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Abstract

Many asset pricing models are based on the assumption that information is symmetrically distributed among investors. Various studies, however, provide evidence for heterogenously informed investors. The existence of investors who are provided with superior information entails several implications for the price discovery process of financial assets.

This paper investigates the informational role of put and call options, listed on the CBOE, for their underlying stocks, traded on the NYSE. If informed investors prefer to trade options, rather than stocks, options are assumed to incorporate new information earlier than stocks. While informed investors, in possession of positive news, are expected to prefer trading out-of-the-money call options, investors with negative news about the underlying are expected to trade out-of-the-money put options. Lead-lag regression models are introduced in order to examine the predictive ability of options. In particular, it is tested whether it is possible to predict future stock mid-quotes by extracting the information contained in current option mid-quotes.

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CHAPTER 1

Introduction

One should hardly have to tell academicians that information is a valuable resource: knowledge is power (Stigler 1961).

Standard models in financial literature assume that options are redundant securities and that their value is solely derived from their underlying assets. This assumption is based on the notion that markets are complete, with symmetrically informed, profit maximizing investors, with no transaction costs or other market frictions. However, in reality we do observe several market frictions which entail markets being imperfect. In this paper I take up the observation of incomplete markets and I investigate the effect of asymmetrically informed investors as a source of market friction. Specifically, I provide a comprehensive analysis of the impact of information on stocks and options and how the existence of heterogeneously informed investors affects trading and pricing of these assets. If information is not symmetrically distributed among investors, some investors are better informed than others. Those investors with superior information, the so-called *informed investors*, aspire to fully capitalize on their informational advantage and thereby maximize the profit of their investments. Given that investors face the choice in which market to initiate a trade, they evaluate the trade-off between liquidity, trading costs and leverage that prevail in a particular market. They invest in those assets which enable them to maximize the value of their information and provide them with a maximized expected profit. The question is, which type of assets informed investors eventually trade in order to succeed.

Understanding in which market informed investors prefer to trade constitutes valuable knowledge not only from an academic point of view. Investors who trade in stock and option markets also have a special interest to know where information based trades occur. If the results indicate that options lead stocks, implying that new information is first reflected in the option market, then investors will pay particular attention to any movements of current option prices since they might signal future stock price changes and the respective direction of the movement. They can capitalize on this information and improve their investment decision.

Knowing which securities informed investors trade and which factors influence their trading decision is also relevant for market makers and regulators. If market makers are able to filter out information based orders, they can set quotes appropriately so as to minimize risks arising from adverse selection. Regulators, on the other hand, would be able to properly design a legal framework that prevents illegal insider trading.

The key hypothesis of this paper is that the preferred trading venue for informed investors is the option market. Even though trading volume of options is lower compared to stocks, making it more difficult for informed investors to hide, one can assume that, due to the increased leverage provided by options, they prefer to trade in the option market. Information based trading in option markets involves that information is first incorporated in options. Thus, options reveal additional information not yet revealed by underlying stocks. Stocks will eventually react to the information contained in options, but with a lag. This interrelation between options and stocks can be analyzed with lead-lag regressions, whereby options are assumed to lead stocks. The option lead is expected to be more pronounced for options with a lower level of moneyness, given that the lower the moneyness, the higher is the leverage effect. The second hypothesis to be tested in this analysis therefore concerns option moneyness. It is hypothesized that moneyness is significant in explaining future stock price movements and that the degree of significance decreases with the level of moneyness.

The main results of the empirical tests indicate that option mid-quotes appear to lead stock mid-quotes for at least one trading day. However, this lead is not unidirectional. It can be shown that also stocks lead options. Thus, the interrelationship between stock and option markets is characterized by mutal learning.

The remainder of this paper is organized as follows. In Chapter 2 the relevant prior research on information based trading in option markets and the implications on underlying stocks is summarized and discussed. Chapter 3 provides an in-depth analysis of the role of information in financial markets and how asset pricing models change if information is assumed to be asymmetrically distributed among investors. In Chapter 4 the various trading mechanisms, which are currently available, are described and compared. Chapter 5 is dedicated to examining the incentive for informed investors to either trade options or stocks. The determinants, which might induce investors to trade in the option market are presented in Chapter 6. If investors choose to trade in the option market, instead of trading stocks, this entails several consequences for the market and its participants. These ramifications are analyzed in Chapter 7. The data applied for testing the hypotheses are presented in Chapter 8 and the results of the empirical analysis in Chapter 9. The last chapter, Chapter 10, summarizes and concludes this study.

CHAPTER 2

Literature Review

'The investment environment resembles a jungle – a dangerous and exotic place' (Bodie et al. 2008). Investors commit their money and capital to this environment because they expect to obtain additional profit or income and because they are aware of the necessity to balance their current needs with requirements that arise in the future (Bodie et al. 2008). Malkiel 1999 describes the fascination of investing as a gamble whose success depends on the investors´ ability to predict future events. Success is thereby determined by the discrepancy between predicted and realized outcomes of the pursued investment strategy. But, what happens if investors don´t base their investment choice on mere predictions, but on private information about the future value of the investment? Being aware of future movements in the investment environment, which asset should those investors with superior information trade? The very basic assumption developed in this paper is that rational investors initiate a trade in the asset that, by capitalizing on their informational advantage, enables them to maximize their expected profit. When investors can only choose between trading stocks and options, it is expected in this paper that investors can achieve their aim with options.

This paper is based on one of the most fundamental questions in asset pricing: how and when is information incorporated into asset prices. The purpose of this study is to analyze the role of information in the option market and what effect information based trading has on the underlying equity market. Specifically, the informational role of option trades on the Chicago Board of Options Exchange for their underlying stocks listed on the New York Stock Exchange is investigated. It is examined whether informed investors prefer to trade options rather than stocks and whether new information is first incorporated in options. There is a wide range of literature which examines the informational role of option markets and whether various option measures predict activities in equity markets. Black 1975 was the first to claim that due to the higher leverage provided by options, informed investors might favour to trade options rather than the underlying stock. The empirical evidence on information based trading in stock and option markets and the predictive ability of options, however, is mixed. While some studies arrive at the conclusion that informed investors prefer to trade options by providing evidence for an informational lead of option markets, others predict that the underlying equity market is the preferred trading venue for investors with superior information.

One strand of literature investigates the predictive ability of option prices. Manaster and Richard J. Rendleman 1982 for instance, investigate the informational role of call option prices. Applying a modification of the Black-Scholes model which takes into account dividend payments, they determine implied stock prices and implied standard deviations. By comparing implied with observed stock prices, they find evidence that implied stock prices of listed call options contain information not yet fully reflected in observed stock prices. Specifically, they show that closing option prices reflect information which is not incorporated in underlying equity prices for a period of 24 hours. Stephan and Whaley 1990 find evidence for exactly the opposite. They analyze the relationship between option prices and underlying equity prices using intraday data. They detect that equity prices lead option prices. Chan and Chung 1993 use a nonlinear multivariate regression model in order to replicate the study of Stephan and Whaley (1990). They demonstrate that the results of Stephan and Whaley (1990) can be considered spurious due to infrequent trading of options. Instead, Chan et al. (1993) find that by applying average bid-ask quotes in lieu of transaction prices, stocks no longer appear to lead options.

Other studies use option trading volume instead of prices to analyze information based trading. They examine the predictive ability of option trading volume for stock trading volume.[1] Using daily closing data Anthony 1988 is able to show that option trading volume leads stock trading volume. Vijh 1988 contests this finding and claims that the result is biased because daily prices instead of intraday data are used. Easley, O'Hara, and Srinivas 1998 investigate the informational content of option trading volume and its predictive ability for future stock price movements. They aggregate option trades into trades being initiated due to positive news and negative news. They show that certain types of option trades are information based and contain information for future stock price movements. Chan, Chung, and Fong 2002 analyze the predictive ability of stock and option quote revisions as well as stock and option net trading volume. Using intraday data for NYSE stocks and options listed on the CBOE they find that, while stock net trading volume has significant predictive ability for both, stock and option quote revision, no such predictability can be identified for option net trading volume. However,

[1]For instance Cao, Griffin, and Chen 2005, Pan and Poteshman 2006

they are able to show that both, option quote revision and stock quote revision have predictive ability for one another.

In a new research stream studies are based on measures being derived from option pricing formulas. The majority of these studies focuses on implied volatilities. They indicate that volatility skews and volatility spreads, calculated by inverting particular option pricing formulas, reveal information about future stock price movements[2].

With my analysis I aspire to shed light on the informational role of option markets and resolve at least some of the ongoing controversy. This study contributes to the existing literature by using very recent data and by employing a model which, to the best of my knowledge, in that particular form has not yet been tested. However, before the empirical model and results are presented and discussed, it is important to understand the theoretical background upon which this study is based. To begin with, Chapter 3 describes the role information play in financial markets.

[2] For example David Weinbaum 2010, Zhang, Zhao, and Xing 2010, and Jin, Livnat, and Zhang 2012

CHAPTER 3

The role of information in financial markets

Financial markets are the venue where financial assets are traded. The role of financial markets is that of a central planner which enables an efficient allocation of capital to real assets (Bodie et al. 2008). One crucial function of financial markets is to allocate funds among investors by transmitting capital from agents with excess savings to agents with negative savings. In doing so, investors enable an intertemporal transfer of funds and the smoothing of consumption over time. In times of high earnings, investors can invest excess funds and acquire financial assets and in times of low earnings they can sell the assets providing them with additional funds for consumption needs. Another crucial function of financial markets is the production of information, which is then reflected in prices (Marini 2005). Operating in financial markets permits agents to share and hedge risks either by the means of buying insurance or by exploiting the correlation among securities. Rational individuals use the information set they are provided with in order to make appropriate trading and investment decisions. Thereby they influence and determine security prices. In this environment information serves as a link between investors and prices (Bodie et al. 2008). In order to analyze the price formation of security prices, it is crucial to understand how and to what extent investors incorporate their information in investment decisions. The focus of this paper is to determine the role of financial markets in producing information and how this translates into the price discovery process of stock and option prices. In order to understand the importance of information in financial markets and the theoretical background upon which the hypotheses, developed in this paper, are built, the first part is dedicated to examining the economic concept of information in more detail.

The role of financial markets as distributors of capital is based on the assumption that markets are efficient and that security prices fully reflect all available information. In fact, most economic models used to determine the price of a certain security rest upon the simplifying assumption of perfect capital markets. According to Fama and Miller 1972 a perfect capital market is a frictionless and competitive market, where all investors possess perfect information and have homogenous expectations about the future price of an asset. There are no transaction costs and buyers and sellers of securities are competitive price takers, implying that no individual investor can alter the market price with his individual investment decision (ibid.). Provided that markets are efficient in the sense of perfect capital markets, then prices must reflect all available information and investors have no inducement to invest time and money to gather additional information.

If prices fully reflect[1] all available information and if trading occurs in a frictionless environment, then, according to the efficient market hypothesis (Fama 1970), price movements do not occur in the wake of the trading process but follow a random walk. Prices only change if new, unexpected information is released. The notion of *all information in perfect capital markets* refers to the assumption that all investors know the distribution of expected future returns as well as the correlation matrix. Reality, though, reveals a different story: share prices do not follow a random walk and trading does not take place in perfect capital markets (Schwartz and Francioni 2004). The most commonly used model in modern portfolio theory to determine required rates of return and prices of securities, the *Capital Asset Pricing Model* (CAPM)[2], is designed upon the assumption of perfect capital markets. Even though it is commonly agreed upon that in the real world, perfect capital markets do not exist (Fama and Miller 1972), models like the CAPM are commonly used in practice because they provide a convenient way to understand how prices evolve (Schwartz and Francioni 2004). Nevertheless, these models only permit to formulate approximations to real world phenomena (Fama and Miller 1972).

One reason why the assumption of perfect capital markets is not suppoerted by real world observations might arise from an asymmetric distribution of information. This notion seems rather realistic given that an enormous amount of raw information is available in the market which has to be gathered, processed and analyzed in order to be of avail. In case the production of information requires a certain amount of money and time, it does not turn out

[1]The term ´fully reflect´ is very generally stated and has to be defined more specifically in order to be empirically testable. Fama 1970 defines information as being ´fully reflected´ if all available information is utilized to determine the conditional expected value of returns and prices.

[2]The CAPM was separately developed by three economists: Sharpe 1964, Lintner 1965a and Lintner 1965b, and Mossin 1966

profitable for everyone to invest in information gathering. Only those investors who earn a net profit from producing information will do so (Stigler 1961). Kim and Verrecchia 1991 show that the extent to which investors engage in information gathering depends on the marginal costs of acquiring information and the individual risk tolerance of investors. Investors with high risk tolerance or lower information gathering costs are more likely to invest in information acquisition. The remaining investors will use the information contained in security prices. In that sense, investors face a trade-off between investing in information production and inferring information from security prices. Markets are deemed to be in equilibrium with respect to the information production process if investors for whom the benefits of gathering information exceed the costs, invest in information production, while all other investors infer information from observed prices (Schwartz and Francioni 2004).

Thus, with respect to the level of information, investors can be subdivided into two groups: *informed investors* and *uniformed investors*. Whether investors are informed or uniformed depends on the information set they are provided with. Information itself can be classified into *public*, *private* or *inside information*, contingent on whether there exist any restrictions on accessing the information. Public information refers to information which is widely dispersed in the market and available to all individuals. Private information refers to information possessed by individuals as a result of their own information analysis and formation of expectations. Inside information, by contrast, applies to information owned by individuals who have a special relationship to the information source (Schwartz and Francioni 2004). Trading on the basis of inside information does in principle not constitute an illegal action. The U.S. Securities and Exchange Commission (*http://www.sec.gov/rules/final/33-7881.htm*) distinguishes between legal and illegal insider trading. Insider trading is legal when corporate insiders trade stocks of their own corporation and report this trade to the SEC. Illegal insider trading by contrast, refers to the trading of securities on the basis of nonpublic information about the security, which includes the breach of a fiduciary duty[3].

Depending on what type of information investors have, they form different expectations about the future value of assets and therefore make different investment decisions. Informed investors, in addition to having access to public information, possess private and/or inside information. They trade on the basis of an information set not available to all market participants. Uniformed investors, so-called *liquidity traders*, on the other hand, are only provided with public information. They trade for reasons not directly dependent on future payoffs of securities (Admati and Pfleiderer 1988).

Security prices play a crucial role in the relationship between informed

[3]Section 10(b) of the Act (15 U.S.C. 78j)

and uninformed investors because they act as a transfer vehicle. As such, prices aggregate diverse bits of information and convey information from informed to uninformed investors. Given that markets are not perfect and investors have heterogeneous expectations about the future value of an asset, prices are determined as a weighted average of the different expectations of investors about future developments (Schwartz and Francioni 2004). Uninformed investors have no information other than that contained in security prices and therefore, if they are rational they base their investment decision on the information they can extract from prices. It is of particular interest to the uninformed investors that prices are efficient in the sense that they reflect all available information. The fundamental idea of prices aggregating and communicating information is based on Hayek 1945, who claimed that in order to understand prices, one has to take into account their role as a vehicle of efficient information transmission.

Whether fully informative prices can be observed in reality and how to test for efficiency in security prices, is described in the following subsections.

3.1 Informational efficiency of markets

Prices are presumed to be informationally efficient if they exhibit the following characteristics (Schwartz and Francioni 2004):

- They appropriately reflect all currently available information as well as the underlying value of securities.
- An optimal amount of resources is allocated to the production of information.
- They transfer information from informed to uninformed investors.
- They guarantee dynamic efficiency with respect to how new information is distributed and incorporated.

