1.374	**
XOM	0.0352		-0.0205		0.801	**	-0.064		1.289	**
GE	-0.0125		-0.0019		1.103	**	0.111	**	1.426	**
HD	0.0205		-0.0072		1.060	**	-0.081		1.708	**
INTC	-0.0088		0.0064		1.501	**	-0.399	**	1.939	**
IBM	0.0033		0.1934	**	0.841	**	0.152	**	1.350	**
JNJ	0.0141		-0.0225		0.451	**	0.066		1.140	**
MCD	0.0482		-0.0303		0.543	**	-0.039		1.451	**
MRK	0.0051		-0.0391		0.661	**	0.025		1.669	**
MSFT	0.0143		-0.0484		1.142	**	-0.211	**	1.536	**
PFE	-0.0400		0.1111	*	0.684	**	0.005		1.462	**
PG	-0.0041		0.0058		0.439	**	0.073		1.344	**
TRV	0.0356		0.0221		0.975	**	-0.033		1.621	**
UTX	0.0447		-0.0563		0.951	**	0.010		1.357	**
UNH	0.1046	**	-0.1080		0.673	**	0.266	**	1.952	**
VZ	0.0055		0.0079		0.739	**	-0.076		1.438	**
WMT	-0.0125		0.0847		0.623	**	-0.002		1.409	**
DIS	0.0299		-0.0204		1.051	**	0.046		1.560	**

The recorded α_1 estimates contain only two significant observations, a low number, which could point to simple coincidence. The β_1 parameter estimates for nine different underlying stocks are significantly different from zero. This suggests that several of the underlyings indeed show different price behavior when trading close to an option strike. More specifically we might intuitively expect the CAPM β to decline when the underlying is trading near a strike. This because the previously discussed round number and option pinning effects would (if present) come at the expense of the market-following behavior of each underlying. We observe however mixed estimates for β_1 with only three out of nine significant estimates being negative.

It is remarkable to see that the Bank of America stock has a β_1 parameter estimate as high as 0.7 which results in a total β coefficient of over 2 in case the stock trades close to a strike. Also this stock shows a highly positive though not significant α_1 estimate. We can relate this positive estimate to what we saw for this stock in the two samples of Table 3. Average returns in the "Near" sample are an annualized 70% higher than the ones in the "Far" which is consistent with a positive estimate for α_1. The insignificance of this high α_1 estimate together with the high estimate for σ indicates high standard errors and therefore a lot of dispersion in the data for this underlying.

The β_1 parameter estimate for Intel Corporation on the contrary is more in line with the intuitive statement made above. A negative estimate of about -0.4 reduces the CAPM β when the underlying closed near a strike price considerably towards zero. A slightly positive though not significant α_1 estimate is again in accordance with what was found earlier in Table 3. It is however fair to say that this slightly positive α_1 is not solely responsible for the difference between the "Near" and "Far" sample. The combination of the β_1 parameter and the timing of positive and negative market returns also has a large part in this difference.

Off course the model that is applied here implicates several assumptions which are up for dispute. Therefore we extend the model in further paragraphs to investigate what happens to the suggested effects if we relax some assumptions.

4.1.2 Conditional error variance

We assume in paragraph 4.1.1 that the error variance is constant. In this section, this assumption is relaxed and four different conditional variance equations are introduced to assess the effect of allowing for heteroskedasticity in the error terms.

Similar to allowing the α and β coefficients of the original CAPM model to alter in the event of closing near a strike on the previous trading day, there is also a chance that the error variance, σ takes on a different value on that occasion. We can allow for this by combining our optimization function derived in Appendix 2 with a conditional variance formulated as

$$\sigma_t = \sigma_0 + \sigma_1 D_{t-1}^{strike} \quad (4.3)$$

In this formulation, the error term is drawn from a normal distribution with mean zero and standard deviation of either σ_0 in case the previous day's closing price was not near a strike or $\sigma_0 + \sigma_1$ if it was. Parameter estimates incorporating this conditional variance equation are listed in Table 5.

Table 5: Parameter estimates of CAPM model with dummy for nearness to strikes and error variance conditional on dummy. This table shows the results of estimating a model as proposed in equation 4.2 with normal errors with conditional standard deviations as defined in equation 4.3 to 27 stocks. The D_t^{strike} dummy in these equations takes value 1 if the day's closing price of the underlying is within $ 0.30 of an existing option strike in the underlying. Significance levels of the parameters are 1 % for ** and 5 % for * all measured in difference to zero.

Ticker	α0	α1	β0	β1	σ0	σ1
MMM	0.0315	-0.0113	0.777 **	0.024	1.188 **	0.002
AA	0.0360	-0.0585	1.451 **	-0.100	2.101 **	-0.082
AXP	0.0032	-0.0031	1.400 **	0.050	1.695 **	0.005
BAC	0.0260	-0.6916 **	1.380 **	0.630 **	2.222 **	0.738 **
BA	0.0319	-0.0001	0.932 **	-0.040	1.622 **	0.005
CAT	0.0118	0.0158	1.091 **	0.127 **	1.583 **	0.022
CVX	0.0359	-0.0135	0.807 **	0.044	1.319 **	0.001
CSCO	-0.0338	0.0488	1.585 **	-0.421 **	2.184 **	-0.247 **
KO	0.0425	-0.0473	0.467 **	0.044	1.296 **	-0.018
DD	-0.0850 **	0.0813	0.936 **	0.175 **	1.448 **	-0.272 **
XOM	0.0298	0.0881	0.784 **	0.016	1.297 **	-0.050
GE	-0.0049	-0.0024	1.103 **	0.111 **	1.424 **	0.005
HD	-0.0319	0.1647 **	1.059 **	-0.083	1.738 **	-0.105 *
INTC	0.0165	-0.0333	1.501 **	-0.399 **	2.058 **	-0.327 **
IBM	-0.0155	0.0439	0.841 **	0.144 **	1.351 **	0.002
JNJ	0.0643 **	-0.1230 *	0.450 **	0.066	1.094 **	0.232 **
MCD	0.0507	-0.0338	0.533 **	0.006	1.458 **	-0.030
MRK	-0.0384	-0.0352	0.661 **	0.029	1.698 **	-0.102 *
MSFT	0.0598	0.0115	1.143 **	-0.214 **	1.642 **	-0.263 **
PFE	-0.0290	0.1196 *	0.684 **	0.004	1.465 **	-0.010
PG	-0.0269	0.2327 **	0.456 **	-0.007	1.377 **	-0.230 **
TRV	0.0371	-0.0120	0.976 **	-0.047	1.620 **	0.007
UTX	0.0437	-0.0206	0.951 **	0.010	1.357 **	0.000
UNH	0.0459	0.2871 **	0.673 **	0.264 **	1.851 **	0.310 **
VZ	0.0001	0.1780 **	0.738 **	-0.077 *	1.508 **	-0.247 **
WMT	0.0014	0.0403	0.624 **	-0.002	1.412 **	-0.012
DIS	0.0694 *	0.1141 *	1.046 **	0.053	1.610 **	-0.175 **

The parameter estimates in this table indeed suggest that allowing the error variance to depend on the dummy is a significant improvement to the original model for almost half of the stocks under consideration indicated by a significant σ_1 parameter. We find that this extension of the model results in more significant readings for the other parameter estimates as well. Especially the α_1 estimates attain a larger number of additional significant values. This suggests that the effect of the conditional variance, left out in the paragraph 4.1.1 result in a disturbance of the estimation process there.

With this set-up we can also re-examine the estimates for Bank of America (BAC) and Intel Corporation. For Bank of America we find that the very high β_1 estimate which was so remarkable in Table 4 is still high. The α_1 estimate also catches the eye right away with a very significant -0.7 where it was estimated to be about 0.16 with the constant error variance setting. Hence we can state that this conditional variance setup has a huge influence for this specific stock which we can also derive from the significance of the σ_1 estimate which is large and positive. This highly positive estimate is in accordance with the statistics presented in Table 3. There it was found that the standard deviation in the "Near" sample was a lot higher than that in the "Far" sample for Bank of America. The highly positive σ_1 estimate underlines this. The β parameter estimates for Intel Corp are not much different from the previous estimates without conditional variance. For the α parameter estimates signs have changed, but nothing significant is observable there. Still a very significant σ_1 parameter is estimate for this stock. Contrary to Bank of America, this parameter is estimated negatively however. The negative estimate is in accordance with the differences in the standard deviations we observe for Intel's split samples in Table 3.