According to Fama 1970 markets are efficient if prices always fully reflect all available information. If future prices do not evolve randomly but are serially autocorrelated and therefore predictable, markets are not informationally efficient and prices do not follow a random walk. Predictable price changes indicate that current prices do not properly reflect expectations and information of all market participants (Campbell, Lo, and MacKinlay 1997). Investors are provided with different information sets and therefore have different expectations. Whether investors are able to make excess returns by making use of their respective information can be examined by testing the efficiency of markets. The so-called *Efficient Market Hypothesis* (EMH) tests the null hypothesis that markets are efficient. The EMH analyzes three forms of efficiency: weak form efficiency, semi-strong form efficiency and strong form efficiency. Markets are assumed to be weak form efficient, if no excess returns can be realized by analyzing past prices (or historical returns). Semi-strong efficiency implies that no excess returns can be realized from the information that is incorporated in public information, including the information reflected in past prices. Markets are strong form efficient if prices reflect all information, including public and inside information (Schwartz and Francioni 2004). If markets are not efficient, informed investors can profit from their informational advantage at the expense of uninformed investors and outperform the market.

3.1.1 Weak form efficiency

In markets that are weak form efficient, previous price movements of securities and trading volume comprise no informational content. Thus, technical analysis of historical data is without merit to investors. If the expected value of a stock´s future price movement is zero and therefore unpredictable, and if successive price changes are independently and identically distributed, prices are expected to follow a random walk (Kendall and Hill 1953). The argument behind the random walk assumption is that due to unpredictable and random price changes future directions and steps cannot be forecasted on the basis of past observations. For stocks this means that short-run price changes cannot be predicted (Malkiel 1999). This assumption implies that current prices are an unbiased estimator of future prices and prices change only in response to the arrival of new information. Thus, prices which follow a random walk are supposed to be efficient (Bodie et al. 2008).

One way to test for weak form efficiency in markets is by examining serial correlation of stock market returns (Fama 1970). If returns appear to be serially correlated, prices do not follow a random walk and hence, markets are not a frictionless, informational efficient trading environment (Schwartz and Francioni 2004). Fama 1970 analyzes serial correlations between successive log price changes for each of the 30 stocks listed on the Dow Jones Industrial Average between 1957 and 1962. Applying time intervals of one, four, nine and sixteen days, Fama does not find evidence for linear lagged dependence of price changes, implying a serial correlation coefficient close to zero. The test for weak form market efficiency was repeated many times by researches. The absence of serial correlation between price changes and therefore the weak form efficiency of prices, is now commonly confirmed (Spremann 2007).

3.1.2 Semi-strong form efficiency

Tests for semi-strong form efficiency investigate how fast prices incorporate new information. If markets are semi-strong efficient, all publicly available information is already reflected in prices. The information set comprises, in addition to past prices, fundamental data of the firm (Bodie et al. 2008).

Semi-strong efficiency is typically tested using event studies. These studies are designed to test whether abnormal returns[4] can be realized before and/or after certain events occur. Events hereby refer to news announcements like earnings or dividend announcements, stock splits, announcements of mergers or acquisitions (Schwartz and Francioni 2004, Fama 1970). Semi-strong form efficiency implies that the incident causing prices to move, is the announcement of the event and not the event itself, because new information is incorporated immediately after becoming public. At the time when the actual event takes place, prices already reflect the relevant information. Hence, if investors invest in the analysis of fundamental data, they won´t be rewarded with the realization of abnormal returns.

The first paper testing for semi-strong form efficiency was published in 1969 by Fama et al. 1969. They investigate the effect of stock splits on security returns. Their dataset encompasses all 940 stock splits which were listed on the New York Stock Exchange (NYSE) between 1927 and 1959. Given their empirical results, they conclude that the stock market is efficient, at least to the extent that prices reflect the information inherent in stock splits.

In the economic literature some anomalies that contradict with the semi-strong form efficiency are documented. One of the most important anomalies is the so-called *size effect* (Bodie et al. 2008). The size effect, originally observed by Banz 1981, shows that average risk-adjusted returns for stocks of small firms are, on average, higher than those of large firms[5]. Evidence of the size effect demonstrates that investing in fundamental analysis can be beneficial for investors (Bodie et al. 2008). Other such market anomalies include the *book-to-market effect* (Fama and French 1992) and the *price/earnings ratio effect* (Basu 1977). Fama and French 1996 propose a three factor model, including asset betas, size and book-to-market ratios to explain cross-sectional variations in asset returns. They find that the size and book-to-market factors contribute significantly to the explanatory power of the model.

3.1.3 Strong form efficiency

The strong form efficiency refers to prices reflecting all information available in the market including public as well as private information. Many studies[6]

[4] Abnormal returns are calculated as the difference between expected returns and actual returns.

[5] Acharya and Pedersen 2005 estimate a liquidity adjusted capital asset pricing model and their results suggest that liquidity risk can explain the small firm effect.

[6] Evidence that insider trading results in risk-adjusted returns that exceed benchmark returns is, for instance, provided in Jaffe 1974a and Jaffe 1974b, Seyhun 1986, and Meulbroek 1992. Niederhoffer and Osborne 1966 find evidence that specialists on the NYSE use their

provide evidence that the hypothesis of strong form efficient markets is violated. Thus, insiders are able to realize abnormal returns when trading on private information (Schwartz and Francioni 2004).

In order to establish a fair trading environment, the Securities and Exchange Commission (SEC) regulates insider trading since 1934[7]. These regulations are not commonly perceived as being beneficial for trading. Proponents of the regulation argue that insider trading deters the trading environment because it leads to a loss of liquidity in the market, it sets wrong managerial incentives and it promotes a perception of unfair and untrustworthy capital markets. In turn, opponents of the regulation argue that insider trading is beneficial because it results in more informationally efficient security prices (Fishman and Hagerty 1992). Fishman and Hagerty, however, show that, even though with insider trading the aggregate amount of information available in the market is increased, under certain circumstances insider trading can lead to less efficient stock prices.

On the basis of the discussion provided above it can be concluded that capital markets are not perfect and that prices are not informationally efficient, at least not in the semi-strong and strong form. Therefore, it is necessary to incorporate the existence of asymmetric information when calculating equilibrium prices of securities. In the following section it is demonstrated how equilibrium prices in imperfect capital markets with asymmetric information can be determined and how the existence of asymmetric information is internalized in the price formation process[8].

3.2 The impact of information on the financial market equilibrium

It is widely acknowledged that the two most important motives for trade are liquidity and information (Admati and Pfleiderer 1988). If capital markets are assumed to be perfect, information is homogeneously distributed among all investors and information based trades do not occur. This implies that information is an exogenous variable to the trading process. Investors don´t use the knowledge of the equilibrium price to update their beliefs and modify their investment decision. The equilibrium price in perfect capital markets is solely determined by the intersection of investors' aggregate supply and demand function. This is the so-called *Walrasian equilibrium* in which prices only serve as a mechanism to allocate scarce resources (Jong and Rindi 2009).

superior information about unfilled limit orders to achieve profits.

[7] *http://www.sec.gov/rules/final/33-7881.htm*, According to SEC rule 10b-5 (§240.10b-5) it is unlawful for insiders to trade on nonpublic information without first publishing the information.

[8] The following section is mainly based on Jong and Rindi 2009

However, if information is asymmetrically distributed among investors, some investors have better information than others. As a consequence, prices act as a vehicle of information. Hence, information is perceived endogenous to the decision making process. In order to implement an optimal trading decision, rational investors consider not only their own information set but also the information contained in asset prices. Rational uninformed, or less informed, investors extract information revealed by observed prices in order to form expectations and alter their investment decisions accordingly. Thus, prices perform two functions: they allocate scarce resources and they serve as an information signal. If the additional role of prices as an information signal is accounted for, the Walrasian equilibrium no longer holds. The new equilibrium is called *rational expectation equilibrium* and refers to a situation where the equilibrium price represents the price at which investors are not provided with any additional incentive to trade (Jong and Rindi 2009). The idea of a rational expectation equilibrium is based on four seminal papers by Grossman[9], which are all linked by the very idea that, if information is asymmetrically distributed among investors, the trading activity reveals information.

3.2.1 Equilibrium with symmetric information

In the case of symmetric information, all market participants are provided with the same information set, which is applied to form homogenous expectations about the future value of the asset. In perfect capital markets equilibrium is achieved when supply and demand of investors are equal. In the literature this is referred to as Walrasian equilibrium. The optimal amount investors demand is determined by maximizing their expected wealth. The only factor causing a different allocation of funds between risk-free and risky assets across investors is the investor specific degree of risk aversion (ibid.).

How the equilibrium price can be found if information is assumed to be symmetrically distributed is demonstrated below. Given that all investors agree upon the distribution of the risky asset, the expected future value $\tilde{F}$ is assumed by all investors to be (Jong and Rindi 2009):

$$\begin{gathered} \tilde{F} = \tilde{d} + \tilde{\varepsilon} \\ \tilde{d} \sim N(E[\tilde{d}], \sigma_d^2) \\ \tilde{\varepsilon} \sim N(0, \sigma_\varepsilon^2) \end{gathered} \tag{3.1}$$

$\tilde{d}$ and $\tilde{\varepsilon}$ are assumed to be independent of each other with $\tilde{\varepsilon}$ being a

[9] Grossman 1977, Grossman 1978, Grossman 1981a, and Grossman and Stiglitz 1980

White Noise disturbance term which can be interpreted as a random public news component. Only the informed investors observe the realization $\tilde{d}$. In a symmetric equilibrium two scenarios can occur (Jong and Rindi 2009):

1. All investors are perfectly informed and observe $\tilde{d}$, resulting in a distribution of $\tilde{F}$ given by:
$$\tilde{F} \sim N(\tilde{d}, \sigma_\varepsilon^2)$$

2. Nobody has any information regarding the future value of the asset apart from the observed market price. In this case the distribution is given by:
$$\tilde{F} \sim N(E[\tilde{d}], \sigma_d^2 + \sigma_\varepsilon^2)$$

Investors choose their demand function so as to maximize their expected utility from wealth $E[U(\tilde{w})]$. Investors can allocate their disposable monetary resources between risky and risk-free assets. This results in the following optimization function for the individual investor[10]:

$$Max_x E[U(\tilde{w})]$$

with
$$\tilde{w} = X \cdot \tilde{F} + (I_f - X \cdot p)(1 + r_f) \tag{3.2}$$

where X determines the investor´s demand for the risky asset and p its respective price. I_f represents the initial endowment of the risk-free asset whose price is normalized to 1. At the end of the period the risky asset has an expected value of $\tilde{F}$ and the risk-free asset has a certain value of $(1 + r_f)$. Since the expected value of the risky asset is a normal random variable, so is the final wealth $\tilde{w}$.

After taking the first derivative the following result is obtained:

$$E[u'(\tilde{w})(\tilde{F} - p(1 + r_f))] = 0 \tag{3.3}$$

Which can be written as:

$$E[u'(\tilde{w})]E[\tilde{F} - p(1 + r_f)] + Cov[u'(\tilde{w}), (\tilde{F} - p(1 + r_f))] = 0 \tag{3.4}$$

Applying Stein´s formula to the covariance term and substituting $\tilde{w} = X \cdot \tilde{F} + (I_f - X \cdot p)(I + r_f)$ we get

$$E[u'(\tilde{w})]E[(\tilde{F} - p(1 + r_f)] + E[u''(\tilde{w})]X \cdot Var(\tilde{F}) = 0 \tag{3.5}$$

[10] For the purpose of simplicity, investors' initial endowment of the risky asset is disregarded.

This equation can be rearranged in order to get the equilibrium price:

$$p = \frac{1}{1+r_f}[E(\tilde{F}) + \frac{E[u''(\tilde{w})]}{E[u'(\tilde{w})]}X \cdot Var(\tilde{F})] \tag{3.6}$$

The term $\frac{E[u''(\tilde{w})]}{E[u'(\tilde{w})]}$ determines the degree of risk aversion (A) of investors. If we assume investors´ utility functions are characterized by constant absolute risk aversion (CARA) the utility of wealth is equal to:

$$u(\tilde{w}) = -e^{(-A \cdot \tilde{w})}$$

And the price equation simplifies to:

$$p = \frac{1}{1+r_f}[E(\tilde{F}) - A \cdot X \cdot Var(\tilde{F})] \tag{3.7}$$

Where A represents aggregate risk aversion with $A = \sum_{i=1}^{N} a_i$ being the sum of individual investors' risk aversion. X defines aggregate demand with $X = \sum_{i=1}^{N} x_i$ which is equal to aggregate supply Z.

Investors´ individual demand finally becomes:

$$x_i = \frac{E(\tilde{F}) - p(1+r_f)}{Var(\tilde{F}) \cdot a_i} \tag{3.8}$$

The price equation shows that in perfect capital markets the equilibrium price is equal to the expected value of the risky asset minus a discount for risk (Jong and Rindi 2009). The individual demand for risky assets in a symmetric equilibrium only differs across investors according to investors´ individual degree of risk aversion.

If the distribution of $\tilde{F}$ is accounted for, the price equation and the individual demand function in the case with all investors being perfectly informed can be rewritten as:

$$p = \frac{1}{1+r_f}[\tilde{d} - \frac{1}{\sum_{i=1}^{N} \frac{1}{a_i}}(\sigma_\varepsilon^2)X] \tag{3.9}$$

$$x_i = \frac{\tilde{d} - p(1+r_f)}{(\sigma_\varepsilon^2) \cdot a_i} \tag{3.10}$$

If no investor has any additional information apart from the market price, the price equation and the individual demand function can be rewritten as:

$$p = \frac{1}{1+r_f}[E(\tilde{d}) - \frac{1}{\sum_{i=1}^{N}\frac{1}{a_i}}(\sigma_d^2 + \sigma_\varepsilon^2)X] \tag{3.11}$$

$$x_i = \frac{E(\tilde{d}) - p(1+r_f)}{(\sigma_d^2 + \sigma_\varepsilon^2)a_i} \tag{3.12}$$

Comparing the above results illustrates that in the case with information, the risk component is reduced. Even if it is assumed that the expected value is very close to the signal, in the case with no information, the remaining uncertainty leads to higher prices. Furthermore, the results show that investors will exhibit positive demand and thus buy the asset if their expectation about the future value of the asset or the signal exceeds the compounded price. This is the case if the information consists of good news about the asset, implying that the asset is currently undervalued by the market. By contrast, investors will sell the asset if the expected value or the signal is lower than the compounded price. The only factor governing different demand functions among investors is investors´ diverging degree of risk aversion.

3.2.2 Equilibrium with asymmetric information

In imperfect capital markets with asymmetrically distributed information, in general two equilibrium scenarios exist (Jong and Rindi 2009):

1. Naive expectations equilibrium
2. Rational expectations equilibrium

In both scenarios informed investors α as well as uninformed investors $(1-\alpha)$ trade in the market. At the beginning of the trading period investors agree upon the distribution of the risky asset with $\tilde{F} \sim N(E[\tilde{F}], Var(\tilde{F}))$. Informed investors, however, receive a signal $\tilde{S}$ about the future value of the asset. Thus, informed investors not only possess public, but also private information. They employ the following demand function:

$$x_i = \frac{\tilde{d} - p(1+r_f)}{(\sigma_\varepsilon^2)a_i} \tag{3.13}$$

Uninformed investors, by contrast, do not receive any private signal and thus base their demand function only on the original assumed distribution of $\tilde{F}$ which results in:

$$x_i = \frac{E(\tilde{d}) - p(1+r_f)}{(\sigma_d^2 + \sigma_\varepsilon^2)a_i} \tag{3.14}$$

Assuming that the aggregate demand of informed and uniformed investors equals aggregate supply Z, the equilibrium price in a naive expectations equilibrium is given by:

$$\alpha(\frac{\tilde{d}-p(1+r_f)}{(\sigma_\varepsilon^2)a_i})+(1-\alpha)\frac{E(\tilde{d})-p(1+r_f)}{(\sigma_d^2+\sigma_\varepsilon^2)a_i}=Z \tag{3.15}$$

$$p=\frac{1}{1+r_f}[\frac{\alpha\cdot\tilde{d}}{(\sigma_\varepsilon^2)a_i}+\frac{(1-\alpha)E(\tilde{d})}{(\sigma_d^2+\sigma_\varepsilon^2)a_i}-Z]\frac{1}{[\frac{\alpha}{(\sigma_\varepsilon^2)a_i}+\frac{(1-\alpha)}{(\sigma_d^2+\sigma_\varepsilon^2)a_i}]}$$

The above equation demonstrates that the equilibrium price is determined as a weighted average of the respective expectations of informed and uninformed investors and of the aggregate supply function. Investors are supposed to be naive if they do not extract any information from the equilibrium price in order to update their expectations of $\tilde{F}$. If uninformed investors do consider the information contained in security prices in order to update their expectations, equilibrium prices are formed by the means of a rational expectations equilibrium (Jong and Rindi 2009).

A market in which information is dispersed among investors might fail its function of allocating resources efficiently, resulting in a misallocation of resources, relative to markets with symmetrically distributed information. In order to achieve an equilibrium with efficient allocation, the transfer of information from investors with superior information to uninformed, or less informed, investors is essential (Grossman 1981a).

In a rational expectations equilibrium informed investors base their demand function solely on the signal they receive. This information revealed by the signal is assumed to be sufficient implying that no additional information is contained in security prices. Uninformed investors, taking into account that prices contain information, condition their investment decision on the prices they observe. Moreover, investors do factor in that their investment decision has an impact on prices and that others do the same. Thus, the behavior of investors in a rational expectations equilibrium is governed by investors' awareness that prices of securities reveal information and by strategic considerations. The resulting demand functions for an uninformed investor (x_{Ui}) and an informed investor (x_{Ii}) can be derived as (Jong and Rindi 2009):

$$x_{Ui}=\frac{E[\tilde{F}|p]-p(1+r_f)}{a_i\cdot Var(\tilde{F}|p)} \tag{3.16}$$

$$x_{Ii}=\frac{E[\tilde{F}|S]-p(1+r_f)}{a_i\cdot Var(\tilde{F}|S)} \tag{3.17}$$

Uninformed investors form a conjecture about the equilibrium price. They expect the price to be a linear function of informed investors´ signal and of uninformed investors´ demand. They then use this conjecture to estimate $E[\tilde{F}|p]$ and $Var(\tilde{F}|p)$. If all available information is reflected in the market price, then the rational expectation equilibrium is fully revealing. In a so-called *full communication equilibrium* the market price is strong form efficient and hence all the information conveyed by the signal is fully reflected in the market price resulting in $E[\tilde{F}|p] = E[\tilde{F}|S]$. Thus, a full communication equilibrium is the same as a Walrasian equilibrium with all investors being perfectly informed. This leads to the following equilibrium demand and price functions:

$$x_{Ui} = x_{Ii} = \frac{\tilde{d} - p(1 + r_f)}{(\sigma_\varepsilon^2)a_i} \tag{3.18}$$

$$p = \frac{1}{1 + r_f}[\tilde{d} - \frac{1}{\sum_{i=1}^{N} \frac{1}{a_i}}(\sigma_\varepsilon^2)Z] \tag{3.19}$$

The price function illustrates that prices are equal to the expected payoff less a discount for aggregate risk (Jong and Rindi 2009). If prices do evolve according to this function, then prices are strong form efficient as they perfectly reflect the insiders´ signal as well as all public information. Uninformed investors then can perfectly infer all information from market prices. This equilibrium results in an allocation which is the same as if all investors have access to all information (Grossman 1981a). The price formation process postulated by a rational expectations equilibrium can be modeled by a mechanism where agents submit their demand functions to a centralized auctioneer who sets the market price according to the observed order flow, like in the model proposed by Kyle 1985.

Grossman and Stiglitz 1980 contest the rational expectation model because it implicitly assumes that uninformed investors can perfectly extract information from prices without incurring any costs. Hence, there is no incentive for investors to invest in the information gathering process if it is possible to infer all information from market prices. This demonstrates that under certain conditions it is impossible for markets to be strong form efficient and to fully reflect all available information[11]. Grossman and Stiglitz (1980) therefore desgin a model which is not fully revealing. They assume that the supply function is not fixed but additionally comprises a random component. The supply function in their model is given by:

[11] It is therefore, under certain circumstances, impossible for prices to be strong form efficient.

$$\tilde{Z} = Z + \tilde{\varphi}$$
$$\tilde{\varphi} \sim N(0, \sigma_{\varphi}^2) \quad (3.20)$$

The noise component in the supply function can be motivated by the existence of investors who only trade for liquidity reasons. In this model the equilibrium is not fully but only partially revealing, because uninformed investors cannot perfectly extract all information from market prices. Thus, a rational expectations equilibrium can be of two different forms, depending on the amount of information revealed by prices: fully revealing and partially revealing. If an equilibrium is fully revealing, prices efficiently reflect all available information and therefore are strong form efficient. If prices do not reflect all available information, then they are only partially revealing and are assumed to be semi-strong efficient (Vives 2008). Grossman 1977 argues that, when noise acts as an additional determinant of prices, in an equilibrium where only a spot market exists, informed and uniformed investors hold different beliefs about the future price of assets. If a futures market is introduced, informed traders can make profits from trading on their private information in the futures market and uniformed traders can use this information incorporated in futures prices (ibid.).

What this section is supposed to demonstrate is that investors use information about the future value of assets to determine their investment decision and that information is able to reduce risk. If only a certain proportion of investors is informed and base their investment decision on their private signal, then current prices can act as a vehicle of information. In the case of asymmetric information, investors´ demand functions are not only contingent on their individual degree of risk aversion, but also on the set of information available to them. The market price is more informative the more investors there are in the market place. If uninformed investors use market prices to extract information, depends on whether the trading environment is characterized by a rational expectations equilibrium or not. Hence, prices perform two roles: on the one hand they clear the market as in the Walrasian equilibrium by efficiently allocating scarce resources and on the other hand they transfer information to less informed investors. In the empirical literature there are several studies estimating the effect of information on asset prices. For instance, Easley, Hvidkjaer, and O'Hara 2002 show that stocks which exhibit a higher probability of information based trading provide investors with higher expected returns. This implies that information risk is a priced factor and can explain some of the cross-sectional variation in stock returns. Other studies investigating the effect of information on asset prices and returns include Easley and O'Hara 2004, Admati 1985 and Wang 1993. Each of these studies shows that asymmetric information can affect asset prices.

The way orders are processed and how the existence of potentially informed investors is handled depends on the design of the trading environment, the market microstructure. The market microstructure determines the mechanism behind the trading process, which affects the price determination. In the next chapter an in-depth description of the different trading mechanisms and the effect on the evolution of trading prices is presented.

CHAPTER 4

Trading mechanisms and the market microstructure of financial markets

The trading environment of financial markets differs with respect to the implemented market microstructure, which determines the types of trading sessions and the order execution systems. The decisive function of each trading mechanism is to transform funds of potential investors into realized transactions. The key result of this transformation process is called *price discovery*, the identification of a market clearing price (Madhavan 1992). The speed and accuracy of the price discovery process differs with respect to the established trading mechanism. Understanding the relationship between trading mechanism and price formation is important, since various empirical studies show that the trading structure influences the behavior of security prices[1].

On the basis of order execution systems it can be distinguished between order-driven and quote-driven markets as well as hybrid markets which constitute a mixture of order- and quote-driven systems. In an order-driven market traders submit buy and sell orders to a centralized marketplace, where the price is either determined simultaneously with the transmitted order or afterwards. There are usually no intermediaries except for the brokers who transmit their clients´ orders, but the brokers do not operate on their own account[2]. Prices in order-driven markets are determined according to certain precedence rules which rank and match orders. Investors in order-driven markets can either transmit market orders or limit orders. When submitting a market order,

[1]See for example Amihud and Mendelson 1987, Amihud, Mendelson, and Murgia 1990, and Stephan and Whaley 1990

[2]A liquidity increasing market maker can be added to the system like the specialist in the New York Stock Exchange.

investors only specify the quantity they intend to buy or sell. In doing so, investors do not face any execution risk, but they have to be aware of potential price risk. Thus, market orders are appropriate for investors who are less sensitive to prices and who want their orders to be executed immediately. With limit orders investors specify both, the price and quantity at which they are willing to trade. Investors face no price risk, but execution risk since buy orders will only be executed at the specified price or below and sell orders at the specified price or above. If execution is not possible immediately, the order is placed on the limit order book where it is either executed against a matched incoming order, or it is cancelled. Limit orders on the limit order book determine the price at which market orders will be executed. In that sense, limit orders provide liquidity to the market and increase the market depth, while market orders consume liquidity (Jong and Rindi 2009).

In quote-driven markets, prices are set by market makers (dealers) who trade on their own account and thereby act as liquidity suppliers (Vives 2008). In order to profit from their liquidity providing activity, market makers quote bid prices lower than ask prices (Schwartz and Francioni 2004). The main difference between auction (order-driven) and dealership (quote-driven) markets is that in auction markets orders are submitted to a centralized trading mechanism and transacted at a single price, whereas in dealership markets orders are submitted to a dealer who executes them on his own account at present quotes (Röell and Pagano 1992).

4.1 Theoretical Models for auction and dealership markets

Since the 1980s the listing of securities on not only one, but on multiple exchanges has become more common (Röell and Pagano 1992). This multiple security listing implies that an investor who wants to trade a certain security faces the choice on which exchange he prefers to trade. The market microstructure can influence the trading decision of investors and therefore the trading volume in markets. In order to identify which structure is favorable for certain investors, it is crucial to assess the tradeoffs and the various differences between auction and dealership markets. According to Röell and Pagano, the advantage of dealership markets is that investors don´t face execution risk but higher average costs for ordinary trades compared to auction markets. Execution risk is defined as the transaction price risk, which is zero in the case of dealership markets, since orders are executed immediately. Average costs are lower in auction markets because auction markets are supposed to exhibit a higher degree of pre-trade transparency (Röell and Pagano 1996), which results on average in narrower spreads compared to the dealership market. The rationale why the dealer sets wider spreads is that, at the time when he receives an incoming order, he does not know the trading history of his counterparty. Nevertheless, dealership markets being less anonymous, offer investors the opportunity to negotiate with dealers for better prices (Röell and Pagano 1992).

These differences in market structures suggest that the price charged for a security depends on whether it is traded in an auction or in a dealership market. In the financial literature there are two models, which describe the price formation process in auction and dealership markets which are the Kyle model (Kyle 1985) and the Glosten-Milgrom model (Glosten and Milgrom 1985). The following section briefly describes these two models.

4.2 Price formation in auction and dealership markets

As already mentioned above, the main difference between auction and dealership markets is that in auction markets all orders are submitted to a centralized trading mechanism where all outstanding orders are then executed at the same price, while in dealership markets orders are delivered to individual dealers who execute them at present bid and ask quotes (Röell and Pagano 1992). Kyle 1985 proposes a dynamic model with sequential trading which enables to identify the price formation in auction markets and the role information plays in this process. In the basic model three types of traders participate:

1. One risk-neutral informed trader who receives a perfect signal about the true value of the asset.
2. Various random noise traders who are not price sensitive and only trade for liquidity reasons.
3. Perfectly competitive risk-neutral market makers.

Both, the informed trader as well as the liquidity traders, submit market orders which are then executed in a batch auction at the same price. Given that traders can only submit market orders but no price-contingent orders, they cannot learn from current prices. The Kyle model rests upon the assumption that the informed investor acts strategically. Even though he takes the pricing formula as given, the informed investor chooses the size of his order so as to maximize the profit he can realize by capitalizing on his private information, while simultaneously taking into account the impact his order has on the current auction price as well as on future trading opportunities. He is aware of the effect his order might have on prices and that by trading too agressively, too much information is revealed. Noise traders camouflage information based trades and allow informed investors to conceal their information. Market makers, however, do not know whether the order they observe stems from informed or liquidity traders, they only observe the aggregate order flow. Thus, they are not able to distinguish between information based trades and pure liquidity related trades. The price market makers set reflects all public information and the information they can extract from the aggregate order flow. Thus, the price is expected to be semi-strong form efficient. Prices only fluctuate as a result of news in the order flow (Kyle 1985).

The Kyle model (Kyle 1985) entails several implications concerning how insiders trade on their information and the effects of informed trading on market liquidity. In equilibrium, market liquidity and the trading strategy of insiders are interrelated. According to Kyle, market liquidity in a continuous auction equilibrium comprises the following transactional properties of markets: tightness, depth and resiliency. Tightness refers to the costs associated with turning around a security position over a short time period. Depth refers to the trade size needed to move the price, and resiliency is defined as the speed by which prices recover from random shocks. In order to detect the optimal trading strategy, the informed investor conjectures the tightness, depth and resiliency of the market, whereby depth and resiliency depend on the existence of informed and liquidity traders. Market depth, the inverse of market impact, is inversely related to informed trading and proportional to noise trading. The model predicts that the deeper the market, the better informed investors can hide behind insiders and therefore the more aggressively they will trade on their information. Aggressive trading, in turn, makes orders more informative and increases market learning by moving prices closer to fundamental values. Thus, inside trading in the Kyle model has two main impacts: it results in an increase of price volatility and leads to better price discovery (ibid.).

Admati and Pfleiderer 1988, who formulate a model in the spirit of Kyle (1985), show that the higher the level of informed trading in a market, in which the inside information is symmetrically distributed among informed investors, the more concentrated are liquidity traders in that market. They argue that informed traders compete with each other in order to maximize the value of their informational advantage and thereby increase the welfare of liquidity traders[3].

The Kyle model and the study of Admati and Pfleiderer demonstrate, that in a liquid market both, informed as well as uninformed investors, participate.

[3]If informed traders are provided with different information, this may not be true, if informed investors with diverse information enter the market, the terms of trade might be impaired.

Informed investors prefer trading in liquid markets in order to camouflage their identity and liquidity traders benefit from informed trading since more information is revealed. An illiquid market, by contrast, might be a signal for the existence of excessive informed trading or informed trading on the basis of diverse information, which eliminates benefits for liquidity traders and consequently those for informed investors.

The Glosten and Milgrom 1985 model demonstrates how asymmetric information affects price determination in a dealership market. In this model prices are posted by a specialist (market maker) and orders arrive sequentially. Given that the size of orders is restricted to one in this model, only the direction of orders is supposed to contain information.

In the basic Glosten-Milgrom model the market makers are risk neutral and earn zero expected profit, due to the assumed perfect competition among market markers. The price at which the market maker is willing to buy an asset is referred to as *bid price*, and the price at which he is willing to sell, as *ask price*. The existence of agents with superior information about the true value of the asset results in a positive spread between bid and ask prices, with ask prices being higher than bid prices. The market maker faces an adverse selection problem since he cannot identify whether an incoming order is submitted by an informed trader, who knows the true value of the asset, or by an uninformed trader. Therefore, by setting quotes with a bid-ask spread, market makers can compensate the potential losses arising from trading with insiders, with gains from trading with liquidity traders. For investors this spread constitutes trading costs which they take into account when making their trading decision. In this setting, the bid-ask spread is only information related[4].

As in the Kyle model, prices in the Glosten-Milgrom model are semi-strong form efficient, since market makers determine prices conditional on their information set and conditional on the direction of the order. Thus, the ask price equals the conditional expected value of the asset given that the incoming order is a buy order, and the bid price equals the conditional expected value given that the arriving trader wants to sell. The spread between bid and ask prices increases with the probability of insider trading and with the informational advantage of insiders. Prices then fluctuate due to a random public news component and due to the gradual incorporation of private information conveyed by orders (Glosten and Milgrom 1985).

Both, the Kyle model and the Glosten-Milgrom model suggest that prices reflect information and incorporate the potential existence of investors with superior information. Insiders choose to trade in the market where they can

[4]Glosten and Milgrom 1985 also propose a model that not only considers the adverse selection component of the bid-ask spread, but also inventory costs and order processing costs, where market makers are risk-averse and can earn positive monopoly rents.

maximize the value of their information, which depends on market liquidity.

For the purpose of this study informed investors can choose between two markets. They can either directly trade a stock in the NYSE or indirectly trade the security by acquiring an option position in the CBOE. The potential influence of the respective market microstructure of the NYSE and the CBOE on the trading decision of investors is analyzed in the following section.