Another usual component of conditional variance equations is some form of autoregressive process. This autoregressive element introduces the phenomenon of volatility clustering in the estimation process. The lagged residuals of the estimation as well as lagged conditional variance terms are applied to construct the variance term of the current residual distribution. In general applications, the first lags are applied in this setup resulting in GARCH (1,1) models. This kind of setup might however not be optimal in this application as there will be many occasions on which the previous day's stock price was already near a strike. This would imply that both the lagged conditional variance as well as the lagged residual is already lower than usual. As a result, the standard GARCH (1,1) model may not be the best way to assess the effect of being near a strike on the conditional variance. Therefore the same reasoning as in Driessen et al (2013) is followed. Hence we will only consider adding residuals that are lagged 10 days or more for the conditional variance equation. Three different formulations of the conditional variance equation with AR-terms are considered in this report: one complex variant and two simpler versions which are both nested in the complex one. We consider first the complex setup

$$\sigma_t = \sigma_0 + \sigma_1 D_{t-1}^{strike} + \sigma_2 \varepsilon_{t-10}^2 + \sigma_3 \varepsilon_{t-11}^2 + \sigma_4 \varepsilon_{t-12}^2 + \sigma_5 \varepsilon_{t-13}^2 + \sigma_6 \varepsilon_{t-14}^2, \quad (4.4)$$
$$\text{with } \varepsilon_t = \hat{R}a_{e,t} - Ra_{e,t}.$$

In this setup, the estimation errors over the five day period between 10 and 14 days previously each have their own coefficient in forecasting today's conditional error variance. A somewhat simpler version is

$$\sigma_t = \sigma_0 + \sigma_1 D_{t-1}^{strike} + \sigma_2(\varepsilon_{t-10}^2 + \varepsilon_{t-11}^2 + \varepsilon_{t-12}^2 + \varepsilon_{t-13}^2 + \varepsilon_{t-14}^2). \quad (4.5)$$

This form restricts the complex setup in the sense that the coefficient of each lagged error is bound to be the same. This reduces the amount of parameters that is to be estimated by 4 relative to the complex form. A second simplification we consider is

$$\sigma_t = \sigma_0 + \sigma_1 D_{t-1}^{strike} + \sigma_2 \varepsilon_{t-10}^2. \quad (4.6)$$

In this setup, the same basics as in the complex setup are present, albeit that only the coefficient for the lagged error of 10 days ago is allowed to deviate from zero. Hence, this also reduces the amount of parameters by 4 relative to the complex formulation.

These three setups can be tested and compared to each other, by coupling them to the return formulation of equation (4.2) and estimating the three different models on the available data. The likelihoods of the two simpler setups can both be compared with LR-tests to the complex version as they are both nested in the complex formulation. The resulting LR-test statistics can then be compared to the asymptotical theoretical distribution which is Chi-squared with 4 degrees of freedom for both comparisons. I list these test statistics as well as their significance in Table 6.

The conditional variance formulation in equation (4.6) is for all stocks significantly worse than the more elaborate setup of equation (4.4). For the conditional variance formulation in equation (4.5), this is only the case for a couple of stocks. For a majority of stocks, the difference between this concise formulation and the complex one is not significant. Hence we opt for the conditional variance setup from equation (4.5) to proceed with because of the simpler formulation with less parameters. Parameter estimates obtained with the original return formulation in equation (4.2) combined with this conditional variance setup are listed in Table 7.

Table 6: Test statistics of LR-tests on three different conditional variance setups in original CAPM type model. In the table, LR-test statistics are listed for two simple conditional variance setups (defined in equations (4.5) and (4.6)) versus their complex counterpart in equation (4.4). Significance levels of the LR-tests are 1 % for ** and 5 % for *.

Ticker	4.5 vs 4.4	4.6 vs 4.4
MMM	1.99	214.28 **
AA	7.86	281.66 **
AXP	5.42	492.07 **
BAC	12.45 *	1085.43 **
BA	1.02	203.00 **
CAT	71.53 **	202.21 **
CVX	9.75 *	341.16 **
CSCO	16.91 **	349.33 **
KO	6.91	537.97 **
DD	0.93	294.32 **
XOM	1.35	273.03 **
GE	22.20 **	492.09 **
HD	37.72 **	239.99 **
INTC	8.88	267.93 **
IBM	5.18	258.37 **
JNJ	1.93	506.57 **
MCD	3.02	142.83 **
MRK	19.32 **	37.10 **
MSFT	3.67	313.31 **
PFE	9.73 *	293.13 **
PG	114.62 **	782.47 **
TRV	7.75	299.57 **
UTX	59.52 **	371.09 **
UNH	11.53 *	91.23 **
VZ	37.61 **	507.21 **
WMT	1.08	560.65 **
DIS	3.49	112.46 **

The σ_2 parameter that is added to the conditional variance equation appears to be significantly different from zero for all underlyings. This results in different estimates for all other parameters as well, including significant parameters. Therefore we can identify this autoregressive term as a useful addition to the model, improving the quality of the return equation parameter estimates. The addition of this parameter is also of large influence on the estimates for the other parameters in the conditional variance equation. We find that it invokes changes in both the σ_0 and σ_1 estimates. Note that there is now also more consistency in the σ_1 estimates which are generally negative.

Table 7: Parameter estimates of CAPM model with dummy for nearness to strikes and error variance conditional on dummy and lagged errors. This table shows the results of estimating a model as proposed in equation (4.2) with normal errors with conditional standard deviations as defined in equation (4.5) to 27 stocks. The $\boldsymbol{D_t^{strike}}$ dummy in these equations takes value 1 if the day's closing price of the underlying is within $ 0.30 of an existing option strike in the underlying. Significance levels of the parameters are 1 % for ** and 5 % for * all measured in difference to zero.

Ticker	α0	α1	β0	β1	σ0	σ1	σ2
MMM	0.0109	0.0219	0.813 **	0.052	0.944 **	-0.005	0.032 **
AA	-0.0214	0.0331	1.343 **	0.113 *	1.483 **	-0.158 **	0.027 **
AXP	0.0413	-0.0486	1.241 **	0.054	1.020 **	0.014	0.043 **
BAC	-0.0018	-0.1355 *	0.957 **	0.521 **	1.015 **	0.067	0.056 **
BA	0.0462	-0.0326	0.969 **	-0.028	1.265 **	-0.034	0.027 **
CAT	0.0671 *	0.0063	1.166 **	-0.004	1.282 **	-0.035	0.023 **
CVX	0.0247	0.0017	0.802 **	0.080	0.912 **	-0.079 *	0.046 **
CSCO	0.0387	-0.0325	1.367 **	-0.264 **	1.445 **	-0.020	0.028 **
KO	0.0208	0.0088	0.518 **	0.088 **	0.799 **	-0.063 *	0.057 **
DD	0.0152	-0.0429	1.000 **	0.140 **	1.015 **	-0.116 **	0.037 **
XOM	-0.0173	0.0003	0.829 **	-0.044	0.909 **	-0.117 **	0.049 **
GE	-0.0094	0.0118	1.069 **	0.136 **	0.895 **	-0.015	0.056 **
HD	0.0206	-0.0290	1.116 **	-0.153 **	1.241 **	-0.211 **	0.038 **
INTC	0.1157 **	-0.0329	1.306 **	-0.267 **	1.413 **	-0.106 *	0.030 **
IBM	0.0148	0.0143	0.787 **	0.118 *	0.996 **	-0.065	0.037 **
JNJ	0.0067	0.0391	0.466 **	0.028	0.759 **	-0.087 **	0.054 **
MCD	0.0396	0.0063	0.555 **	-0.007	1.122 **	0.030	0.029 **
MRK	0.0455	-0.1031	0.665 **	0.017	1.537 **	-0.052	0.011 **
MSFT	0.0395	-0.0709	1.077 **	-0.198 **	1.167 **	-0.084 *	0.033 **
PFE	-0.0708 *	0.1002 *	0.759 **	-0.038	1.084 **	-0.102 **	0.038 **
PG	0.0365	0.0001	0.479 **	0.052	0.824 **	-0.033	0.063 **
TRV	0.0170	0.0072	0.896 **	0.152 *	1.152 **	-0.052	0.034 **
UTX	0.0529 *	0.0163	0.988 **	-0.031	1.007 **	-0.055	0.040 **
UNH	-0.0269	0.1900 **	0.582 **	0.275 **	1.429 **	0.186 **	0.023 **
VZ	0.0892 **	-0.0803 *	0.705 **	-0.119 **	0.982 **	-0.101 **	0.046 **
WMT	0.0044	-0.0373	0.662 **	-0.045	0.967 **	0.019	0.037 **
DIS	0.0120	0.0705	0.998 **	0.142 **	1.402 **	-0.242 **	0.018 **

Specifically for Bank of America it appears that the addition of the AR term has resulted in the σ_1 estimate becoming insignificant where it was highly positive in the formulation without AR terms. Further we see that the α_1 estimate decreased a lot though it is still significantly different from zero. The size and sign of the β_1 parameter estimate are still remarkable and significant. For Intel Corporation, the addition of the AR terms to the conditional variance equation has mainly results for the α_0 estimate. This is suddenly positive and significant. For the other parameters estimates only small changes are observed.

4.2 Alternative variables indicating option activity

Option strikes are generally defined to be round numbers. Therefore there may be a mixture of round number effects and actual option effects around strikes. By applying the setups of paragraph 4.1 all these mixed effects are basically assumed to be caused by the presence of an option strike only. A possible way to split the effects is by introducing additional variables into the formulations. These additional variables should be indicative of option activity only and unrelated to round numbers if they were to be of help for this purpose.

4.2.1 Open Interest Ratio

The option open interest at the nearest strike over all expiration dates qualifies for this purpose as it indicates exactly how much financial interest exists around a strike at expiration. We should see this financial interest in the options in relation to a form of financial interest in the underlying. This interest in the underlying can be approximated by the trading volume in the underlying. Trading volumes vary greatly from one day to another. A much used alternative for daily trading volume is therefore the average trading volume over the past 20 trading days, which behaves much more smoothly. A potential additional variable would therefore be a combination of this option open interest and the average daily trading volume in the underlying over the past 20 days referred to as the Open Interest Ratio from here on:

$$OIR_t^{strike} = \frac{\sum_T OI_t(K,T)}{1/_{20} \sum_{t-20}^{t} V_i}. \tag{4.7}$$

In this definition OI_t is the open interest on day t in options with strike K and maturity T. V_i denotes the trading volume in the underlying stock at day i. Summary statistics on this variable are included in Appendix 3.

Applying this new variable in the return equation and in the conditional variance equation with AR terms yields the new return equation (4.8) and conditional variance equation (4.9). Parameter estimates obtained with this formulation are listed in Table 8.

$$Ra_{e,t} = \alpha_0 + \alpha_1 D_{t-1}^{strike} OIR_{t-1}^{strike} + (\beta_0 + \beta_1 D_{t-1}^{strike} OIR_{t-1}^{strike}) Rm_{e,t} \tag{4.8}$$

$$\sigma_t = \sigma_0 + \sigma_1 D_{t-1}^{strike} OIR_{t-1}^{strike} + \sigma_2(\varepsilon_{t-10}^2 + \varepsilon_{t-11}^2 + \varepsilon_{t-12}^2 + \varepsilon_{t-13}^2 + \varepsilon_{t-14}^2) \tag{4.9}$$

Table 8: Parameter estimates of CAPM model taking open interest into account and error variance conditional on open interest and lagged errors. This table shows the results of estimating a model as proposed in equation (4.8) with normal errors with conditional standard deviations as defined in equation (4.9) to 27 stocks. The $\boldsymbol{OIR_t^{strike}}$ variable in these equations is defined in equation (4.7). The $\boldsymbol{D_t^{strike}}$ dummy in the equation takes value 1 if the day's closing price of the underlying is within $ 0.30 of an existing option strike in the underlying. Significance levels of the parameters are 1 % for ** and 5 % for * all measured in difference to zero.

Ticker	α0	α1	β0	β1	σ0	σ1	σ2
MMM	-0.0060	0.0907	0.825 **	-0.031	0.941 **	0.007	0.032 **
AA	0.0166	-0.0026	1.372 **	0.077	1.473 **	-0.145 **	0.026 **
AXP	0.0414	-0.0537 *	1.266 **	-0.028	1.042 **	-0.043 *	0.042 **
BAC	0.0535 *	-0.0455	1.071 **	-0.068	1.051 **	-0.115 **	0.058 **
BA	0.0454	0.0055	0.959 **	0.034	1.262 **	-0.049	0.027 **
CAT	0.0763 **	0.0119	1.185 **	-0.189 **	1.277 **	-0.037	0.024 **
CVX	0.0139	0.0063	0.810 **	0.046	0.907 **	-0.060	0.046 **
CSCO	-0.0009	-0.0116	1.296 **	-0.349 **	1.436 **	-0.010	0.028 **
KO	0.0333	-0.0249	0.535 **	0.022	0.793 **	-0.017	0.056 **
DD	-0.0026	-0.0160	1.049 **	0.012	1.017 **	-0.165 **	0.036 **
XOM	-0.0257	0.0974 *	0.815 **	-0.005	0.915 **	-0.182 **	0.048 **
GE	-0.0186	0.0072	1.140 **	-0.051	0.951 **	-0.157 **	0.053 **
HD	0.0796 **	-0.1220 *	1.032 **	0.104	1.222 **	-0.243 **	0.037 **
INTC	0.1035 **	-0.2305 **	1.198 **	-0.262 **	1.391 **	-0.130 *	0.031 **
IBM	0.0012	0.0267	0.802 **	0.030	1.004 **	-0.086 **	0.036 **
JNJ	0.0244	-0.0001	0.475 **	-0.029	0.765 **	-0.085 **	0.053 **
MCD	0.0574 *	-0.0419	0.547 **	0.035	1.134 **	-0.027	0.029 **
MRK	-0.0266	-0.0301	0.702 **	-0.252 **	1.425 **	0.216 **	0.015 **
MSFT	-0.0177	0.0081	0.998 **	-0.066	1.209 **	-0.227 **	0.032 **
PFE	-0.0595 *	0.0767 *	0.740 **	-0.003	1.074 **	-0.074 **	0.037 **
PG	0.0347	-0.0957 **	0.488 **	0.002	0.853 **	-0.134 **	0.061 **
TRV	0.0339	0.0190	0.908 **	0.120 *	1.171 **	-0.235 **	0.033 **
UTX	0.0536 *	0.0135	0.986 **	-0.050	1.034 **	-0.242 **	0.038 **
UNH	0.0908 **	0.0005	0.701 **	-0.181 *	1.498 **	0.003	0.022 **
VZ	0.0578 *	-0.0039	0.637 **	0.068 *	1.009 **	-0.146 **	0.043 **
WMT	0.0157	-0.0612	0.654 **	-0.009	0.985 **	-0.052 *	0.036 **
DIS	0.0906 **	-0.1417 **	1.067 **	-0.059	1.366 **	-0.202 **	0.018 **

It seems that most stocks with significant α_0 parameter estimates show positive parameters. Most of the significant α_1 parameters estimates are however negative, suggesting that when trading near a strike on the previous day, a large OIR_{t-1}^{strike} has a negative effect on returns. Also observable are several significantly negative β_1 parameter estimates. This can be translated in a lesser degree of correlation with the market return if the previous day's closing price is near a strike and open interest is large relative to average daily trading volume. Nearly all σ_1 estimates are negative meaning that average size of the unexpected returns decreases in case of large open interest and trading near a strike.

When comparing the parameter estimates for this formulation with the ones in paragraph 4.1 for Bank of America, several notable changes are visible. The α_0 estimate becomes significantly positive whereas the β_1 estimate changes from very significantly positive to slightly negative. The σ_1 coefficient is estimated significantly negative whereas there was a slightly positive estimate in the previous formulation with the dummy and AR terms only.

For Intel Corp the parameter estimate signs have not changed relative to the estimates from paragraph 4.1. Note however that the estimates for the α parameters become more significant than they were before and the β_0 estimate is lowered by about 0.1. These changes indicate that the return variation captured by the new combination of the dummy with OIR_{t-1}^{strike} leans for Intel Corp data more towards α.

4.2.1 Open Interest Gamma Ratio

The open interest ratio was included in our formulations to reflect the relative importance of the financial interest in the option markets in relation to the market in stocks of the underlying. The open interest reflects this however only partially. Reason is that the instantaneous financial interest of an option is somewhat different from the terminal interest at expiration (for which the open interest is the perfect indicator). The instantaneous financial interest of an option can be defined as the instantaneous derivative of the option price with respect to the price of the underlying, also denoted with the Greek letter δ. The γ of an option is the second derivative of the option price with respect to the underlying. This γ can be of influence on the underlying returns through the pinning mechanism. We discussed this mechanism briefly in the literature review of Chapter 2. It is a known fact that several market parties (most predominantly the market makers) hedge the δ of the options they buy or sell. This is in most cases done by either selling or buying the underlying in a quantity equal to the option δ but opposite of sign. This hedge is however only perfect if the underlying stays near the price it traded on when the hedge was put in place, as the δ of an option changes when the price of the underlying changes. The γ of an option, which is the derivative of the δ with respect to the underlying determines how much of the underlying stocks are to be sold or bought to maintain a delta-hedged position in the event of a $ 1 price change in the underlying. The total γ of the option position of a delta-hedging party could therefore be predictive of the trading behavior of this party in the event of a price change in the underlying.

For every option seller, there is an option buyer. This leads to a total net γ of zero in the market. We know however that only part of the market participants apply delta-hedging in their trading strategies, such that it is at all times highly likely that the net γ of the delta-hedging market participants is not equal to zero. The exact distribution of the positions at any moment between the different market participants is unknown. It is however plausible that the γ position of the delta-hedging parties is correlated over time with the γ of the overall open interest.

The γ of the open interest can at any time be determined by calculating the γ of all existing options and multiplying each of these with the open interest in that specific option. Summing the γ of these different options provides the total γ open interest in the option market. Similar to the transformation of the open interest into an open interest ratio, this market net γ is also to be seen in perspective to the trading volume in the underlying. Also we are (similarly to what was done for the open interest ratio) not looking for the net γ across all strikes, but only interested in the net γ at the strike nearest to the closing price in the underlying. Equation (4.10) provides the formulation for the additional variable which will be referred to as "Open Interest Gamma Ratio".

$$OI\gamma R_t^{strike} = \frac{\sum_T \gamma_t(K,T) OI_t(K,T)}{{}^1\!/_{20} \sum_{t-20}^{t} V_i} \tag{4.10}$$

The method used for calculating the γ of each option is derived and discussed in Appendix 1. Appendix 3 contains summary statistics on this variable. With this new additional variable, the return equation of the underlying and the conditional error variance formulation change to the ones presented in equations (4.11) and (4.12). Estimates for the parameters in these two equations on the base of the available data are listed in Table 9.

$$Ra_{e,t} = \alpha_0 + \alpha_1 D_{t-1}^{strike} OI\gamma R_{t-1}^{strike} + (\beta_0 + \beta_1 D_{t-1}^{strike} OI\gamma R_{t-1}^{strike}) Rm_{e,t} \tag{4.11}$$

$$\sigma_t = \sigma_0 + \sigma_1 D_{t-1}^{strike} OI\gamma R_{t-1}^{strike} + \sigma_2(\varepsilon_{t-10}^2 + \varepsilon_{t-11}^2 + \varepsilon_{t-12}^2 + \varepsilon_{t-13}^2 + \varepsilon_{t-14}^2) \tag{4.12}$$

Table 9: Parameter estimates of CAPM model taking the gamma of the open interest into account and error variance conditional on open interest gamma and lagged errors. This table shows the results of estimating a model as proposed in equation 4.11 with normal errors with conditional standard deviations as defined in equation 4.12 to 27 stocks. The $\boldsymbol{OIR_t^{strike}}$ variable in these equations is defined in equation 4.10. The $\boldsymbol{D_t^{strike}}$ dummy in the equation takes value 1 if the day's closing price of the underlying is within $ 0.30 of an existing option strike in the underlying. Significance levels of the parameters are 1 % for ** and 5 % for * all measured in difference to zero.