4.3 The Trading Mechanism of the NYSE and the CBOE

NYSE Euronext is a global operator of financial markets in the U.S. and Europe. One third of equities traded worldwide are listed on the NYSE Euronext marketplace. The NYSE as part of the NYSE Euronext Group is the world´s largest stock exchange by market capitalization (*http://www.nyse.com,*). In the remainder of this article only NYSE equities are considered since stocks listed on the NYSE are included in the empirical study.

Since 2005 the New York Stock Exchange is organized as a hybrid trading mechanism which starts the trading day with a batch auction and then proceeds as a quote-driven mechanism with a designated specialist for each stock traded on the exchange (Jong and Rindi 2009). This hybrid mechanism implies that customers can submit their orders to brokers as well as directly to the electronic limit order book (*http://www.nyse.com,*). The specialist, being responsible for assuring liquidity and fair prices, manages the limit order book and trades with the brokers. He can either trade on his own account or, in the case of abnormal price changes, announce the current order imbalance in order to attract new orders. Brokers can either submit orders directly to the limit order book or to the specialist. If orders are sent to the specialist, brokers might establish a long-term relationship to the specialist and thereby reduce risk of adverse selection resulting from asymmetric information (Jong and Rindi 2009). Incoming orders are allocated to specialists either directly through the Super Designated Order Turnaround Direct+ System[5] (SuperDot Direct+) or indirectly through floor brokers (*http://www.infosci.cornell.edu*). If specialists receive an order from floor brokers they can decide whether to trade on their own account or to place it on the limit order book waiting for an appropriate counterparty (Jong and Rindi 2009).

Trading in the NYSE is executed on the basis of price and time rules, as well as precedence and parity rules. Price rules are absolute which indicates that a lower ask always has priority over a higher ask. Concerning the precedence

[5]SuperDot System is an electronic order-routing system with which more than 95% of orders are delivered to the specialists. SuperDot mainly deals with small orders. Larger orders are delivered indirectly through floor brokers.

rule, orders from floor brokers and orders submitted through the SuperDot System always have priority over a specialist´s order given that all have the same price. Strict time priority is only applicable to the first order transmitted to the market. Finally, there is a size priority rule which requires that orders, which suffice to satisfy the entire incoming quantity, possess priority (Jong and Rindi 2009).

The hours of operation for NYSE equities starts at 7:30am EST when the NYSE accepts and acknowledges orders. Until the designated market maker starts the opening auction at 9:30am EST, orders can be entered and cancelled. In order to guarantee accurate pricing, the NYSE allows for initial public offerings (IPOs) and listed companies with news announcements to open later than 9:30am EST. Beginning at 9:28am EST the designated market maker disseminates indicative market price information. At 9:30am EST the market maker starts opening each security, whereby securities with less than 10,000 shares of open interest and no broker interests, can be opened automatically (*http: // www. nyse. com,*). The specialist aggregates the incoming orders, which are either transmitted electronically or via floor brokers, and then identifies the opening and closing price of the security. The specialist determines security prices so as to minimize the order imbalance. In the NYSE trade is possible between 09:30am (opening auction) and 4:00pm EST (closing auction) and is conducted in a continuous auction format (Jong and Rindi 2009).

The Chicago Board Options Exchange (CBOE) is the largest U.S. options exchange. It provides investors with the opportunity to trade equity options, index options as well as ETF options (*http: // www. cboe. com*). The CBOE started trading call options in 1973 and put options in 1977 (Hull 2006). The exchange is organized as a hybrid market which enables investors to either submit their orders electronically to the limit order book or to brokers who handle orders through open outcry. Since 1999 the CBOE applies a designated primary market maker system. Trading on the CBOE starts at 8:30am CST and ends at 3:00pm CST (*http: // www. cboe. com*)[6].

The CBOE often determines position and exercise limits for trading option contracts. Position limits specify the maximum number of option contracts an individual investor can trade on one side of the market, whereby long calls and short puts as well as long puts and short calls are treated as belonging to the same market side. Exercise limits generally equal position limits, but they specify the maximum number of option contracts that can be traded within a period of five consecutive trading days. These limits are introduced in order

[6]Thus, given that Eastern Standard Time (EST) is five hours behind Greenwich Mean Time and Central Standard Time (CST) is six hours behind GMT-Greenwich Mean Time, the NYSE and the CBOE open and close trading at exactly the same time. http://wwp.greenwichmeantime.com/time-zone/usa/time-zones/

to prevent the market from being excessively influenced by the trades of an individual investor (Hull 2006).

Given the above discussion it can be concluded that there is no significant difference in the trading mechanism between the NYSE and the CBOE. Hence, if only the trading mechanism is considered, investors should be indifferent between trading on either exchange. Assuming that both exhibit the same trading mechanism, there must prevail other characteristics that make investors trade in either the stock or the option market. In the following chapter various factors, which influence the trading decision of investors and ultimately result in either stock or option trades, are defined.

CHAPTER 5

Trading in stock and option markets

The main purpose of this paper is to find evidence that informed traders prefer to trade in the option market rather than in the stock market. In order to formulate a valid model which is qualified to proof this assumption, it is crucial to identify factors that might justify informed trading in options.

Section 4.3 shows that the microstructure of the trading environment does not constitute a determinant for informed trading, since both markets, the NYSE and the CBOE, are organized as a hybrid market mechanism with a designated market maker as a provider of liquidity. Therefore, the microstructure is not included as a driver of informed trading in the analysis.

The Kyle model as well as the Glosten-Milgrom model suggest that informed investors choose to trade in a way that enables them to maximize their expected profit. Therefore, in which market, the stock market or the option market, informed investors eventually trade, depends on the expected profits the respective securities generate. There are various slightly different definitions of profits, but basically the profits for investors can be defined as *'the difference between total revenues and total costs a specific operation entails (*http://www.iasplus.com*)'*. According to the International Accounting Standards (ibid.) revenue is defined as the *'gross inflow of economic benefits (cash, receivables, other assets) arising from ordinary operating activities for an entity (such as sales of goods, sales of services, interest, royalties, and dividends)'*. The costs associated with trading are referred to as trading costs. The general idea of trading costs is discussed below.

5.1 The concept of trading costs

If an investor has selected the assets he intends to trade, all he needs to do is implement his decision. However, in reality the assets eventually traded are different from those initially perceived as ideal. Perold 1988 attributes this difference between the ideal portfolio and actually traded portfolio, the real portfolio, to an *'implementation shortfall'*. The idea is that in reality there is a difference between trading on the paper, where an investor identifies his ideal portfolio, and trading in the market, due to implementation costs. These costs can constitute a considerable impairment on the performance of the portfolio and reduce the net return, the profit, to the investor. The notion of implementation costs suggests that any divergence of the real portfolio from the paper portfolio must be attributed to trading costs (ibid.). Generally stated, given market microstructure frictions, the existence of trading costs results in a deviation of transaction prices form equilibrium prices (Jong and Rindi 2009).

The literature generally distinguishes two types of trading costs: explicit trading costs and implicit trading costs. Explicit trading costs are any payments to the broker like commissions, brokerage fees net of any rebates, and taxes. The size of the commission depends on the type of the broker, who may either be a full-service broker or a discount broker. Discount brokers charge much lower commissions since they only provide the basic services and basic information of price quotations. Irrespective of these commission payments, investors also have to pay implicit trading costs, the costs from interacting with the market (Bodie et al. 2008). These implicit trading costs exist because orders may be executed at a very high ask or at a very low bid due to a relatively large order size or due to infrequent trading in the respective security. Implicit trading costs include the costs related to the bid-ask spread[1] and market impact, as well as opportunity costs. The bid-ask spread is the cost of a round-trip and is defined as the difference between the price at which liquidity providers are willing to sell (ask) and the price at which they are willing to buy (bid) (Schwartz and Francioni 2004). Stoll 1978 claims that the bid-ask spread can be subdivided into three components:

- adverse selection costs
- inventory holding costs
- order processing costs

The adverse selection component of the spread arises due to asymmetric information. As shown in Kyle 1985 and Glosten and Milgrom 1985, market

[1]Demsetz 1968 was the first who related the bid-ask spread to costs of trading.

makers factor in the probability of informed trading when quoting prices. The bid-ask spread increases with the probability of informed trading given that market makers want to be compensated for their expected loss when trading against insiders. The inventory holding cost component of the bid-ask spread only arises if market makers are risk-averse. In real markets, dealers as liquidity suppliers, are required to continuously provide quotes. Thus, they frequently hold undesired portfolio positions that deviate from their efficient frontier. In order to rebalance their portfolio, dealers change their bid and ask quotes so as to encourage a trade by the public of the opposite direction. The assumption of risk aversion of market makers is crucial, since only risk-averse dealers are concerned about potential unfavorable price changes (Stoll 1978 and Jong and Rindi 2009). The incorporation of inventory holding costs as a spread component has often been criticized since in reality dealers diversify their positions by trading in many different securities and they engage in risk sharing arrangements (Copeland and Galai 1983). The third component of the bid-ask spread is related to order processing costs, the costs of handling an order. Order processing costs are usually modeled as fixed costs per share (Jong and Rindi 2009). Glosten and Harris 1988 estimate a two component model in order to identify the relative importance of the various spread components. Their price impact regression includes order processing costs, which are assumed to have a transitory effect on prices, and an adverse selection component, which is assumed to have a permanent effect, since it results in a revision of market makers´ expectations. Glosten and Harris (1988) find a significant impact of adverse selection and order processing costs on price changes. But their model is subject to several limitations. The most severe drawback of their study is that they do not take into account inventory risk of risk-averse market makers. In their study the effect of inventory holding costs and adverse selection costs are lumped together. This results in an overestimation of the adverse selection component (ibid.).

Huang and Stoll 1997 propose a model which decomposes the spread into three components. In order to overcome the identification problem of disentangling inventory holding costs from adverse selection costs, they assume that not the entire order flow is ´news´, but part of it is predictable. Only the unpredictable part enters the updating of expectations about fundamentals. They assume that the order flow follows an autoregressive process of order one (AR1). Their results show that all three components have a significant positive influence on price changes, whereby order processing costs seem to have the largest impact. They also find that the spread components differ significantly relative to trade size (ibid.).

The other two drivers of implicit trading costs, beyond the bid-ask spread, are market impact and opportunity costs. Market impact refers to the additional costs that accrue if a trader wants a large order to be executed quickly. The market demands a compensation for absorbing a large order. Due to market impact, the effective spread increases with order size. Investors should also consider opportunity costs, the costs associated with a delay of order execution or the omission of a trade (Schwartz and Francioni 2004).

The respective trading costs an investor incurs, is the absolute difference between the mid-quote of the bid-ask spread and the price paid for acquiring the asset, or the price received for selling it (Loeb 1983). The magnitude of the total trading costs is related to the liquidity of the market. In a liquid market, defined by Kyle 1985 as a tight, deep and resilient market, trading costs are relatively low, compared to less liquid markets. Stated differently, a market with low trading costs is a relatively liquid market (Schwartz and Francioni 2004). Thus, in order to maximize their profits, investors do take liquidity into account. Unfortunately, liquidity is not a directly observable variable and therefore needs to be estimated in order to assess expected trading costs. Information about explicit trading costs like brokerage commissions or stock exchange trading fees, by contrast, is publicly available (Treynor 1971)[2].

The main driver of implicit trading costs is the bid-ask spread (ibid.).The spread can be measured either on the basis of bid and ask quotes, as *quoted spread*, *effective spread* or *realized spread*, or it can be measured on the basis of transaction prices (Jong and Rindi 2009). The quoted spread measures the average difference between the best bid and ask quote. One issue of measuring illiquidity as quoted bid-ask spread is that it is a noisy estimate of illiquidity given that many large trades occur outside the spread (Brennan and Subrahmanyam 1996). Another drawback is that the quoted spread may vary during the trading day and hence not properly measure actual trading costs. The effective spread, by contrast, measures the absolute deviation of the actual transaction price from the bid-ask mid-quote. The bid-ask mid-quote is used as a proxy for the equilibrium price at the time of the trade. However, given that the equilibrium price may change with a trade due to the existence of asymmetric information, an alternative method to estimate the spread additionally considers the bid-ask mid-quote after the trade was executed. This is the so-called realized spread (Jong and Rindi 2009). The estimation of the abovementioned spread measures requires at least access to bid and ask quotes. Very often these quotes are not observable. In order to overcome this problem, Roll 1984 proposes a model to infer spreads directly from transaction prices. Roll argues that trades occur either at the bid or at the ask quote. This implies that price changes (returns) between consecutive transactions are negatively serially correlated due to a *bid-ask bounce*. The Roll model indicates that the spread is equal to two times the square root

[2] The paper was published under the pseudonym Bagehot.

of the negative covariance of successive price changes. The model is subject to various limitations. If any of its stringent assumptions are violated, the Roll measure yields a biased estimate of the spread and if price changes are positively serially correlated, the spread cannot even be estimated (Jong and Rindi 2009).

One general drawback of using spread measures as a proxy for implicit trading costs is that the spread is not necessarily capable of identifying trading costs for large trades (Acharya and Pedersen 2005). Therefore, often other proxies for illiquidity are applied, including measures of the market impact of transactions and the probability of information based trading, the so-called *PIN measure* (Jong and Rindi 2009). The probability of information based trading as a measure of microstructure risk was introduced by Easley, Hvidkjaer, and O'Hara 2002. It determines the adverse selection costs due to asymmetric information and the risk that the transaction price deviates from its equilibrium value. Amihud 2002 proposes another estimation of illiquidity using daily data. This so-called *ILLIQ measure* essentially proxies Kyle´s lambda, the price impact. The ILLIQ measure is calculated as the ratio of absolute daily stock return to daily trading volume, averaged over a certain time period:

$$ILLIQ_t = \frac{1}{D}\sum_{d=1}^{D}\frac{|\Delta P_d|}{V_d} \tag{5.1}$$

where D denotes the number of trading days, ΔP_d the price change on a particular trading day and V_d the gross order flow (buy plus sell orders). The gross order flow in the formula is used as a proxy for net order flow (buy minus sell orders) because many exchanges do not provide data for net order flow (Jong and Rindi 2009).

Amihud (2002) finds evidence that expected excess stock returns are an increasing function of this illiquidity measure. Thus, the risk premium not only compensates for market risk but also for illiquidity risk (Amihud 2002). Brennan and Subrahmanyam 1996 estimate illiquidity as price impact of trades and they as well find that stocks with a high illiquidity measure are less attractive for investors. Another method for estimating the impact of illiquidity on price changes is using price impact regressions like those proposed by Glosten and Harris 1988 and Huang and Stoll 1997, which allow for identifying the various spread components.

Whether the existence of trading costs has an impact on prices and returns has been tested in many empirical studies. Acharya and Pedersen 2005 test the effect of illiquidity costs on asset returns. They show that liquidity is a priced factor. Investors are willing to pay for liquidity or otherwise want to be compensated for buying illiquid assets. They find that a liquidity adjusted capital asset pricing model is qualified to explain the size effect. Amihud and Mendelson 1986 analyze the effects of trading costs on the investment decision with data on New York Stock Exchange issues between 1961 and 1980. They argue that investors maximize the expected returns net of trading costs (liquidity costs). They define liquidity in terms of bid-ask spreads and use the spread as a measure of trading costs. They find evidence that the gross return investors demand is positively related to trading costs. In particular, they show that the least liquid stocks on average exhibited an 8.5% higher per annum return than the most liquid stocks over a 20-year period. Hasbrouck 2009 also finds this positive link between effective spreads and returns, but the evidence is mixed. He detects two issues regarding this relation. First, Hasbrouck shows that this effect is concentrated in January. And second, he identifies that the estimated coefficients for the trading costs are too high to be economically reasonable. However, the effects of trading costs on investment decisions are related to the expected holding period of investors. Following Amihud and Mendelson 1986, for short-term investors it is better to pay up for liquidity in order to get the lowest bid-ask spread. If, by contrast, investors expect to hold an asset over a longer period it pays off to invest in higher spread assets so as to profit from higher returns. Thus, investors do factor in trading costs when making their investment decision, whereby the extent of the influence depends on the individual trading behavior of investors and their preferences, as well as on the characteristics of the trading process (Jong and Rindi 2009). However, there are also various researchers who find that liquidity is not a priced factor. Studies arriving at this conclusion include Eleswarapu and Reinganum 1993, and Chalmersa and Kadlec 1998. Easley, Hvidkjaer, and O'Hara 2002 argue that one possible explanation for this mixed evidence is that it is rather difficult to disentangle the effect of liquidity from the noise in asset returns.