Ticker	α0	α1	β0	β1	σ0	σ1	σ2
MMM	0.0127	1.029	0.826 **	-20.21	0.943 **	0.52	0.032 **
AA	-0.0047	-0.200	1.368 **	48.23 *	1.425 **	-0.10	0.027 **
AXP	0.0288	0.037	1.269 **	-49.73	1.028 **	-0.03	0.043 **
BAC	0.0389	-0.066	1.054 **	-10.78	1.018 **	-0.06	0.059 **
BA	0.0300	2.026	0.966 **	-34.61	1.262 **	-3.16	0.026 **
CAT	0.0766 **	-0.037	1.164 **	11.58	1.275 **	-0.07	0.023 **
CVX	0.0145	0.087	0.811 **	38.24	0.901 **	0.07	0.046 **
CSCO	-0.0042	-0.063	1.252 **	-53.73	1.431 **	0.22	0.028 **
KO	0.0279	0.013	0.541 **	-1.38	0.786 **	-0.09	0.057 **
DD	-0.0007	0.997	1.063 **	3.91	0.977 **	-1.44	0.038 **
XOM	-0.0105	0.268	0.822 **	-49.23	0.882 **	-0.01	0.050 **
GE	0.0235	-14.219	1.135 **	-11.02	0.922 **	-19.72 **	0.056 **
HD	0.0632 *	0.042	1.068 **	-45.07	1.153 **	0.18	0.040 **
INTC	0.0486	-0.212	1.167 **	-34.30	1.369 **	0.15	0.031 **
IBM	0.0211	-0.046	0.802 **	20.87	0.989 **	-0.03	0.036 **
JNJ	0.0058	0.289	0.474 **	-13.86	0.747 **	0.07	0.054 **
MCD	0.0495 *	0.002	0.552 **	2.53	1.127 **	-0.11	0.029 **
MRK	0.0024	-0.006	0.671 **	0.00	1.520 **	-0.01	0.011 **
MSFT	0.0026	2.384	1.016 **	-49.87 **	1.129 **	-4.67	0.032 **
PFE	-0.0333	-0.106	0.753 **	-19.56 *	1.037 **	0.21	0.039 **
PG	0.0110	-0.014	0.490 **	-0.05	0.823 **	0.01	0.063 **
TRV	0.0329	-0.532	0.910 **	94.18	1.148 **	0.67	0.034 **
UTX	0.0547 **	-0.155	0.981 **	7.94	1.001 **	0.08	0.039 **
UNH	0.0930 **	-0.048	0.678 **	-11.71	1.498 **	0.01	0.023 **
VZ	0.0433	0.061	0.659 **	-4.28	0.961 **	-0.08	0.044 **
WMT	0.0096	0.275	0.657 **	-23.81	0.971 **	0.24	0.037 **
DIS	0.0208	0.139	1.059 **	-24.39	1.327 **	-0.32	0.019 **

The rationale behind the formulation was that this new Open Interest γ Ratio should be able to capture option activity better than the previous OIR variable. This intuitive assumption is not translated into (a lot of) significant α_1, β_1 and σ_1 parameter estimates. Still it is observable that two thirds of the β_1 parameter estimates are negative. The lack of significant estimates could indicate that there actually exist no significant effects of option activity on the CAPM parameters. From the previous setup where the OIR was applied as additional variable, the conclusion was however that there are significant effects. These are predominantly negative for β_1 as is more or less confirmed here. From this fact, I conclude that the previously found effects on the β are confirmed, but the OIγR is not the ideal variable for detecting these. Hence, in the next paragraph, we leave this setup and carry on with the formulation from paragraph 4.2.1 applying the OIR variable.

4.3 Full panel formulation

Up until this paragraph, all the parameter estimates are based on the data for one underlying stock only. Hence, we obtain 27 different sets of parameter estimates for each model formulation. This also means that the magnitude (and even the sign) of the effects of option activity and nearness to strike varies across the different underlyings.

For several of the underlying stocks, significant effects of nearness to strike in combination with option activity are found, especially in the formulation used in paragraph 4.2. In case these individual effects have the same sign for a majority of stocks it is suggested that these effects hold in general. It is statistically however more powerful, if we can confirm a significant effect over all underlyings. To be able to do this, the relevant parameters for the option strike nearness effects (α_1, β_1 and σ_1) are to be estimated on the entire dataset, composed of the 27 different samples of the different underlyings. Allowing the other parameters to vary across the different underlyings ensures that only the effects we are looking for are assigned to the relevant option strike nearness parameters. This is formalized in the return and conditional variance formulations in equations (4.13) and (4.14) which are based on the original equations (4.8) and (4.9).

$$Ra_{e,t,i} = \alpha_{0,i} + \alpha_1 D_{t-1,i}^{strike} OIR_{t-1,i}^{strike} + (\beta_{0,i} + \beta_1 D_{t-1,i}^{strike} OIR_{t-1,i}^{strike}) Rm_{e,t} \quad (4.13)$$

$$\sigma_{t,i} = \sigma_{0,i} + \sigma_1 D_{t-1,i}^{strike} OIR_{t-1,i}^{strike} + \sigma_{2,i}(\varepsilon_{t-10,i}^2 + \varepsilon_{t-11,i}^2 + \varepsilon_{t-12,i}^2 + \varepsilon_{t-13,i}^2 + \varepsilon_{t-14,i}^2) \quad (4.14)$$

In these formulations, the index “i” is added to variables and parameters to indicate that these are specific for underlying “i”, rather than common for all underlyings. The parameter estimates resulting from this setup are listed in Table 10. To reduce the computational costs, standard errors are only calculated for the three common parameters in Panel A on the base of a reduced Hessian matrix with fixed specific parameters.

The estimated common parameters in Panel A clearly confirm our previous observations as both β_1 and σ_1 are estimated significantly negative over the entire panel. The α_1 parameter estimate is slightly positive but not significant. We can compare the company specific parameters to the ones estimated previously in Table 8. Here we observe some sign changes for α_0 and minor changes in the β_0 estimates that stay within 0.1 of the old estimates. Larger changes are visible in the σ_0 estimates which are considerably lower for this panel formulation. These lower estimates for σ_0 come however with higher σ_2 estimates. This results in a lower base level of the conditional variance compensated for by a higher autocorrelation effect invoked by the higher σ_2 estimate.

Table 10: Parameter estimates of panel formulation of CAPM model taking open interest into account and error variance conditional on open interest and lagged errors. This table shows the results of estimating a model as proposed in equation (4.13) with normal errors with conditional standard deviations as defined in equation (4.14) to 27 stocks. The $\boldsymbol{OIR_t^{strike}}$ variable in these equations is defined in equation (4.7). The $\boldsymbol{D_t^{strike}}$ dummy in the equation takes value 1 if the day's closing price of the underlying is within \$ 0.30 of an existing option strike in the underlying. Significance levels are only calculated for panel A and are 1 % for ** and 5 % for * all measured in difference to zero.

Panel A: Common parameters

	α1	β1	σ1
Common	0.0011	-0.138 **	-0.085 **

Panel B: Parameters specific for underlying

Ticker	α0	β0	σ0	σ2
MMM	0.000	0.954	0.562	0.051
AA	0.002	1.409	1.276	0.056
AXP	0.006	1.262	0.557	0.092
BAC	0.002	1.089	0.638	0.067
BA	0.000	1.158	1.518	0.038
CAT	0.000	1.120	0.594	0.057
CVX	0.004	0.962	0.393	0.049
CSCO	0.009	1.256	0.409	0.093
KO	0.004	0.609	0.719	0.055
DD	0.001	0.976	0.754	0.052
XOM	0.002	0.820	0.478	0.074
GE	0.003	1.324	1.108	0.015
HD	-0.005	1.042	0.336	0.048
INTC	0.002	1.095	0.918	0.049
IBM	0.005	0.844	0.667	0.044
JNJ	0.002	0.371	0.439	0.068
MCD	-0.001	0.571	0.600	0.054
MRK	0.000	0.766	0.671	0.062
MSFT	0.003	1.048	0.702	0.076
PFE	0.005	0.833	0.526	0.052
PG	0.004	0.493	0.585	0.074
TRV	0.001	0.877	0.597	0.046
UTX	0.002	0.950	0.432	0.037
UNH	0.004	0.767	0.766	0.090
VZ	0.000	0.782	0.461	0.072
WMT	0.008	0.574	0.469	0.059
DIS	-0.003	1.095	0.977	0.038

The estimated common parameters fit Bank of America rather nicely. Although the common α_1 estimate has a different sign than the one observed specifically for this stock in Table 8, both are not significant. The common β_1 and σ_1 are pretty similar to the original specific estimates. The α_0 estimate for this specific stock changed from significantly positive to slightly negative and the β_0 estimates are practically equal. Regarding the σ_0 and σ_1 estimates we indeed see a lower base variance but higher autocorrelation in this name as indicated previously.

For Intel Corp a highly significant negative α_1 parameter was estimated in Table 8. Obviously this negative parameter is not confirmed by the entire panel, hence the discrepancy here. The other common parameter estimates have the same sign as the original specific estimates but are both smaller in magnitude. These changes have their effect on the α_0 β_0 and σ_0 estimates, as these reflect now part of the effect that was in paragraph 4.2.1 attributed to the strike nearness. The resulting estimates for all three parameters are as a result of this effect lower in this common estimation set-up than they were previously.

4.4 Asymmetric effects of closing below and above strikes

An assumption that is embedded in the original return setup in equation 4.2 and the construction of the dummy variable is that closing near a strike either above or below the strike makes no difference to the effect on the estimated return. We can assess whether this is a reasonable assumption by adjusting the setup to reflect the different occasions on which the underlying closes slightly above and slightly below the nearest strike. A practical way to do this is by splitting the original dummy variable into two new dummies, one taking a value 1 only when the day's closing price is near and above a strike and a second with value 1 only when the day's closing price is near and below a strike. Including the two dummy variables results in the following formulation

$$Ra_{e,t} = \alpha_0 + \alpha_{1+} D_{t-1}^{strike+} + \alpha_{1-} D_{t-1}^{strike-} + (\beta_0 + \beta_{1+} D_{t-1}^{strike+} + \beta_{1-} D_{t-1}^{strike-}) Rm_{e,t} \qquad (4.15)$$

The conditional variance equation that is assumed for the estimation residuals is taken to be similar to equation (4.4) with as only change the split dummy.

$$\sigma_t = \sigma_0 + \sigma_{1+} D_{t-1}^{strike+} + \sigma_{1-} D_{t-1}^{strike-} + \sigma_2 (\varepsilon_{t-10}^2 + \varepsilon_{t-11}^2 + \varepsilon_{t-12}^2 + \varepsilon_{t-13}^2 + \varepsilon_{t-14}^2) \qquad (4.16)$$

Taking this new proposition to the data we can generate estimates for the parameters in equations (4.15) and (4.16). As our interest lies in the parameters affected by the different choice of dummy variables, we include only the estimates of parameters in relation to these variables in Table 11 with the same parameters estimated from equations (4.2) and (4.4) for comparison.

The parameter estimates in this table and their significance give a first impression about the presence of asymmetric effects. This first impression is however not enough to formalize the presence or absence of significant asymmetric effects. The effects can be formalized by means of a Likelihood Ratio test between the restrictive model (consisting of equations (4.2) and (4.4)) and the unrestrictive model (equations (4.15) and (4.16)). Likelihood Ratio test statistics of these combinations are listed in the final column of Table 11.

Table 11: α_1 β_1 and σ_1 parameter estimates of CAPM model with dummy for nearness to strikes only versus split dummies for above and below strike and error variance conditional on dummies and lagged errors. This table shows the results of estimating the α_1 β_1 and σ_1 parameters as proposed in equation (4.2) together with their + and – counterparts stemming from equation (4.7) with normal errors with conditional standard deviations as defined in equation (4.6) and (4.8) to 27 stocks. The D_t^{strike} dummy in the equations takes value 1 if the day's closing price of the underlying is within $ 0.30 of an existing option strike in the underlying. The $D_t^{strike+}$dummy takes value 1 if the day's closing price is within $ 0.30 above an existing option strike. The $D_t^{strike-}$dummy takes value 1 if the day's closing price is within $ 0.30 below an existing option strike. Significance levels of the parameters are 1 % for ** and 5 % for * all measured in difference to zero.

Ticker	α1	α1+	α1-	β1	β1+	β1-	σ1	σ1+	σ1-	LR-test
MMM	0.022	0.016	0.060	0.052	0.033	0.039	-0.005	-0.053	-0.031	0.52
AA	0.033	0.029	0.001	0.113 *	0.123	0.106	-0.158 **	0.018	-0.117 *	3.93
AXP	-0.049	-0.026	-0.093	0.054	0.101	0.050	0.014	-0.021	0.048	4.61
BAC	-0.135 *	-0.045	0.224 **	0.521 **	0.477 **	0.630 **	0.067	-0.029	0.168 **	6.17
BA	-0.033	0.057	-0.042	-0.028	-0.016	0.009	-0.034	0.010	-0.046	0.34
CAT	0.006	0.011	-0.086	-0.004	-0.061	0.029	-0.035	0.127	-0.173 **	16.14 **
CVX	0.002	0.104	-0.115	0.080	0.089	0.076	-0.079 *	-0.061	-0.048	2.54
CSCO	-0.033	-0.055	0.082	-0.264 **	-0.277 **	-0.248 **	-0.020	0.040	-0.092	6.63
KO	0.009	-0.031	-0.053	0.088 **	0.116 **	0.043	-0.063 *	-0.159 **	0.034	14.38 **
DD	-0.043	-0.112 *	-0.006	0.140 **	0.175 **	0.141 **	-0.116 **	0.049	-0.035	6.98
XOM	0.000	-0.029	0.116 *	-0.044	0.029	-0.028	-0.117 **	-0.030	-0.117 **	2.66
GE	0.012	-0.036	0.028	0.136 **	0.230 **	0.040	-0.015	0.049	-0.096 **	24.85 **
HD	-0.029	-0.021	-0.010	-0.153 **	-0.184 **	-0.110	-0.211 **	-0.038	-0.031	3.39
INTC	-0.033	0.030	0.042	-0.267 **	-0.268 **	-0.281 **	-0.106 *	-0.169 **	-0.001	5.73
IBM	0.014	0.069	-0.010	0.118 *	0.105	0.133 *	-0.065	-0.017	-0.080	2.63
JNJ	0.039	0.003	0.103 *	0.028	-0.007	-0.023	-0.087 **	-0.089 *	-0.061	6.37
MCD	0.006	-0.042	-0.034	-0.007	-0.021	-0.037	0.030	-0.037	0.010	3.43
MRK	-0.103	0.191 **	-0.010	0.017	0.044	-0.153 *	-0.052	-0.446 **	0.137 *	90.96 **
MSFT	-0.071	0.086	0.075	-0.198 **	-0.170 **	-0.218 **	-0.084 *	-0.240 **	-0.053	25.62 **
PFE	0.100 *	-0.020	0.124 *	-0.038	-0.019	-0.010	-0.102 **	-0.089 *	-0.030	9.00 *
PG	0.000	-0.046	0.083	0.052	0.079	-0.158 **	-0.033	-0.117 *	-0.046	14.75 **
TRV	0.007	0.042	0.022	0.152 *	-0.098	0.361 **	-0.052	-0.263 **	0.144	33.67 **
UTX	0.016	0.102	-0.050	-0.031	0.037	0.016	-0.055	0.037	-0.119 *	3.46
UNH	0.190 **	-0.227 *	-0.205 *	0.275 **	0.349 **	0.197 *	0.186 **	0.028	0.227 **	14.47 **
VZ	-0.080 *	0.004	0.129 *	-0.119 **	-0.095 *	-0.136 **	-0.101 **	-0.192 **	-0.129 **	16.60 **
WMT	-0.037	-0.092	-0.036	-0.045	-0.120 *	-0.010	0.019	-0.026	0.066	7.25
DIS	0.071	0.167 *	0.097	0.142 **	0.044	-0.010	-0.242 **	-0.144 **	-0.086	7.23

The parameter estimates for several stocks indicate some asymmetric behavior simply on the base of discrepancies between the estimates for the “+” and “-“ variant of each parameter. This asymmetric behavior is however only formalized in the LR-test results, which assesses whether the differences between the variants are large enough to speak of significant asymmetric behavior. From these test results, we conclude that for about a third of the stocks significant asymmetric effects are present.

For Bank of America, the α_1 and σ_1 parameter estimates in the model allowing for asymmetric behavior seem to be seriously different from each other. For the β_1 estimates, this is however not so much the case. This last fact and the dominance of this parameter in the estimation process have led to the result of the LR-test, indicating no significant asymmetric behavior.

In the Intel Corp parameter estimates it is especially remarkable that both the α_1 parameter estimates in the asymmetric formulation (which are nicely in line with each other) have a different sign than their symmetric counterpart. Furthermore all the β_1 estimates are nicely in line where the σ_1 estimates show a somewhat larger spread. Overall it seems again as if the β_1 estimates are dominant resulting in the LR-test not rejecting symmetry here.

5 Robustness to nearness to strike definition

All the observations that are made so far are based on supposed formulations to entangle the option strike nearness effects from all other effects on the returns of underlying securities. To assess the value of these observations it is essential knowing to which degree these observations are the result of choices in our formulation and to which degree the observations are robust to these.

Up until now we haven't discussed the construction of the nearness to strike dummy D_t^{strike} widely. Its construction is posed as a given without any further ado. Question is however whether the exact formulation of this dummy has a detrimental effect on the found results. Therefore we perform parameter estimations with variations to the dummy measure in paragraph 5.1 and assess to what degree our previous observations hold. In paragraph 5.2 we abandon the formulation in the form of a dummy and formulate a continuous variable indicating strike nearness.

5.1 Dummy measure variation

The return formulations in chapter 4 all include the nearness to strike dummy D_t^{strike}. This dummy is constructed by taking the distance of the day's closing price in the underlying to the nearest existing option strike on that day. If this distance is smaller than \$ 0.30 the dummy takes value 1, if this is not the case, the dummy takes value zero.

We would like to know how robust our findings are to changes in the \$ 0.30 measure that is applied. To assess this, the estimation of the parameters in the formulation from paragraph 4.2.2 with the Open Interest Ratio (which delivered the most interesting results) is redone. This time however the dummy variable is based on four other measures: \$ 0.10, \$ 0.20, \$ 0.40 and \$ 0.50 while maintaining the same OIR variable. The parameter estimates for the α_1, β_1 and σ_1 parameters with the original \$ 0.30 measure as well as with these four additional measures are listed in Table 12 for each of the 27 underlying stocks. Varying the measure between \$ 0.10 and \$ 0.50 has some implications. A small measure results in only a small selection of closing prices that are deemed close to a strike. On the other hand, all the closing prices that are deemed close to a strike are indeed very close, such that any strike effects (if present) should be the most exposed for the ones selected. A larger measure results in a larger set of closing prices that are close to a strike. The effects that are supposed to be detected are probably however less pronounced for this larger set.