The following section identifies the potential revenues and costs associated with trading in the stock and option market.

5.2 Revenues and costs of stock trades

The main difference between stocks and options stems from the very nature of the two securities. A stock is an equity security which provides the investor with an ownership share in the issuing corporation (Bodie et al. 2008), whereas options are contracts that only certify investors the right to buy or sell an underlying asset in the future (Hull 2006). The ownership share entitles stock holders with voting rights in the issuing firm which permits them to appoint the firm´s board of directors and to vote on special issues (Gitman and Madura 2001). Investors who buy stocks expect to earn returns by receiving dividends as well as by realizing capital gains through an increase in the share price.

While the payment of dividends is at the discretion of the firm, the capital gains depend on the future value of the stock (Gitman and Madura 2001). Given that the future value is not known at the time an investment decision is made, investors who do not possess any superior information try to predict the future value on the basis of public information. They base their predictions of future price movements on the assumption that stock prices change according to a certain stochastic process. Stock prices are generally assumed to follow a Markov process, which is consistent with the weak form of market efficiency (Hull 2006). In order to get an estimate of the future value, investors sample random outcomes for securities. A commonly used method for sampling the process followed by stock prices is the *Monte Carlo simulation.* This technique assumes that stock prices change during a certain time interval as a function of a constant expected return and a constant variance multiplied by a Wiener process (ibid.). The Monte Carlo simulation enables potential investors to sample future time series of stocks, which can be used to form estimates about future capital gains or losses.

After forming expectations about future values of assets, investors are able to determine expected returns. The total expected return $E[r_t]$ of a stock over a time period t is commonly defined as (Gitman and Madura 2001):

$$E[r_t] = E[\frac{C_t + P_t - P_{t-1}}{P_{t-1}}] \tag{5.2}$$

with C_t measuring any income (cash flow) received, including dividends, during the holding period. P_t and P_{t-1} respectively define the price of the stock at time t and at time $t-1$. The total expected return on a stock investment comprises income payments and capital gains. Returns are calculated as ´expected´ returns since their calculation is based on predicted, uncertain values.

The expected return, however, is only one side of the coin. Markowitz 1952 argues in his seminal paper that, in order to select a certain portfolio, investors do not only care about expected returns, but also take the inherent risk of the investment into account. In this setting, risk, describing the uncertainty about the future value, is measured by the asset´s standard deviation (Hull 2006). Moreover, following Acharya and Pedersen 2005, liquidity is a priced factor and investors additionally consider liquidity risk, not only market risk, when determining the required rate of return of their investment.

Depending on the uncertain future value of the stock, and on whether the issuing company pays out dividends during the holding period, a stock investment either generates a gain at the end of the holding period or it results in a loss of the entire invested capital. According to Gordon 1959, investors buy shares if they expect to acquire dividend payments. The so-called *Gordon* *growth model* (Gordon 1959) predicts that the intrinsic value of a stock is equal to the net present value of the future series of dividends, assuming that dividends grow at a constant rate. Capital gains are disregarded in this model because unless one expects prices to grow forever, the expected discounted value of the stock must shrink to zero as time passes. Thus, the price investors are willing to pay for a stock is given by (ibid.):

$$P_0 = \frac{D_1}{r - g} \tag{5.3}$$

Where r defines the constant cost of equity capital of the firm and g the constant dividend growth rate. Foerster and Sapp 2005 show that stock prices calculated on the basis of this model are a good approximation of actual prices.

In order to select an investment strategy, investors are not only concerned about risk-adjusted returns, but also about the liquidity of the potentially traded securities. As discussed in section 5.1, in case investors trade a security they face various explicit and implicit trading costs, which are negatively correlated with liquidity. Amihud 2002 shows that ex-ante expected excess stock returns are positively related to market illiquidity, whereby the illiquidity effect is more pronounced for stocks of small firms. Amihud and Mendelson 1986 estimate a significant positive relationship between quoted bid-ask spreads and stock returns, indicating that higher spread assets yield higher net returns for investors. Easley et al. (2002) employ their PIN measure to estimate whether the existence of private information affects stock returns. They estimate the PIN measure for individual stocks listed on the NYSE for the period 1983 to 1998 and then test whether these information probabilities can explain cross-sectional variations in stock returns. They find that stocks with a higher PIN measure exhibit higher rates of return. A 10 percentage point difference in PIN for two individual stocks results in a 2.5% difference in their respective expected returns per annum. Their main result indicates that information has an effect on stock prices (Easley, Hvidkjaer, and O'Hara 2002).

The empirical evidence predicts that the valuation of assets should incorporate the cost of transacting. Amihud and Mendelson 1986 propose a model which is a generalization of the Gordon growth model to determine the value of assets, where trading costs, measured by the relative bid-ask spread, are included. Their model describes a market in which investors with different expected holding periods trade securities with different spreads. They assume that the price P of an asset is a function of a perpetual per-period dividend D, the required risk-adjusted return r, the relative spread S and the expected trading frequency μ. They define the expected spread adjusted return an investor i requires for holding an asset j as the difference between the gross market return on the asset and its expected liquidation cost per unit of time.

It is calculated as (Amihud and Mendelson 1986):

$$r_{ij} = \frac{D_j}{P_j} - \mu_i S_j \tag{5.4}$$

where $\frac{D_j}{P_j}$ is the gross return of asset j and $\mu_i S_j$ is the expected liquidation cost. This relation shows that the expected spread-adjusted return depends on both, the individual investor as well as on the asset. Investors choose to trade that asset which provides them with the highest spread-adjusted return r_i^*. The gross return they demand for acquiring an asset is given by:

$$\frac{D_j}{P_j} = r_i^* + \mu_i S_j \tag{5.5}$$

And the value of the asset is defined as:

$$P_j = \frac{D_j}{r_i^* + \mu_i S_j} \tag{5.6}$$

The idea of this equation is that investors, apart from the required net return, require a compensation for the expected per period trading cost. The equilibrium value of asset j is therefore equal to the present value of a perpetual dividend (a perpetual cash flow) discounted at the expected gross return (Amihud and Mendelson 1986).

Using the CAPM setting, the risk-adjusted return of asset j investor i demands can be written as:

$$E[r_{ji}] = r_f + \beta_j[E(r_M) - r_f] + \mu_i S_j \tag{5.7}$$

Hence, the expected return is a linear function of the risk-free rate of return, the market risk premium, and the liquidity premium (Jong and Rindi 2009).

Amihud and Mendelson 1986 conduct an empirical analysis of this relationship using data for NYSE stocks for the period 1960 to 1979. Their main hypothesis is that the expected return of an asset is an increasing and concave function of the spread. They are able to show that illiquidity increases the required rate of return on assets. Amihud 2002 re-estimates the Amihud and Mendelson (1986) regression using the ILLIQ measure as a proxy for trading costs, instead of the relative bid-ask spread. He as well arrives at the conclusion that trading costs raise the required return. However, given the generally recognized assumption that the average return of small firms tends to be larger, Amihud additionally includes the market capitalization as a control variable in the regression analysis. He finds that firm size is an important driver of expected returns, but illiquidity persists significant in explaining variations in cross-sectional returns for all size groups. Thus, the relation between spread and expected return cannot be explained by the size effect[3].

The discussion suggests that investors, in order to maximize their profit, compare the trading costs associated with different securities and markets, before undertaking an investment decision. Trading stocks on the NYSE entails brokerage and commission fees, which depend on the broker or designated market maker an investor assigns the execution of his order to. Registered dealers and brokers have to pay several trading fees such as transaction fees, facility and equipment fees, system processing fees, registration and regulatory fees, trading license fees and others. Fees are only charged if dealers take liquidity away from the market. If they provide liquidity, they are granted a credit. The size of the fee or credit depends on the type of the order (http://www.nyse.com). In addition to these transaction fees, investors have to take into account potential taxes related to stock trades which reduce their expected return. In particular, investors have to consider taxes related to capital gains if they sell the stock, as well as taxes on dividends received. Brennan 1970 was the first who incorporated personal taxes of investors in the determination of risk-adjusted returns. He proposes a modified CAPM which takes into account that investors seek to maximize their after tax income. According to U.S. fiscal law, individuals have to pay taxes on their gross income (minus any allowed deductions) which, amongst others, includes gains derived from dealings in property and dividends[4]. With regards to capital gains the U.S. law distinguishes between short-term and long-term capital gains and losses, whereby the former refers to the sale or exchange of capital assets hold for no longer than one year, and the latter to the sale or exchange of capital assets hold for more than one year[5]. Short-term capital gains are taxed on an investor´s ordinary tax rate, depending on the respective tax bracket of the investor. Long-term capital gains result in a lower effective tax rate than short-term capital gains (Gitman and Madura 2001).

Implicit trading costs, measured by the effective bid-ask spread and market impact, are generally very low on the NYSE, compared to other markets like the NASDAQ, which by contrast offer lower explicit trading costs. Many trades on the NYSE are executed with prices inside the quoted spread, because floor brokers can offer bid quotes above or ask quotes below the specialist´s quote (Bodie et al. 2008). Studies analyzing patterns of the bid-ask spread, like McInish and Wood 1992 and Brock and Kleidon 1992, show that the bid-ask spread on the NYSE varies over the trading day in a U-shaped pattern, whereby the spreads are widest immediately after the opening and prior to the close of the trading day.

[3] Amihud and Mendelson 1986 arrive at the same result.

[4] 26 USC §61 – Gross income defined

[5] 26 USC §1222 (1-4) – General Rules for Determining Capital Gains and Losses

In the following section it is shown how the picture changes when options, instead of stocks, are traded.

5.3 Revenues and costs of option trades

Purchasing an option provides the holder only with a contract which entitles him the right to buy or sell the underlying asset in the future for a predetermined price. There are generally two types of options: call options and put options. Call options give the holder the right to buy an underlying asset by a certain future date at a predetermined price, whereas put options give the holder the right to sell the asset. Underlying securities for which option contracts are traded include stocks, commodities, currencies or other types of financial assets[6]. If the option´s underlying is a stock, the option contract specifies the right to buy or sell 100 shares at a certain strike price. The date specified in the contract is denominated *expiration date* and the specified price is known as exercise or *strike price*. While the holder of a call option expects the value of the underlying to increase, the holder of a put option is hoping that the underlying asset´s value decreases in the future. Options can either be European or American. European options can only be exercised on the expiration date itself and American options, by contrast, can be exercised at or before the expiration date (Hull 2006). In the United States exchange traded stock options are American options. The CBOE additionally offers so-called FLEX options (Flexible Exchange Options) which enable investors to customize their option contract (*http://www.cboe.com*). These options comprise nonstandard terms such as strike prices that differ from those offered by the exchange, different expiration dates, or European instead of American style contracts (Hull 2006).

The following two subsections respectively describe the profits and costs associated with trading options.

5.3.1 Determining the value of option contracts

In each option trade there are two counterparties involved: the buyer of the option (investor with a long position in the option) and the seller, the so-called writer of the option (investor with a short position). The payoff for buyers of option contracts is conditional on the price movements of the underlying. The payoff from a long position in a European call looks as follows (Hull 2006):

$$max(S_T - K, 0)$$

[6] In this study underlying assets correspond to stocks.

S_T represents the value of the underlying asset at the expiration date T and K the strike price of the call. This payoff structure illustrates that the option will be exercised only if at expiration the value of the underlying exceeds the strike. Otherwise, the option will not be exercised and expires worthless. The payoff structure from a long position in a European put option is determined as:

$$max(K - S_T, 0)$$

European put options will only be exercised if the strike price at the expiration date exceeds the value of the underlying. Thus, if the future value of the underlying deviates from the predetermined exercise price in a way that provides the holder with a positive payoff, the option will be exercised. The payoff structures indicate that the maximum amount buyers of options can lose is the price of the option, in case they let the option expire worthless. Call options provide investors with a downside protection and with an infinite upside potential. Put options also offer downside protection but in contrast to call options, they have a limited upside potential equal to the strike price. Both types of options provide investors with a form of leverage since they magnify the financial consequences (Hull 2006).

Writers of option contracts face exactly the reverse payoff structure. They receive a premium (fee), paid by option buyers upfront, in return for selling an option contract and assuming the risk and the obligation to fulfill the contract. The payoff for the writer therefore consists of an upfront cash payment equal to the price of the option, minus any potential future liabilities in case the holder exercises the option. The option writer has no downside protection and the maximum profit he can realize equals the price at which the option contract is sold (Hull 2006).

The total value of an option consists of an intrinsic value and a time value. The intrinsic value of an option is the maximum between zero and the value of an option if exercised immediately. The time value refers to the value that arises from the time left until maturity. Thus, the sum of the intrinsic value and the time value determines the price investors have to pay in order to acquire an option. The price of stock options mainly depends on six factors (Hull 2006):

- the current price of the stock S_t
- the strike price K
- the time to expiration T
- the volatility of the stock price σ

- the risk-free interest rate r_f
- expected dividends D

The particular effect of these factors on the option value depends on whether the option is a call or put option. Differences between American and European options only exist concerning the impact of the time to expiration. The value of American put and call options definitely increases with the time to expiration. For European options this positive relationship is not always observable. With regards to the other factors, the effects on stock option prices are the same for American and European options: the value of call options increases with the current stock price, volatility and the risk free rate, and it decreases with the strike price and the amount of future dividends. The value of put options increases with the strike price, volatility and the amount of future dividends and it decreases with the current stock price and the risk-free rate (Hull 2006).

How the values of European call and put options are related to each other can be represented by the so-called *put-call parity.* The relationship looks as follows:

$$c + Ke^{-rT} + D = S_0 + p \tag{5.8}$$

Where c and p respectively represent the price of European call and put options, S_0 the current price of the underlying stock at $t = 0$, Ke^{-rT} the present value of the cash position and D the present value of the expected dividend during the life of the option. This relationship shows that the value of a portfolio, consisting of a long position in a call option plus a certain amount of cash equals the value of a long position on a dividend-paying stock and a long position in a put. For this relation to hold, the strike price and the expiration date of the call and put option are required be the same. If the equation does not hold, arbitrage opportunities exist (Hull 2006). The put-call parity condition was developed by Stoll 1969. He argues that the existence of put-call parity entails that stock prices follow a random walk, implying that markets are efficient and that all information about future price movements of the stock is already incorporated in the current stock price. Therefore, he claims that put and call prices have no predictive ability for future stock prices (ibid.).

The put-call parity defines the relationship between put and call options and shows that the respective prices of put and call options are interrelated and independent of option traders (Stoll 1969). A key point for the pricing of derivatives is that the derivative and the underlying are both subject to the same sources of uncertainty (Hull 2006). There are various models for option pricing, but the two most commonly used are the *binomial tree*, developed by

Cox, Ross, and Rubinstein 1979 and the *Black-Scholes* formula, developed by Black and Scholes 1973 and extended by Merton 1973.

Constructing a binomial tree is a convenient and popular way for pricing options. It is a discrete option pricing formula based on the fundamental economic principles of arbitrage methods. The basic idea behind binomial tree valuation is that a riskless portfolio of stocks and options, which earns a risk-free rate of return, can be constructed. Given that the appropriate number of shares is bought, the stock position is qualified to replicate future call returns (Cox, Ross, and Rubinstein 1979). The number of stocks required for each option in the portfolio, in order to create a riskless hedge, is called the *option delta*. The option delta determines by how much the price of an option changes, given a change in the value of the underlying stock. While the delta of call options is positive, put option delta is negative (Hull 2006)[7]. Cox, Ross, and Rubinstein 1979 show that in a risk-neutral world, the current value of put and call options can be interpreted as their expected future value, discounted at the risk-free rate of interest.

Investors´ individual attitude towards risk does not influence the value of options. The only assumption made concerning investors´ preferences is that they prefer more wealth to less wealth. Hence, they have an incentive to exploit arbitrage opportunities and take advantage of market mispricing. The value of options is also independent of the probability of stock prices moving up or down, because options´ values are calculated in terms of the price of the underlying stock. Thus, the probability of the stock price to move up or down is already reflected in the price of the stock. The essential ingredient of pricing options by arbitrage considerations is the two state process. Current stock prices are assumed to follow a binomial process, i.e. stock prices can change from their beginning-of-period value to only two ex-dividend values at the end of the period. The only variables required for determining the value of options by applying the binomial tree method are the price of the underlying, the strike price of the option, the range of upward or downward movements of the underlying stock price and the interest rate (Cox, Ross, and Rubinstein 1979).

Cox et al. demonstrate that if the time period between price changes converges to zero, implying a continuous trading process, the binomial tree valuation coincides with the Black-Scholes formula. Even though the binomial model is a rather flexible and simple method for valuing options, the Black-Scholes model is far easier to use. The Black-Scholes model is also based on the fundamental assumptions of risk-neutral valuation. Given that stocks and options are subject to the same source of uncertainty, stock price movements,

[7] Black and Scholes 1973 define the option delta as the elasticity of the option price with respect to the stock price.

a riskless portfolio consisting of stocks and options can be set up[8]. For call options the riskless portfolio is composed of a long (short) position in a stock, and a short (long) position in the option (Black and Scholes 1972). In any short time period, the price of the option is perfectly correlated to the price of the option. One crucial difference between the binomial tree model and the Black Scholes model is that, in the latter, the riskless portfolio has to be rebalanced frequently, given that it is only riskless for a very short period of time. A key characteristic of the Black-Scholes model is that the value of the option does not depend on any risk preferences of investors (Hull 2006). Instead, the value of the option is only a function of the stock price and time (Black and Scholes 1972).

In order to derive the formula for valuing options, Black and Scholes assume *'ideal conditions'* in stock and option markets. In particular they adopt the following assumptions (Black and Scholes 1973):

- The short-term interest rate is known and constant over time
- The stock price follows a random walk in continuous time and the distribution of the stock return is lognormal
- The stock pays no dividends during the life of the option[9]
- The option is European
- There are no transaction costs or taxes
- The risk-free rate of interest is constant and the same for all maturities
- Short-selling is permitted
- There are no arbitrage opportunities

Given these assumptions, the value of the option only depends on the value of the underlying stock, time and other variables taken as known constants. The prices of European call and European put options, according to the Black-Scholes model, are determined as follows (ibid. and Hull 2006):

$$c = S_0 N(d_1) - Ke^{-rT} N(d_2) \tag{5.9}$$

$$p = Ke^{-rT} N(-d_2) - S_0 N(-d_1) \tag{5.10}$$

where

[8]In particular, according to Itô´s lemma, the Wiener process underlying the option and the stock are the same (Hull 2006, p.291).

[9]The formula can be modified in order to take dividends into account. See Black F. (1975); p.41 and p.61

$$d_1 = \frac{ln(\frac{S_0}{K}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} \tag{5.11}$$

$$d_2 = \frac{ln(\frac{S_0}{K}) + (r - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T} \tag{5.12}$$

In the formula c denotes the price of a European call, p the price of a European put, S_0 the price of the underlying stock at time 0, K the strike price, r the continuously compounded risk-free rate, σ the stock price volatility, T the time to maturity of the option and *N(d)* the cumulative probability distribution function for a standardized normal distribution. The expression $N(d_2)$ can be interpreted as the probability that a call option will be exercised in a risk-neutral world, which is the risk-adjusted probability $Pr(S_T > K)$[10]. For call options $Ke^{-rT}N(d_2)$ is therefore the present value of the contingent payment (the current value of the exercise price). $S_0N(d_1)$ represents the present value of the contingent receipt of the option. Black and Scholes interpret $N(d_1)$ as the amount of shares required in the portfolio in order to create a riskless hedge (Black and Scholes 1972). Even though the original Black-Scholes model was designed to determine the value of European options, it can easily be extended to enable the valuation of American type options (Hull 2006). Black and Scholes 1972 empirically test their option pricing formula. Their results indicate that option prices for buyers and sellers of options deviate from the prices predicted by the formula. Buyers of options incur higher prices than those predicted by the formula, whereas option sellers receive approximately the predicted price. Black and Scholes attribute this divergence between buying and selling prices to the large transaction costs in the option market which effectively have to be paid by option buyers.

When determining option prices according to the Black-Scholes formula the parameters of the model need to be appropriately specified. The big unknown in the model is the volatility of the stock price. The strike price and time to expiration are known, the stock price and the interest rate can be observed but the volatility needs to be estimated. The historical volatility is an often used estimator for future volatility. The main drawback of this approach is that the volatility of stock prices may change over time and other factors, apart from past volatility, can be helpful in estimating future volatility (Black 1975). In practice, investors usually use the volatilities implied by observed option prices, the so-called *implied volatilities* (Hull 2006). Implied volatilities are especially important for uninformed, or less informed, investors, since they reflect the market´s information about future stock price volatilities (Black 1975). Other

[10]For put options it is the probability that the put option will be exercised, which equals $Pr(K > S_T)$

models to estimate volatilities, which take into account that volatilities change over time are for instance the *exponentially weighted moving average* (EWMA) model, the *autoregressive conditional heteroscedasticity* (ARCH) model, and the *generalized autoregressive conditional heteroscedasticity* (GARCH) model (Hull 2006).

How the stock price volatility is estimated is at the discretion of those using the model. The values for put and call options, obtained by applying an option pricing formula, are not necessarily consistent with the values that can be observed in the market. One reason is that the market might come up with a different estimate of stock price volatility. When an option seems to be overpriced by the market, indicating that the market value is higher than the value implied by the option pricing formula, the market´s estimate of the stock´s volatility might be higher than the estimate applied in the formula. By contrast, in case the option price seems undervalued, the market´s estimate of the stock price volatility might be lower than that used in the formula (Black 1975). If investors are aware of this mispricing and are able to appropriately interpret the informational content revealed, they can internalize this information in their trading strategy. Ang, Bali, and Cakici 2010 estimate the impact of put and call option implied volatilities on future stock returns. They find that positive innovations in call option implied volatilities predict an increase in the future return of the underlying, whereas positive innovations in put implied volatilities predict a decrease in the future stock return. Innovations in options implied volatilities are used by Ang et al. as a measure of the arrival of news in option markets[11]. These results indicate that investors with positive information about future stock price movements buy call options and thereby increase the implied volatilities. Investors with negative information by contrast, engage in put option trades, which decreases implied volatilities. There are several other studies which also find evidence that option implied volatilities predict future returns of underlying stocks[12].

Moreover, any deviations of observed option prices from those indicated by the Black-Scholes formula seem to be related to option moneyness and time to expiration (Black 1975). Informed investors who discover certain options which are over- or underpriced, will try to initiate a trade. Those investors who hold an overpriced option will sell it, and investors who do not own the option will write it. Investors who do not hold an underpriced option will buy it, and investors who have written an underpriced option will try to buy it back.

[11]Ang et al. also find reverse predictability i.e. stock returns predicting future options implied volatilities. Thus, both securities, options and the underlying stocks, play a crucial role in the price formation in each others´ market.

[12]See Jin et al. (2012), Cremers and Weinbaum (2010), Xing et al. (2010), and Ofek et al. (2004)

5.3.2 Trading costs in option markets

As for trading stocks, investors in option markets also incur trading costs. Explicit trading costs, like commissions, usually consist of a fixed cost plus a certain proportion of the total value of the trade. Commissions for option trades have to be paid on two accounts: when an option contract is bought or sold, and when the option is exercised (Hull 2006). Additional trading costs, investors should consider when trading options, are taxes. In the U.S. the general rule is that gains and losses from trading options on stocks are taxed as capital gains or capital losses. For both, the buyer and the seller of an option, a capital gain or loss may be realized when the option expires worthless, or when the option position is closed out[13]. Option traders certainly also have to pay the bid-ask spread since, like in stock markets, market makers in option markets face order processing costs, inventory holding costs and asymmetric information costs (ibid.). Thus, in option markets as well, liquidity is a decisive driver of option trades. Christoffersen and Mehdi Karoui 2012 find evidence for an illiquidity premium in equity option markets. Increasing illiquidity in options decreases the price of options and increases their future expected return, across all moneyness and maturity categories. They show that the level of illiquidity of the underlying stock is negatively correlated with the return of the option, since a rise in illiquidity of the underlying stock increases the costs for replicating the option, which in turn increases the option price and decreases the expected future return of the option. Their findings coincide with the hedging argument for the use of options. Vijh 1990 examines the liquidity of the CBOE option market by measuring the market depth and bid-ask spreads. He compares the market depth and bid-ask spread of the CBOE with the NYSE and shows that investors face a trade-off between the high market depth of the CBOE and the low bid-ask spread of the NYSE. They explain this result with differences in the market mechanism of the CBOE and the NYSE. However, today these differences in the market mechanism do not exist anymore, as demonstrated in section 4.3 of this paper. Chan, Chung, and Johnson 1995 compare the intraday spread patterns of the stocks traded on the NYSE and options traded on the CBOE. Consistent with the literature they find a U-shaped spread pattern for NYSE stocks. Option spreads, however, exhibit a very different spread pattern. Option spreads are shown to decrease sharply after the market opening but to even out thereafter. They argue that the wide spread of both markets at the beginning of the trading day is due to greater uncertainty, whereas the difference in spreads at the end of the trading day again results from differences in market mechanisms. Mayhew 2002 also investigates the bid-ask spreads of equity options. He assumes that the main

[13] 26 USC §1234 – Options to buy or sell

drivers for option bid-ask spreads are the price of options, the option trading volume and the volatility of the underlying stock. His analysis shows that multiple-listed options have lower effective and quoted spreads than single-listed options. This difference, though, is negatively related with trading volume. The liquidity of options therefore seems to play an important role for investors when making their trading decision. They take into consideration that options with lower levels of liquidity incur higher trading costs, which, in turn, reduces their expected profit.

Margin requirements are also assumed to have an effect on investors´ trading decision. In order to trade options on the CBOE investors are required to fulfill certain margin requirements (*http://www.cboe.com*). Margins thereby serve as collateral in order to cover some of the counterparty risk and to assure that traders of a financial contract are able to satisfy their obligations. Only writers of options are required to supply margins, since only writers of option contracts have an obligation to fulfill the contract. The margin account consists of either cash and/or cash-near securities like Treasury Bills. Usually the initial margin constitutes 5% to 15% of the total value of the contract, with more volatile contracts requiring higher initial margins. Margin requirements can vary between brokerage firms (Bodie et al. 2008). In the option market 'margin' additionally refers to the opportunity for option buyers to purchase options on credit, whereby the customer of the option pays only part of the costs and borrows the balance from the brokerage firm. If investors buy options on credit, they have to deposit securities as collateral for the borrower (*http://www.cboe.com*). In the CBOE in order to buy put as well as call options with 9 months or less until expiration, the price has to be paid in full. Sellers of uncovered put and call options are obliged to deposit on a margin account 100% of the proceeds of the option plus 20% of the total value of the contract, minus the value by which the option is out-of-the-money (ibid.). John et al. 2000 show that margin requirements influence an informed investor´s decision of where to trade, in the option or in the stock market. They show that margin requirements affect trading strategies pursued by investors and hence the resulting equilibrium prices. When margin requirements are not binding, in equilibrium investors split their trades between stocks and options, even though they exhibit a bias towards stocks, given that stocks are more sensitive to information than options. By contrast, when margin requirements for trading either asset are binding, informed investors´ trading decision depends on the leverage provided by the option relative to the stock.

CHAPTER 6

Determinants of stock and option trades

The value of a stock option is closely related to the value of its underlying stock. How the value of an option changes, given small changes in the underlying, is defined by the hedge ratio (Black and Scholes 1973). The hedge ratio determines the number of stocks required in order to get almost the same (dollar) position in stocks than when directly trading one option. This means, an investor who intends to acquire a position in a stock basically has two ways of getting it:

1. He can directly invest in the stock.
2. He can trade an equivalent position in options.

The crucial question is, which security do informed investor trade - the stock or the option? If informed investors are assumed to be rational, they aspire to maximize their expected profit. Their decision will depend on the expected return and expected costs associated with their particular trading strategy. Sometimes it turns out to be beneficial for informed investors to trade directly in the stock market and sometimes the option market is the preferable trading venue. Investor-specific characteristics and the goal traders intend to achieve with their security market interactions, are decisive factors for determining the optimal trading strategy of informed investors.

The basic rationale behind stock and option trades is fundamentally different. The main reasons for trading stocks are the expectation of receiving dividends and the realization of capital gains, in addition to acquiring an ownership share in the corporation. By contrast, the main reasons for trading options are hedging, speculation and arbitrage (Hull 2006). Speculation, of course, is also prevalent in stock trades since investors speculate on the expected future rise or fall of the value of stocks. If uninformed investors choose to trade in the option market, they are most likely hedgers, given that they do not have any superior information about future stock price movements. They just intend to hedge their existing stock positions (long or short) against future unfavorable price movements using option contracts. There are various hedging strategies an uninformed investor could pursue, like holding a long position in a stock plus a short position in a call. This strategy is referred to as *writing a covered call*. Furthermore, hedgers could acquire a short position in a stock combined with a long position in a call option, which is the reverse of writing a covered call. Moreover, a hedging strategy could consist of combining a long position in a stock and a long position in a put option, which is denoted *protective put*. Or, the reverse of a protective put, a short position in the stock plus a short position in a put option (Hull 2006). Informed investors, by contrast, possess superior information about future price movements of stocks. Depending on the type of information investors have, they choose to trade options, stocks or both, such that they can fully capitalize on their informational advantage. If they are provided with good information, implying that the value of a certain stock is expected to increase in the future, investors can either directly buy the stock, buy a call option on that stock, or sell a put option on that stock. If informed investors know that the value of a certain stock will decrease in the future, implying bad information about the underlying, they can either short the stock, buy a put option on that stock, or sell a call option. Certain combinations of options also allow investors to capitalize on their information. *Bull spreads* or *bear spreads* can be used if investors respectively have good or bad information (ibid.). However, investors who perceive their information as qualified to be verified by future stock price movements, will not enter into these spread strategies since, even though they limit the downside risk, they also limit the upside potential of the investment.

Privately informed, profit maximizing investors are expected to consider several factors in order to develop an ideal trading strategy (Chan and Chung 1993). Black 1975 and Diamond and Verrecchia 1987 define some of these driving factors. Following Black 1975, trading costs constitute an important determinant of stock and option trades. Explicit trading costs are often lower in the option market compared to an equivalent trade in the underlying stock. One explanation for this observation is that the brokerage charge for trading options is sometimes lower than for trading stocks (ibid.). However, the cost savings related to commission fees in option trades are only prevalent for short-term trading strategies. If investors try to take an equivalent of a stock position, by constantly buying and selling options, investors end up paying more than what they would have paid for directly acquiring the stock (ibid.).

Another component of trading costs, the bid-ask spread, is also expected to affect investors' trading decision. Black 1975 argues that market makers, or specialists, in option markets quote higher spreads than for equivalent positions in stock markets, given that market makers expect information based trading to be more likely in option rather than in stock trades. Thus, market makers, in order to break even, are required to set higher spreads in the option market[1]. Black bases his argument on the following assumptions (ibid.):

1. Informed investors can get *'more action'* for trading an option compared to trading an equivalent stock position.

2. If an investors is provided with bad information about future stock price movements, it is easier to write call options than to short stocks. The proceeds from writing the option can be invested in order to earn interest.