Table 12: α_1 β_1 and σ_1 parameter estimates of CAPM model with dummy for nearness to strikes taking option open interest into account and conditional variance with different settings for generating the dummy variable. This table shows the results of estimating the α_1 β_1 and σ_1 parameters as proposed in equation 4.8 with normal errors and conditional standard deviations as defined in equation 4.9 for 27 stocks. The D_t^{strike} dummy in the equations takes value 1 if the day's closing price of the underlying is within \$ X of an existing option strike in the underlying. In this table X varies from \$ 0.10 to \$ 0.50 in steps of \$ 0.10. Significance levels of the parameters are 1 % for ** and 5 % for * all measured in difference to zero.

	α1					β1					σ1				
Ticker	0.10	0.20	0.30	0.40	0.50	0.10	0.20	0.30	0.40	0.50	0.10	0.20	0.30	0.40	0.50
MMM	0.03	0.12	0.09	0.05	0.02	0.03	-0.11	-0.03	-0.03	-0.02	-0.19 **	-0.02	0.01	0.03	-0.01
AA	0.00	0.00	0.00	0.13 *	-0.03	0.20 *	0.00	0.08	0.04	0.05	-0.05	-0.09 *	-0.15 **	-0.10 *	-0.23 **
AXP	-0.02	-0.08 *	-0.05 *	-0.04	0.01	-0.08	-0.03	-0.03	-0.02	-0.05	-0.01	-0.01	-0.04 *	-0.07 **	-0.06 **
BAC	-0.14 **	-0.06	-0.05	-0.05	-0.04	0.02	-0.05	-0.07	-0.10 **	-0.12 **	-0.02	-0.09 **	-0.11 **	-0.14 **	-0.17 **
BA	0.07	0.01	0.01	-0.01	-0.08	-0.15	0.00	0.03	-0.14 *	-0.14 **	-0.23 **	-0.02	-0.05	-0.16 **	-0.15 **
CAT	-0.08	0.02	0.01	0.00	-0.02	-0.10	-0.18 *	-0.19 **	-0.07	-0.04	0.04	-0.03	-0.04	0.00	0.06
CVX	-0.03	-0.04	0.01	-0.04	0.02	-0.05	0.05	0.05	0.02	-0.02	0.01	0.00	-0.06	-0.01	-0.04
CSCO	0.03	-0.09	-0.01	-0.08	0.01	-0.42 **	-0.31 **	-0.35 **	-0.31 **	-0.31 **	-0.04	-0.39 **	-0.01	-0.08	-0.01
KO	-0.03	-0.02	-0.02	0.00	0.00	0.04	0.05	0.02	0.03	-0.01	-0.01	0.00	-0.02	-0.03 **	-0.05 **
DD	0.06	0.02	-0.02	-0.03	-0.08 **	0.08	0.02	0.01	0.06	0.06	-0.13 *	-0.15 **	-0.16 **	-0.16 **	-0.13 **
XOM	0.09	0.08	0.10 *	0.05	0.05	-0.03	-0.03	0.00	-0.04	0.02	-0.18 **	-0.19 **	-0.18 **	-0.19 **	-0.21 **
GE	0.10	0.01	0.01	0.01	0.01	-0.08	-0.04	-0.05	-0.02	-0.06 *	-0.17 **	-0.16 **	-0.16 **	-0.13 **	-0.15 **
HD	-0.25 **	-0.14 *	-0.12 *	-0.08	-0.19 **	-0.04	-0.05	0.10	-0.06	-0.08	-0.21 **	-0.22 **	-0.24 **	-0.27 **	-0.27 **
INTC	-0.28 *	-0.25 **	-0.23 **	-0.22 **	-0.18 *	-0.14	-0.12	-0.26 **	0.03	0.03	-0.18	-0.11	-0.13 *	-0.14 **	-0.14 **
IBM	0.03	0.02	0.03	0.05	0.03	0.16 *	0.09	0.03	0.09 *	0.09 *	-0.01	-0.07 *	-0.09 **	-0.04	-0.06 **
JNJ	0.03	0.06 *	0.00	0.05 *	0.02	-0.10 *	-0.06	-0.03	-0.07 **	-0.08 **	-0.08 **	-0.08 **	-0.09 **	-0.08 **	-0.08 **
MCD	-0.04	-0.08 **	-0.04	-0.03	-0.01	0.08	0.05	0.04	0.00	-0.01	-0.12 **	-0.09 **	-0.03	-0.07 **	-0.07 **
MRK	0.39 **	-0.30 **	-0.03	-0.15 *	-0.07	-0.05	-0.11	-0.25 **	-0.09	-0.19 **	0.62 **	0.36 **	0.22 **	0.18 **	0.20 **
MSFT	0.08	0.09	0.01	0.01	-0.08	-0.04	-0.09	-0.07	-0.10 *	-0.09 *	-0.21 **	-0.18 **	-0.23 **	-0.20 **	-0.28 **
PFE	0.09	0.09 *	0.08 *	0.04	0.04	-0.13 *	-0.03	0.00	-0.03	-0.02	0.05	-0.03	-0.07 **	-0.02	-0.04
PG	-0.02	0.03	-0.10 **	0.04	-0.05 *	-0.03	-0.01	0.00	0.05	-0.03	-0.12 **	-0.07 *	-0.13 **	-0.07 **	-0.15 **
TRV	-0.04	0.07	0.02	0.07	0.05	0.93 **	0.19 *	0.12 *	0.10 *	0.19 **	-0.03	-0.21 **	-0.24 **	-0.25 **	-0.18 **
UTX	0.06	-0.06	0.01	0.01	0.01	-0.01	-0.02	-0.05	0.00	-0.02	-0.22 **	-0.19 **	-0.24 **	-0.24 **	-0.28 **
UNH	-0.06	-0.06	0.00	0.07	-0.06	-0.32 **	-0.22 *	-0.18 *	-0.27 **	-0.29 **	0.17	0.03	0.00	-0.08	-0.01
VZ	-0.05	0.01	0.00	-0.01	0.00	0.06	0.01	0.07 *	-0.07 *	-0.05	-0.14 **	-0.14 **	-0.15 **	-0.13 **	-0.11 **
WMT	0.02	-0.03	-0.06	0.01	-0.01	0.01	0.00	-0.01	0.03	0.02	0.04	0.00	-0.05 *	-0.05 *	-0.03
DIS	-0.06	0.01	-0.14 **	0.03	0.06	-0.14	-0.10	-0.06	0.18 **	0.01	-0.14 **	-0.21 **	-0.20 **	-0.19 **	-0.29 **

As becomes clear from the table, the parameter estimates are indeed closely related to the choice of the measure. The estimates for the parameters change in size and sometimes also in sign with a different choice of measure. The tendency is however that at least the signs stay the same for parameters for which at least one of the measures results in a significant result. Hence on a single stock basis significant effects are in a vast majority of cases robust to changes in the measure though they may no longer be statistically significant after this change.

The preliminary conclusions that were drawn for the whole set of underlyings in paragraph 4.2.1 seem to hold partially for all choices of measures. The effects of nearness to strike and a large open interest on the α in the CAPM model do not seem to be consistently strongly negative and would based on especially a $ 0.10 and $ 0.40 measure be assessed neutral. This is not the case for the CAPM β. The effect of strike nearness and large open interest on the β is consistently negative across all measures. The same accounts for the negative effect on the σ in the conditional variance equation which is consistent across all measures.

For the Bank of America and Intel Corp stocks we find that the α_1 estimate is rather robust to the choice of measure. There is some variance in the significance level of the estimate, but the sign stays the same for both regardless of the measure. In the β_1 estimate we observe more variance across the different measures. Both stocks experience sign changes in the estimates with different measures. Where the β_1 estimate becomes positive for Bank of America when taking a small measure, this is exactly reversed for Intel Corp. The σ_1 estimates are consistently negative for the both stocks with the estimates becoming more significant with a larger measure.

5.2 Continuous variable instead of dummy

Also the construction of this variable as a dummy can be discussed. Why should the distance to a strike take the shape of a dummy rather than measuring the distance? When abandoning the specification of dummy, but using a transformation of the actual distance to the nearest strike, more information can be captured in this variable. What this variable should look like then is up for discussion. One possible specification is evaluated in this paragraph.

The formulation of this variable should take the actual distance to the nearest strike into account in determining the variable value. For the ease of using this variable, it is further specified that the variable should always take a value between 0 and 1. 1 would then be a logical value for the case where the day's closing price in the underlying is equal to a strike. 0 is reserved for cases in which the day's closing price lies exactly in the middle between two strikes. For the sake of simplicity the rest of the closing prices are assigned a linear interpolation between these two points. The formulation of the variable called V_t^{strike} is therefore

$$V_t^{strike} = \left|1 - \frac{P_t - K_{l,t}}{(K_{h,t} - K_{l,t})/2}\right|, \tag{5.1}$$

In which P_t is the closing price at day t, $K_{l,t}$ is the nearest on day t existing strike below P_t and $K_{h,t}$ is the nearest strike above P_t.. A graphical representation of this variable's definition is included in Figure 3. This new variable replaces the dummy in the formulations from paragraph 4.2.2 and changes the return and conditional variance equations to equations 5.2 and 5.3.