3. Informed investors often trade in the option market, whereby they would not trade at all if the option market did not exist[2].

4. Options provide investors with more favorable implicit borrowing rates and lower margin requirements.

5. Commission fees on single transactions are lower for trading options than for trading stocks.

6. Also investors, who are limited in funds, can participate in the option market given that their built-in truncated payoff offers investors a lower-cost trading vehicle.

Diamond and Verrecchia 1987 show that if investors want to short the underlying stock due to negative information about future price movements, taking such a position in the underlying asset might be prohibited or extremely expensive. Instead, informed investors can trade options, which offer an alternative way to obtain a short position and hence, enable investors to capitalize on their informational advantage without any restrictions. Diamond and Verrecchia model the effects of short-sale constraints and the speed of adjustment of security prices. They demonstrate that, if short selling is prohibited the unconditional informational efficiency of security prices is reduced. However, if short-selling constraints consist of imposing additional costs on trade, informational efficiency can be improved. Their empirical results suggest that if costs of short-selling are reduced, for instance, by trading options, the speed of

[1] Lee and Yi 2001 show that the adverse selection costs of option trades are an increasing function of financial leverage implicit in options.

[2] This assumption implies that the existence of option markets results in more efficient stock markets, given that information first incorporated in options will rapidly transmitted by hedgers into the stock market. See Black 1975, p.62

adjustment to private information can be increased.

However, even though options exhibit higher financial leverage and lower explicit trading costs, at least for short-term trading strategies, informed traders may not always prefer trading options to trading stocks. Option trading volumes are relatively low compared to the trading volumes of underlying stocks, indicating that stocks provide investors with a higher level of liquidity than options. As suggested by the Kyle model, informed investors prefer to trade in a leveraged market with ample liquidity, which provides them with high potential profits and a low probability of detection. Therefore, informed investors can better hide their information in stock markets (Ang, Bali, and Cakici 2010). Moreover, large trades in option markets are not necessarily anonymous, enabling market makers to detect informed investors more easily (Lee and Yi 2001)[3]. And, as predicted by Black 1975, the bid-ask spread for trading options is higher than for trading stocks.

Thus, there are two competing hypothesis: the *liquidity hypothesis* and the *leverage hypothesis*. According to the liquidity hypothesis informed traders intend to minimize trading costs and hide their information, and hence trade the most liquid securities. Given the observation that stocks are usually more liquid than options, the liquidity hypothesis suggests that informed investors should prefer to trade stocks. The leverage hypothesis, by contrast, assumes that informed investors, in order to maximize the value of their information, trade securities which offer them the highest leverage. Under the terms of this hypothesis, informed investors should trade options rather than stocks, since options provide them with highly levered positions (Chen, Lung, and Tay 2005).

Easley, O'Hara, and Srinivas 1998 present a model based on asymmetric information where informed traders can choose to either trade in the stock market or in the option market. They show that, under certain conditions, informed investors prefer to trade the option rather than the stock. This is the case when options' implicit leverage is high and when options are relatively liquid. They find evidence that particular option trading volumes (positive and negative option volumes) contain information about future stock prices, but their empirical tests also suggest that stock prices lead option volumes (which is consistent with option trades being based on hedging purposes).

Based on the assumptions that options provide investors with an increased leverage and an unlimited upside potential, it seems valid to conjecture that informed investors trade options rather than stocks if the expected benefit from

[3] *http://www.cboe.com*, In June 2006 six U.S. option exchanges (American Stock Exchange, Boston Stock Exchange, CBOE, International Securities Exchange, NYSE Arca and the Philadelphia Stock Exchange) created the Options Regulatory Surveillance Authority (ORSA) in order to improve cooperation among the participating exchanges with respect to insider trading investigations.

the information is large enough to offset the higher bid-ask spread prevalent in option markets. In order to camouflage their identity, informed investors not only take into account the level of liquidity of a certain market, they also strategically choose the size of their trade. They are expected to prefer medium-sized trades to hold back some of their information. Anand and Chakravarty 2007 find that informed investors act strategically when choosing the size of their trades by conditioning on the liquidity of the option contract. They show that information based trading in liquid options primarily occurs through medium-sized trades and in illiquid options primarily through small-sized trades, confirming that the liquidity of securities affects informed investors' ability to hide.

The trading decision of informed investors appears to be conditional on many factors, not least on personal characteristics of individual investors. However, even though trading options incurs higher trading costs, it is assumed in this paper that the informational advantage of insiders is large enough to offset this drawback. It is claimed, that the increased leverage of options not only compensates for a higher bid-ask spread and a lower level of liquidity, but also enables informed investors to maximize their expected profit by maximizing the value of their information. Specifically, it is assumed that, if investors have good information, they are more likely to trade out-of-the-money (OTM) calls, rather than at-the-money (ATM) or in-the-money (ITM) calls, because OTM calls provide them the greatest leverage and hence the highest expected return. Moreover, investors in possession of good information should rather buy OTM calls than sell any put option since buying calls not only endows them with downside protection, but also with unlimited upside potential. Shorting put options, by contrast, involves a limited profit but the potential for unlimited risk. The same conclusion is drawn for trading on negative information. If investors have negative information about future stock price movements, they are most likely to buy OTM put options. In accordance with the leverage hypothesis, it is assumed in this paper that the pivotal objective of informed investors is to maximize their expected profit by trading highly levered securities. Therefore, information based trading is expected to occur in the option market, implying that informed investors prefer to trade options rather than stocks. In order to maximize the value of their information, informed investors trade those options which provide them with the greatest leverage. Thus, investors in possession of positive information are assumed to buy OTM call options and investors with negative information to buy OTM put options. These arguments can be summarized in the following hypotheses, which are tested in the empirical part of this paper:

Hypothesis 1: Option prices contain information about the value of underlying stocks which is not contained in observed stock prices. Thus, current option prices have predictive ability for future stock price movements.

Hypothesis 2: The moneyness of options is significant for explaining future stock price movements, with a lower the level of moneyness corresponding to a higher predictive ability of options.

These hypotheses effectively test the efficient market hypothesis since in an efficient market, observed stock prices fully reflect all available information and no derivative security contains additional information. The discovery of option prices revealing information not already incorporated in stock prices, would contradict the idea of efficient markets. The hypotheses are tested using empirical models and the results are presented in the empirical part of this paper.

If it can be shown that information based trading occurs in the option market, this has certain implications and consequences for the underlying stock market. In the following section these potential effects are discussed.

CHAPTER 7

Consequences of information based trading in options

The *Law of One Price* predicts that the market price for two economically identical securities should be the same (Bodie et al. 2008). Given that options are defined as securities whose value depends on, or is derived from, another underlying asset (Hull 2006), no additional information, beyond that already embedded in the price of the underlying, should be incorporated in the price of options. The prices of underlying assets and options should simultaneously incorporate and reflect new information. Any price discrepancy between stock and option prices should immediately be arbitraged away (Chan and Chung 1993). However, options are only redundant securities in a perfect capital market, with no transaction costs, no asymmetric information and no restriction on shorting securities (Ang, Bali, and Cakici 2010). The complete, frictionless market, assumed by Black and Scholes (1973) in their option pricing formula, does not coincide with what can be observed in the real world. The existence of asymmetrically informed investors can induce information based trading in the option market, indicating that informed investors prefer trading options rather than the underlying stocks.

Information based trading in options entails several consequences for stock and option markets. Easley, O'Hara, and Srinivas 1998 predict that, if informed investors tend to trade in certain markets, those markets where information based trades can be observed, lead other markets, where no information based trading takes place. Thus, if the information incorporated in stocks and options deviates from one another, options cannot be replicated by investing in the underlying stock and in short-term interest rates (Ross 1976). Grossman 1988 examines the informational role of real securities and securities synthesized by a dynamic trading strategy. Grossman shows that many investors buy long-term put options in order to insure their investment positions against future price declines and to decrease their risk exposure. If such options are not available in the market, investors can synthesize the asset with a dynamic trading strategy. A problem occurs when investors do not know the exact amount of securities required to replicate the option. In this case options, which are otherwise considered redundant securities, reveal additional information. He argues that, if options can be synthetically replicated, their absence impedes the transmission of information and results in an increase in stock volatility. Thus, the traded option appears to be redundant, but the removal of the option from the market would have real consequences. If options cannot be considered redundant, then they may have an effect on the underlying asset, because equilibrium prices change if non-redundant securities are traded (Back 1993).

Back (1993) uses an extension of the Kyle model of continuous insider trading and shows that, due to the existence of asymmetric information, options cannot be priced by arbitrage methods and are not redundant assets. Even if options appear to be redundant, the volatility of the underlying asset becomes stochastic as a result of the information flow from the option market to the stock market, which precludes the dynamic replication of the option. Contrary to Grossman (1988), Back (1993) shows that nontraded options seem to be redundant, but trading an option can have real consequences since its price incorporates and reveals information about the value of the underlying. Thus, option trades reveal different information than stock trades and the existence of an option market provides the market with a richer class of signals (Back 1993).

If options are not redundant, their prices, trading volume and other option measures reflect different information sets than those of underlying stocks. As a consequence, new information is first incorporated in options. Therefore, following hypothesis 1, it is expected that options, which provide investors with high leverage, like OTM options, to lead stock prices.

Various studies investigate this conjecture of option markets being the preferred trading venue for information based trading. So far however, the empirical results are inconclusive. Lee and Yi 2001, for instance, examine the adverse selection component of the bid-ask spread for options listed on the CBOE and for stock equivalent positions listed on the NYSE. They find that for all trade sizes, the adverse selection component was larger on the CBOE than on the NYSE, showing that trades on the CBOE are generally more information based than trades on the NYSE. When they analyze the sample by trade size, however, they find that, while the adverse selection component for small trades is greater on the CBOE, the contrary is observed for large trades. Thus, the extent of information based trading in option markets appears to decrease with trade size. Several other studies also find evidence for information based trading in options. Others like Vijh 1990, Chan and Chung 1993, Chan, Chung, and Fong 2002 and Chan and Chung 1993 find evidence that stock prices lead option prices. However, this lead disappears when average bid-ask prices instead of transaction prices are used.

The existence of informed trading in option markets affects the price discovery process of stock and option markets. Price discovery is defined by Hasbrouck 1995 as *'the impounding of new information into the security price'*. It identifies the process by which a new equilibrium price is found after investors change their demand function owing to the arrival of new information (Schwartz and Francioni 2004). If informed investors choose to first trade options, price discovery is expected to occur in option markets. Hasbrouck 1995 presents a model, which enables to investigate in which market price discovery takes place if homogenous or closely linked securities are traded in multiple markets[1]. Price discovery in this framework is the innovation of the efficient price. The information share of a particular market determines the contribution of that market to the price discovery in another market. The information share in particular identifies the contribution to the variance of the innovation of the efficient price.

Chakravarty, Gulen, and Mayhew 2004 estimate the contribution of options listed on the CBOE to price discovery in the underlying stocks listed on the NYSE, applying a modification of Hasbrouck's (1995) information share, to be 17% on average. They show that the price discovery in the option market depends on options' implicit leverage, trading volume and spreads, implying that option traders assess both, leverage as well as liquidity[2]. Thus, informed investors prefer trading liquid options, which provide them with an increased leverage. Various other studies also find evidence for significant price discovery in option markets[3]. Pan and Poteshman (2006) show that option trading volume, specifically put/call ratios, incorporate information about future price movements of underlying stocks, whereby this finding is most pronounced for smaller stocks. They find that stocks which reveal positive option signals, exhibiting a low put/call ratio, outperform stocks with negative option signals, exhibiting a high put/call ratio, by over 40 basis points per day on a risk adjusted basis.

The remainder of this paper is dedicated to present the empirical test of the hypotheses that option prices lead stock prices and that the predictive ability of options increases with a lower level of option moneyness.

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[1]Options and stocks can be considered as one security, since they are closely linked by short-term arbitrage considerations.

[2]This relationship was also found by Lee and Yi 2001, Easley, O'Hara, and Srinivas 1998, and Biais and Hillion 1994

[3]For instance Pan and Poteshman 2006, Anand and Chakravarty 2007, and Cao, Griffin, and Chen 2005

CHAPTER 8

Data

Using panel data this study tests whether various option variables have a significant impact on stocks and whether a lead-lag relation between options and stocks exists which, enables to predict changes in stock prices with observed option variables. The data applied in the analysis was extracted from different sources. The option dataset was obtained from OptionData.net (*http://optiondata.net/*), which is owned and operated by OptionCast LLC[1]. The option dataset is comprised of daily data for 248 trading days from January 2^{nd} 2012 to December 31^{st} 2012 and contains bid and ask quotes, closing prices, trading volume, open interest, strike prices and expiration dates for all option contracts trading on American exchanges during this time period. Given that this study focuses on the interrelationship between stocks and options which are listed on the NYSE and the CBOE, options which are not traded on the CBOE and whose respective underling is not traded on the NYSE are removed from the dataset. To ensure that the analysis is based on a representative dataset with sufficient trading activity and variation in the data, only 100 companies with the most actively traded options are included in the study. The option trading activity is calculated as the average of the total trading volume (call trading volume plus put trading volume) in the year 2012 aggregated over all different exercise prices and maturities. Table A.1 in the Appendix lists the resulting companies which are included in the study. In order to obtain a balanced panel, three companies (Las Vegas Sands Corp., Platinum Communications Corp. and Sprint Nextel Corp.) for which data was missing on certain trading days, are deleted from the dataset.

The remaining sample consists of roughly 32,819 observations for each of

[1] A snapshot of the data structure of the initial file is provided in figure A.1. of the Appendix. The snapshot represents only one trading day (01/03/2012)

the quote and volume variables per trading day[2]. In order to further reduce the option dataset the following restrictions are imposed: time to maturity is required to be between 10 and 50 trading days, the bid and ask quotes, as well as closing prices and trading volumes are required to be larger than zero. The time to maturity is calculated as the difference between the time to expiration and the current date. By means of these restrictions, the dataset was abbreviated to contain approximately 3,180 observations per variable per trading day. The last step in filtering the option data is aimed at reducing the data such that for each underlying only one put and one call variable remains. This is realized by calculating the average values for puts and calls respectively, for each underlying and each trading measure[3]. The resulting dataset, on which the regression analysis is based upon, comprises: average put mid-quote, average call mid-quote, average put trading volume, average call trading volume, and a moneyness interaction term for calls and puts respectively, which is calculated as the daily average of the mid-quotes multiplied by the moneyness of the options[4][5]. This calculation is conducted separately for put and call contracts, for each underlying and each trading day for the entire time period. In the regression analysis mid-quotes (the average of bid and ask quotes), instead of closing prices, are used since market makers can change their quotes immediately after new information enters the market, even in the absence of a trade. Prices, by contrast, only change if a new trade is executed.

The stock data was extracted from the Wharton Research Data Services (*https://wrds-web.wharton.upenn.edu/wrds/*) and comprises mid-quotes, trading volume and number of shares outstanding for each trading day from January 2^{nd} to December 31^{st} 2012.

The final dataset includes 244 trading days and 97 cross-sections, represented by the different companies. Table 8.1 provides descriptive statistics of the relevant stock and options variables. Panel A depicts statistics for daily mid-quotes of stocks, call and put options. In Panel B the statistics for the daily trading volume of stocks and options as well as the daily trading volume for options, being separated in calls and puts, is presented. Panel C shows daily illiquidity ratios with illiquidity ratios being measured as in Amihud 2002.

Obviously the average mid-quote of stocks exceeds that of options since

[2]Given that for each company multiple option contracts are traded per trading day, various quotes and trading volume data for put and call options is available each day.

[3]Applying this averaging method, enables to determine, for instance, the average mid-quote of BAC call options on the 05/06/2012.

[4]The interaction term is expected to reflect any variation of the underlying due to changes in the moneyness of options by taking into account the assumed correlation between moneyness and mid-quotes.