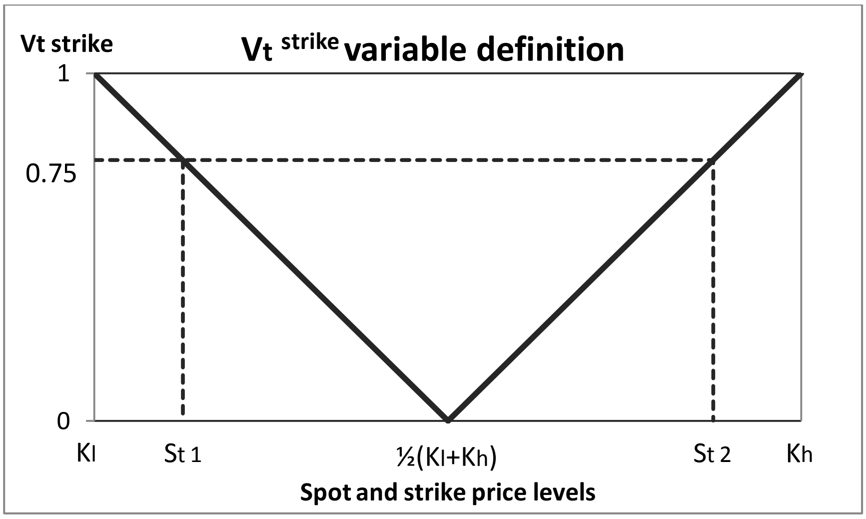

Figure 3: Graphical representation of V_t^{strike} construction. The value of V_t^{strike} is determined on the base of the spot price of the underlying (S_t), the nearest strike on the upside (K_h) and the nearest strike on the downside (K_l). The solid line in the figure represents the value of V_t^{strike} on the vertical axis associated with the value of the spot price relative to the two strikes on the horizontal axis. The dotted line represents the determination of the V_t^{strike} value for two underlying prices: S_{t1} and S_{t2}.

$$Ra_{e,t} = \alpha_0 + \alpha_1 V_{t-1}^{strike} OIR_{t-1}^{strike} + (\beta_0 + \beta_1 V_{t-1}^{strike} OIR_{t-1}^{strike}) Rm_{e,t} \tag{5.2}$$

$$\sigma_t = \sigma_0 + \sigma_1 V_{t-1}^{strike} OIR_{t-1}^{strike} + \sigma_2(\varepsilon_{t-10}^2 + \varepsilon_{t-11}^2 + \varepsilon_{t-12}^2 + \varepsilon_{t-13}^2 + \varepsilon_{t-14}^2) \tag{5.3}$$

The estimates for the α_1, β_1 and σ_1 parameters from this formulation can be compared to the estimates from the original formulation in equation 4.8 and 4.9. These estimates are all visible in Table 13.

Table 13: α_1 β_1 and σ_1 parameter estimates of CAPM model with dummy for nearness to strikes taking option open interest into account and conditional variance compared to estimates incorporating a continuous distance to strike indicator. This table shows the results of estimating the α_1 β_1 and σ_1 parameters as proposed in equation 4.8 incorporating the $\boldsymbol{D_t^{strike}}$ dummy with normal errors and conditional standard deviations as defined in equation 4.9 for 27 stocks. These estimates are flanked by their counterparts resulting from estimating parameters with equations 5.2 and 5.3 using the $\boldsymbol{V_t^{strike}}$ continuous variable. Significance levels of the parameters are 1 % for ** and 5 % for * all measured in difference to zero.

	α1		β1		σ1	
Ticker	Dummy	Cont.	Dummy	Cont.	Dummy	Cont.
MMM	0.091	0.049	-0.031	-0.041	0.007	-0.116 **
AA	-0.003	0.017	0.077	-0.054	-0.145 **	-0.225 **
AXP	-0.054 *	-0.030	-0.028	-0.106 **	-0.043 *	-0.098 **
BAC	-0.045	-0.027	-0.068	-0.382 **	-0.115 **	-0.214 **
BA	0.006	-0.044	0.034	-0.275 **	-0.049	-0.088
CAT	0.012	-0.008	-0.189 **	-0.178 **	-0.037	-0.044
CVX	0.006	0.124 *	0.046	0.029	-0.060	-0.143 **
CSCO	-0.012	0.115	-0.349 **	-0.100	-0.010	-0.159
KO	-0.025	-0.006	0.022	0.011	-0.017	-0.063 **
DD	-0.016	-0.011	0.012	-0.129 **	-0.165 **	-0.224 **
XOM	0.097 *	0.079	-0.005	-0.106	-0.182 **	-0.401 **
GE	0.007	-0.096 **	-0.051	-0.111 **	-0.157 **	-0.205 **
HD	-0.122 *	-0.397 **	0.104	0.136	-0.243 **	-0.169 **
INTC	-0.231 **	-0.256 *	-0.262 **	0.053	-0.130 *	-0.189 **
IBM	0.027	0.026	0.030	0.085 *	-0.086 **	-0.139 **
JNJ	0.000	0.022	-0.029	-0.101 **	-0.085 **	-0.142 **
MCD	-0.042	0.010	0.035	0.011	-0.027	-0.115 **
MRK	-0.030	-0.183 **	-0.252 **	-0.078	0.216 **	0.242 **
MSFT	0.008	0.067	-0.066	0.059	-0.227 **	-0.309 **
PFE	0.077 *	0.010	-0.003	0.001	-0.074 **	-0.097 **
PG	-0.096 **	0.058 *	0.002	-0.041 *	-0.134 **	-0.182 **
TRV	0.019	0.129 **	0.120 *	0.109 *	-0.235 **	-0.265 **
UTX	0.014	0.116 *	-0.050	-0.037	-0.242 **	-0.381 **
UNH	0.001	0.007	-0.181 *	-0.298 **	0.003	-0.378 **
VZ	-0.004	0.029	0.068 *	0.025	-0.146 **	-0.140 **
WMT	-0.061	-0.070	-0.009	0.031	-0.052 *	-0.141 **
DIS	-0.142 **	0.090	-0.059	-0.129 *	-0.202 **	-0.164 **

The parameter estimates for the two different methods of taking strike nearness into account can again be compared to grasp the influence of the method that is applied on the found effects. Clearly there are some substantial changes in the parameter estimates for individual underlyings. We even see the Procter and Gamble (PG) α_1 parameter estimate change from significantly negative to significantly positive. For the β_1 and σ_1 parameter estimates we do not observe such an extremity, however also here the changes in individual parameters are apparent. On a general note, taking an overall stand it seems again as if the effect of strike nearness and a large open interest has a very mixed effect on the α parameter of the CAPM when using the continuous variable approach. This again does not confirm the preliminary conclusion in paragraph 4.2.1 that α is affected negatively by strike nearness and open interest. For the β_1 and σ_1 parameters however we see again a confirmation of our previous conclusions when taking an overall view. The changeover from a dummy to a continuous variable makes no general difference in the negative effect of strike nearness and open interest on the β and σ parameters of the CAPM and conditional variance equation.

For Bank of America the setup with a continuous strike nearness variable results in more pronounced estimates of the option strike nearness effects. The effect on the CAPM α stays insignificant with this different formulation, but the negative β effect increases to a significant level. Also the σ_1 estimate increases in magnitude, though it was already significant in the dummy formulation.

For Intel Corp the presence of an option strike nearness effect on the α is confirmed with this continuous setup. The α_1 estimate increases in magnitude, but becomes slightly less significant indicating larger standard errors for this estimation. The originally found negative β effect vanishes completely by switching over to a continuous nearness to strike indicator. Apparently the observations on this effect are for Intel rather sensitive to changes in the setup and therefore not consistent. The conditional variance parameter σ_1 increases marginally in magnitude and becomes more significantly negative for the continuous case.

6 Conclusion

In this report I investigate the effects of option strike nearness on the behaviour of the underlying stocks. For assessing these effects I pose expanded versions of the CAPM with additional variables indicating option strike nearness and option activity at the nearest strike.

From the different analyses I find that the return effect of trading near an existing option strike alone is mixed for different underlyings. Both significantly positive and negative CAPM α parameters for specific stocks are found. Nearness to an option strike alone also has significant, but mixed effects on the market following behaviour of individual underlying stocks. The size of the unexpected returns shows a consistent decrease under the influence of option strike nearness. When supplementing the nearness to strike variable with the open interest at that particular strike more general effects are found. The effects are generally negative for returns as well as for their sensitivity to the market return or beta and the size of unexpected returns. The negative return effect of the nearness to strike in combination with open interest could not be confirmed in a robustness check. The negative effects on the beta and magnitude of unexpected returns are robust to changes in the appraisal of the nearness to an option strike. These effects also hold when additionally the option gammas of the open interest are taken into account. We therefore conclude that the beta of a stock is generally lowered when it trades near an option strike with a large open interest and unexpected returns decrease in magnitude under these circumstances. This conclusion is in accordance with existing theory on option pinning. The effect on the beta cannot be explained by round number effects because it was not until the open interest at the nearest strike was added to the estimation that the general change in the market beta was found.

7 *Areas for further research*

With the insights I gained during this research I would like to suggest three areas for further research. The results of the formulation incorporating option gammas go against prior expectations. We know of the presence of pinning effects from previous studies by Avellaneda and Lipkin (2003), Jeanin et al. (2008), Ni et al. (2005) and Pearson et al. (2007) and about the role that option gammas play in these effects. Further research into the effect of option strikes on underlying returns with models applying these option gammas would therefore be promising. The theoretical model for delta-hedging effects from Willmot and Schönbucher (2000) can serve as an instrument in this study.

Secondly I suggest research into the practical consequences of the results that are found in this research. The fact that CAPM parameters and variance for individual stocks change under the influence of option strike nearness affects investors' portfolios. Portfolios that are tailored to an investor's specific preferences may become inefficient as a result of the temporary changes in the CAPM parameters. Ghyssels and Jacquier (2005) provide a starting point for research in this direction as they explore the effects of time varying betas of portfolio components on portfolios with a target beta.

Finally it would potentially be possible to set up a profitable trading strategy based on the results in this research. This strategy will be based on the changing market betas of the different constituents of the Dow Jones 30 Index. The changes in the individual stocks' betas under the influence of option nearness might offer opportunities for dispersion trading strategies. A short introduction into such strategies is provided by Avellaneda (2002). I would suggest taking long positions in options on the individual constituents and short index options if market betas are expected to decrease due to option strike nearness. In Avellaneda (2002) a strategy similar to this is documented as a profitable strategy employed by hedge funds.

Appendix 1: Gamma derivation

The derivation of the gamma of a certain option is based on the Black and Scholes formulation for the price of a European call option in combination with that for a European put option paying a continuous stream of dividends:

$$C(S,t) = e^{-q(T-t)}N(d_1)S - N(d_2)Ke^{-r(T-t)} \text{ and } P(S,t) = N(-d_2)Ke^{-r(T-t)} - N(-d_1)Se^{-q(T-t)}$$

$$\text{With } d_1 = \frac{1}{\sigma\sqrt{T-t}}\left(\ln\left(\frac{S}{K}\right) + \left(r - q + \frac{\sigma^2}{2}\right)(T-t)\right) \text{ and } d_2 = d_1 - \sigma\sqrt{T-t}$$

In these formulations, N() is the cumulative distribution of the standard normal density function, S is the spot price of the underlying, K is the strike price of the option, r is the risk-free rate, q is the dividend rate, T is the expiration date, t is the current date and σ is the volatility of the underlying.

By definition the gamma of an option is the second derivative of the option price with respect to the price of the underlying. It appears that the second derivative with respect to the underlying is the same for a put and call option with the same strike, namely:

$$\frac{d^2C}{dS^2} = \frac{d^2P}{dS^2} = \frac{1}{S\sigma\sqrt{T-t}}\frac{dN(d_1)}{dS}$$

In order to calculate this value for every option all parameters that are listed above are to be known. From these parameters, the OptionMetrics database has following information available on every existing option on a daily basis: S, K, T and t. Furthermore, we can approximate r by applying the data from French's personal website. Lacking are however q (the dividend rate) and σ (the volatility of the underlying).

Daily closing bid and ask prices for all options are included in the OptionMetrics database. With these prices, a theoretical closing mid-price can be determined which is together with the already available information enough input for deriving the missing parameters using the Black and Scholes formulations. For deriving q, we start with rewriting the put option price expression and subtract it from the call option (with the same strike) price:

$$P = (1 - N(d_2))Ke^{-r(T-t)} - (1 - N(d_1))Se^{-q(T-t)}$$

$$C - P = e^{-q(T-t)}S - e^{-r(T-t)}K$$

Rewriting this into a formulation for q, this yields:

$$q = -\frac{1}{T-t}\ln\left(\frac{C - P + e^{-r(T-t)}K}{S}\right)$$

This equation is easy to solve analytically.

For determining the market implied value for σ, one is however convicted to using a numerical method. One can choose for either using the call or put option formulation for this purpose. The estimation entails finding the parameter value σ for which the result of the option price formulation is in accordance with the closing mid-price in the market.

At this point, all parameters are either known or estimated, such that the gamma of each option can be calculated with:

$$\frac{d^2C}{dS^2} = \frac{d^2P}{dS^2} = \frac{1}{S\sigma\sqrt{T-t}}\frac{dN(d_1)}{dS}$$

Appendix 2: Likelihood function

The likelihood function that is to be maximized by optimizing parameters is constructed based on a supposed distribution. It is assumed in this study that errors are distributed normally meaning that the likelihood function is to be based on the probability density function of the normal distribution:

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

We are however not looking for the probability of one observation (x) knowing one mean (μ), but for the probability of multiple observations ($Ra_{e,t}$) each with its own estimated mean ($\hat{R}a_{e,t}$). This transforms the probability density function for one observation into one for an entire series of observations:

$$L = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(Ra_{e,t} - \widehat{\hat{R}a}_{e,t})^2}{2\sigma^2}\right)$$

For problems for which T is large, the outcome of likelihood function becomes extremely small, too small for practical numerical optimization. Hence in these cases the log likelihood is used as an optimization target, the log likelihood function becomes:

$$lnL = -\frac{T}{2}\ln(2\pi) - \frac{T}{2}\ln(\sigma^2) - \frac{1}{2}\sum_{t=1}^{T}\left(\frac{(Ra_{e,t} - \hat{R}a_{e,t})^2}{2\sigma^2}\right)$$

Appendix 3: OIR and OIγR summary statistics

Table A: OIR and OIγR summary statistics. In the formulations of Chapter 4, two new variables are introduced. OIR^{strike} and $OI\gamma R^{strike}$ indicate the option open interest at the nearest strike and the option gamma at the nearest strike respectively. Summary statistics on these two variables are listed in the table below. For both variables the mean and standard deviation are included in the first four columns. Also included in column five is the correlation between the two variables as their construction is somewhat similar.

	OIR		OIγR		
Ticker	**Mean**	**St. dev.**	**Mean**	**St. dev.**	**Correl.**
AA	0.89	0.51	0.07	0.10	0.45
AXP	0.76	0.59	0.13	0.19	0.44
BA	0.89	1.16	0.09	0.19	0.63
BAC	1.00	0.76	0.13	0.25	0.35
CAT	0.77	0.43	0.06	0.07	0.40
CSCO	0.78	0.48	0.05	0.07	0.46
CVX	0.75	0.46	0.05	0.08	0.54
DD	0.52	0.33	0.11	0.19	0.38
DIS	1.23	0.81	0.15	0.19	0.56
GE	0.75	0.52	0.09	0.12	0.55
HD	0.72	0.34	0.07	0.07	0.64
IBM	0.98	0.85	0.16	0.17	0.70
INTC	0.66	0.49	0.09	0.11	0.57
JNJ	0.52	0.36	0.09	0.10	0.59
KO	1.18	0.69	0.08	0.13	0.50
MCD	1.23	0.62	0.12	0.14	0.49
MMM	0.91	0.91	0.12	0.21	0.57
MRK	0.81	0.66	0.09	0.12	0.63
MSFT	0.72	0.48	0.10	0.12	0.52
PFE	1.02	0.75	0.17	0.17	0.62
PG	1.15	0.74	0.11	0.13	0.49
TRV	0.53	0.61	0.05	0.07	0.69
UNH	0.68	0.37	0.05	0.08	0.45
UTX	0.62	0.51	0.06	0.15	0.40
VZ	0.95	0.75	0.12	0.14	0.67
WMT	1.11	0.66	0.11	0.12	0.59
XOM	0.75	0.61	0.11	0.16	0.63

References

Avellaneda, M. (2002): Empirical Aspects of Dispersion Trading in U.S. Equity Markets, *Slides from presentation at Le Petit Dejeuner de la Finance, Paris*

Avellaneda, M. and Lipkin, M. (2003): A market-induced mechanism for stock pinning, *Quantitative Finance*, Vol. 3, 417-425

Black, F. and Scholes, M. (1973): The pricing of options and corporate liabilities, *Journal of Political Economy* 81, no. 3, 637-654

Chan, K. (1992): A further analysis of the lead-lag relationship between the cash market and stock index futures market, *The Review of Financial Studies* 5, no. 1, 123-152

Driessen, J., Lin, T., and Van Hemert, O. (2013): How the 52-week high and low affect option-implied volatilities and stock return moments, *Review of Finance* 17, no. 1, 369-401

Fama, E. and French, K. (1992): The cross-section of expected stock returns, *Journal of Financial Economics* 33, 3-56

French, K., (2005): *Data Library*, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Ghyssels, E. and Jacquier, E. (2005): Market Beta Dynamics and Portfolio efficiency, Manuscript, University of North Carolina at Chapel Hill and HEC, University of Montréal

Gulen, H. and Mayhew, S. (1999): Stock index futures trading and volatility in international equity markets, *Journal of Futures Markets* 20, no. 7, 661–685

Harris, L. (1991): Stock price clustering and discreteness, *The Review of Financial Studies* 4, no. 3, 389-415

Ikenberry, D. and Weston, J. (2008): Clustering in US Stock Prices after Decimalisation, *European Financial Management* 14, no. 1, 30-54

Jeannin, M., Iori, G. and Samuel, D. (2008): Modeling stock pinning, *Quantitative Finance*, Vol 8, 823-831

Lundstrum, L. L. and Walker, M. D. (2006): LEAPS introductions and the value of the underlying stocks, *Journal of Financial Intermediation* 15, no. 4, 494–510

Ni, S. X., Pearson, N., and Poteshman, A. (2005): Stock price clustering on option expiration dates, *Journal of Financial Economics* 78, 49–87.

Pearson, N., Poteshman, A. and White, J. (2007): Does Option Trading Have a Pervasive Impact on Underlying Stock Prices?, *AFA 2008 New Orleans Meetings Paper*

Roll, R., Schwartz, E. and Subrahmanyam, A. (2010): O/S, The relative trading activity in options and stock, *Journal of financial economics* 96, 1-17

Schönbucher, P. J. and Wilmott, P. (2000): The feedback effects of hedging in illiquid markets, *SIAM Journal on Applied Mathematics* 61, 232–272.

Sorescu, S. M. (2000): The effect of options on stock prices: 1973 to 1995, *Journal of Finance* 55, 487–514