[5]How the moneyness interaction term is calculated is shown in Chapter 9.

[6]*Stdv.* denotes standard deviation

[7]Daily mid-quotes are calculated as the average of bid and ask quotes on the respective trading day.

Table 8.1: Descriptive statistics of stock and option variables

	Mean	Stdv.[6]	Minimum	Maximum	Skewness	Kurtosis
Panel A: Daily Mid-quotes[7]						
Stocks	53.40	60.68	1.69	498.53	4.00	23.35
Calls	7.00	9.39	0.12	138.88	5.22	44.90
Puts	5.25	7.76	0.17	127.34	7.71	93.84
Panel B: Daily Trading Volume						
Stocks	13,487,945	25,249,625	206,300	669,479,900	9.29	130.96
Options	727.67	2,675.37	1,47	232,264.9	49.49	3,526.39
Calls	468.69	2,521.73	0.20	230,954.2	57.76	4,384.88
Puts	258.71	505.36	0.11	18,333.50	10.68	214.69
Panel C: Daily illiquidity ratio[8]						
Stocks	3.19E-09	2.68E-08	0	2.99E-06	74.02	7,129.394
Calls	0.000989	0.008047	0	1.11	109.20	14,830.54
Puts	0.001976	0.01137	0	0.7015	35.43	1,765.08

by buying put or call options, investors merely acquire the right to buy or sell the underlying in the future. Panel A also indicates that, on average, call mid-quotes are higher than put mid-quotes. Investors seem to be willing to pay a higher price in order to obtain an asset which entitles them the right to buy the underlying asset in the future and, additionally, provides them with an unlimited upside potential. Panel B shows that the average daily trading volume of stocks is far beyond that of options. If trading volume is used as a proxy of liquidity, this finding suggests that stock markets are considerably more liquid than option markets, implying that informed investors can better hide their identity and increase the value of their informational advantage in stock markets. The same conclusion can be drawn when the illiquidity ratio presented in Panel C is considered. Stocks exhibit the lowest level of illiquidity being equivalent to showing the highest level of liquidity. The illiquidity ratio can also be regarded as a proxy for implicit trading costs. Thus, stock markets seem to be the trading venue with the lowest trading costs. When the liquidity of call and put options is compared, Panel B illustrates that call options are more liquid than put options, with call options showing more average trading volume. Panel C supports this result since put options exhibit a higher level of illiquidity than call options.

Based on the findings in table 8.1, the stock market appears to be a less expensive trading venue for informed trades, since stock markets exhibit a higher level of liquidity and less implicit trading costs compared to option markets. However, the higher level of trading volume in stock markets also

[8] The illiquidity ratio is defined as in Amihud 2002, as a measure of implicit trading costs. It is calculated as the absolute price change on a particular day, divided by the trading volume on that day. Instead of prices, mid-quotes are used.

might represent evidence for a lower level of informed trading. Uninformed investors prefer to trade in markets where the proportion of informed investors is rather low. In markets where the probabilty of information based trading is high, market makers quote higher bid-ask spreads in order to compensate their potential loss incurred by trading with insiders. Uninformed investors are eventually those, who have to pay the higher spread. Thus, the higher trading volume in stock markets might be considered an indication for a low level of informed trading in stock markets. The relatively low level of trading volume in option markets might predict a high proportion of investors with superior information. Moreover, the higher implicit trading costs of option markets suggest that the increased leverage provided by those options, which are traded by informed investors, offer a benefit which even exceeds the comparably high implicit trading costs.

CHAPTER 9

Empirical analysis

There are basically two approaches, applied in previous studies, to examine information based trading in option markets. One opportunity is to use *vector error correction models* (VECM). This approach is based on the assumption that prices in stock and option markets share a common implicit efficient price, since both securities are in the short-run closely linked by arbitrage considerations. Actual transaction prices are then a function of the implicit efficient price and an autoregressive adjustment component or a bid-ask spread component. Hasbrouck's information share (Hasbrouck 1995) can be adopted in order to determine the contribution of option market´s innovation to the innovation in the common efficient price. A VECM can be estimated to show that traders in the stock market are responding to a price discrepancy, an error between stock and option markets. This approach is applied for instance by Chakravarty, Gulen, and Mayhew 2004.

A second approach, often used in empirical studies to investigate informed trading in option markets, is using *lead-lag regressions.* In perfect capital markets option prices should neither lead nor lag stock prices, consistent with the assumption that new information is immediately incorporated in security prices and that no arbitrage opportunities exist. Given that in reality we do not observe perfect capital markets, due to information being asymmetrically distributed among investors and other market frictions, one market might lead the other market. This entails that information is first incorporated in the leading market. The information edge of the leading market, associated therewith, can be used to predict future price movements of the market that lags behind. However, even if it can be shown that information is first incorporated in a certain market, or asset, this need not necessarily be an evidence for information based trading. The lead-lag pattern might be spurious. If, for instance, asset A is traded more frequently than another asset B, new information is more likely to be first reflected in asset A, just because asset B may not trade immediately after the new information arrives at the market. Asset B eventually incorporates the news, but with a lag. The price returns of A and B therefore seem to be cross-autocorrelated even though in fact they are temporally independent (Campbell, Lo, and MacKinlay 1997). For the purpose of this study, however, not the arrival or incorporation of public news is analyzed, but how stocks and options respond to private information. If options are shown to lead stocks, this is not assumed to derive from any microstructure frictions or nonsynchronous trading arguments, but owing to information based trading in options. Thus, the leading asset is expected to be traded and to reflect private information first. After the trade is executed and the quote of the traded asset has changed accordingly, the private information eventually becomes public and is incorporated in the lagging asset.

In this study, lead-lag regressions are used in order to analyze the predictive ability of options and to determine how fast new information is incorporated. In particular, lead-lag regressions are supposed to identify which asset reflects new information earlier and in which market informed traders operate.

9.1 Vector autoregression models

To get an idea of the relationship between stock and option markets, the first model to be estimated is a vector autoregressive (VAR) model. VAR models were introduced by Sims 1980 as a generalization of univariate AR models. They enable the identification of any linear dependence or feedback effect within a system of regression models. One limitation of VARs is that all the components of the model need to be stationary in order to use hypothesis tests. Thus, before estimating VAR models it has to be guaranteed that all the components included in the model are stationary. If this is not the case, a cointegration relationship between the components needs to be found and then a vector error correction model (VECM), which takes into account any temporal discrepancy between the variables, can be estimated (Brooks 2008).

The VAR models, estimated in this study, consist of the mid-quote returns of stocks, call and put options, so as to get a preliminary estimate of the relationship between stock and option quotes. To ensure that the included variables are stationary, a Fisher-ADF test of an individual unit root is performed. An *individual root test* is applied in order to allow for different AR coefficients in each of the series. All the unit root tests are conducted on the level with individual intercepts in order to include individual fixed effects. The results are summarized in table 9.1

The results of the Fisher-ADF test suggest that all three variables are stationary on the level, since the hypothesis of a unit root can be rejected for each variable at a 1% significance level. Given these results, a three-dimensional

Table 9.1: Fisher - ADF unit root tests

	Statistic	Probability
Panel A: Null hypothesis: stock mid-quote return has a unit root		
ADF - Fisher Chi-square	5034.49	0.0000
Panel B: Null hypothesis: call mid-quote return has a unit root		
ADF - Fisher Chi-square	4152.08	0.0000
Panel C: Null hypothesis: put mid-quote return has a unit root		
ADF - Fisher Chi-square	4182.49	0.0000

VAR containing stock, call and put mid-quotes can be estimated without being required to find a cointegration relationship. The following three-dimensional VAR is estimated:

$$s_t = \beta_0 + \beta_1 s_{t-1} + \cdots + \beta_k s_{t-k} + \alpha_1 c_{t-1} + \cdots + \alpha_k c_{t-k} + \gamma_1 p_{t-1} + \cdots + \gamma_k p_{t-k} + u_t$$
$$c_t = \beta_0 + \beta_1 c_{t-1} + \cdots + \beta_k c_{t-k} + \alpha_1 p_{t-1} + \cdots + \alpha_k p_{t-k} + \gamma_1 s_{t-1} + \cdots + \gamma_k s_{t-k} + v_t$$
$$p_t = \beta_0 + \beta_1 p_{t-1} + \cdots + \beta_k p_{t-k} + \alpha_1 c_{t-1} + \cdots + \alpha_k c_{t-k} + \gamma_1 s_{t-1} + \cdots + \gamma_k s_{t-k} + e_t$$

s_t, c_t and p_t correspond to the respective daily mid-quote returns of stocks, call and put options. u_t, v_t and e_t are white noise disturbance terms with $E(u_t) = E(v_t) = E(e_t) = 0$ and $E(u_t, v_t) = E(u_t, e_t) = E(v_t, e_t) = 0$. This VAR model contains three variables. The current value of each of the variables depends on k lagged values of the same variable plus previous k values of the other two variables, and error terms. The optimal lag length can be found by employing multivariate information criteria. According to the *Akaike Information criterion*, the optimal number of lags to be included in the VAR presented above is 8. Thus, the VAR model is estimated with $k = 8$.

The coefficients of the individual lags, however, do not appear to be significant for all the lags and the sign and degree of the coefficients is different for different lags (Brooks 2008). Thus, in order to detect potential lead-lag interactions between the series and to draw valid conclusions, Granger causality tests are performed on the estimated VAR models. The test results are presented in Panel A, B and C of Table 9.2

Table 9.2 shows that there appears to be a 'tri-dimensional' feedback effect, since the hypothesis of no Granger causality can be rejected in each case at a 1% significance level. Thus, each variable included in the VAR system Granger causes the others, implying that each variable in the model can be treated as endogenous. Granger causality, however, is only an indication of a correlation between the current value of one variable and past values of other variables.

Table 9.2: VAR Granger Causality/Block Exogeneity Wald Tests

Panel A: Dependent variable: stock mid-quote return			
Excluded	Chi-sq	df	Prob.
Call return	20.69373	8	0.0080
Put return	35.52315	8	0.0000
All	55.68280	16	0.0000
Panel B Dependent variable: call mid-quote return			
Excluded	Chi-sq	df	Prob.
Stock return	1648.207	8	0.0000
Put return	94.27204	8	0.0000
All	1665.294	16	0.0000
Panel C: Dependent variable: put mid-quote return			
Excluded	Chi-sq	df	Prob.
Stock return	1127.029	8	0.0000
Call return	141.8389	8	0.0000
All	1212.471	16	0.0000

Therefore, even though the returns of call and put mid-quotes is found to Granger cause stock returns, this by no means implies that movements in call and put mid-quotes cause movements in stocks. Nevertheless, the test results provide evidence of a causal relationship between stocks and options and the performance of a more in-depth analysis of this relationship is justified.

9.2 Lead-lag regressions

The dataset is structured as panel data, which contain observations on multiple variables observed over the 244 trading days included in the study for each of the 97 companies. There are mainly two models to estimate panel data: the fixed effects model and the random effects model. Both models take into account any common structure in the data (Brooks 2008). Given that it is not possible to determine the appropriate model in advance, each regression is initially estimated twice in order to test the model using fixed effects as well as random effects. Which model appropriately reflects the data is tested using a *redundant fixed effects test* for the fixed effects model and a *Hausman test* for the random effects model. The test results indicate that a model with period fixed effects, as well as a model with period random effects, is supported by the data. Thus, there seems to be no firm-specific heterogeneity and in principle both models could be applied.

In this study, however, each regression is based on a fixed effects model since for all the estimated equations the Adjusted R^2 was significantly higher when using period fixed effects compared to period random effects. The particular method applied for the regression analysis is a *Panel Least Squares* estimation with period fixed effects. However, it is important to be aware of the loss of degrees of freedom which accompanies this approach, since for each of the demeaned variables one degree of freedom is consumed.

9.2.1 Results

Stock returns regressed on option variables

The first models to be estimated analyze the explanatory power of contemporaneous and lagged values of the mid-quote returns of call and put options for variations in stock mid-quote returns. The impact of call and put returns is first estimated separately and then together in one regression. The estimated regressions have the following form:

$$s_t = \alpha + \beta_0 \cdot c_t + \sum_{k=1}^{8} \beta_k \cdot c_{t-k} + \epsilon_t \tag{9.1}$$

$$s_t = \alpha + \gamma_0 \cdot p_t + \sum_{k=1}^{8} \gamma_k \cdot p_{t-k} + \epsilon_t \tag{9.2}$$

$$s_t = \alpha + \beta_0 \cdot c_t + \gamma_0 \cdot p_t + \sum_{k=1}^{8} \beta_k \cdot c_{t-k} + \sum_{k=1}^{8} \gamma_k \cdot p_{t-k} + \epsilon_t \tag{9.3}$$

where s_t, c_t and p_t refer to the stock, call and put return at time t. Following the Akaike Information criterion identified in the VAR models above, the optimal number of lags to include in the analysis is 8. Thus, the lead-lag regressions are estimated with $k = 8$ lags. The results of the regressions are presented in table 9.3[1].

Table 9.3 reports the t-statistics and standard errors for all the variables up to lag 4. The results of model 9.1 show that the contemporaneous and the one day lagged value of the call return are significant. While the contemporaneous call return is highly significant at a 1% level, the one day lagged return is significant at a 5% level. Both coefficients are positive, implying a positive relationship between stock returns and contemporaneous and one day lagged call returns. The significance and positive sign of the one day lagged call return reveals that an increase in the return of call options predicts an increase in the stock return on the following trading day. When the stock return is regressed on contemporaneous and lagged values of put options' returns (model 9.2), the contemporaneous value and four days lagged value are significant on a 1% level, whereby both coefficients appear with a negative sign. The negative and significant coefficient of the four day lagged put return indicates that an increase in the put return is followed by a decrease in the stock return four days later. When the significance of call and put returns is estimated in one single regression (model 9.3) the results basically testify the same but now also the four days lagged call return and the one day lagged put return are

[1] Since none of the variables is found to be significant for lags larger than 4, only the results up to 4 lags are reported.

Table 9.3: Panel Least Squares regressions: Stock mid-quote returns regressed on put and call mid-quote returns

Regressors	(9.1)	(9.2)	(9.3)
α	-0.826139	-1.392933	-1.586938
	(0.000129)	(0.000132)	(0.000129)
c(t)	27.20614***	-	28.41198***
	(0.000762)		(0.000769)
c(t-1)	1.988619**	-	2.444826**
	(0.000763)		(0.000762)
c(t-2)	0.611110	-	0.875210
	(0.000763)		(0.000762)
c(t-3)	-0.351268	-	0.181951
	(0.000763)		(0.000762)
c(t-4)	1.610252	-	2.817824***
	(0.000698)		(0.000763)
p(t)	-	-20.39578***	-22.45113***
		(0.000735)	(0.000724)
p(t-1)	-	-1.193280	-1.862575*
		(0.000720)	(0.000710)
p(t-2)	-	-1.083820	-1.273336
		(0.000720)	(0.000709)
p(t-3)	-	-0.711596	-0.937720
		(0.000720)	(0.000709)
p(t-4)	-	-3.380710***	-4.176182***
		(0.000720)	(0.000709)
R^2	0.250216	0.240743	0.267141
Adj. R^2	0.242270	0.232558	0.258951
S.E. of regression	0.019873	0.020069	0.019721
N.obs.	23255	23255	23255

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Standard errors in parantheses

significant.

The results of the regressions are consistent with *Hypothesis 1*: option returns appear to lead stock returns, for at least one day, implying that options contain information not yet incorporated in stock returns. When the impact of call and put options is estimated in the same regression, an option lead can be observed for lag one and lag four. While the positive sign of the significant coefficients of lagged call returns might represent positive news about the underlying, the negative sign of the significant put returns might provide evidence of negative news about the underlying being earlier incorporated in options. However, there is no valid explanation why the values at lag 2 and lag 3 are not significant, but at lag 4 they are.

In order to test *Hypothesis 2*, stating that informed investors prefer to trade out-of-the money options due to the increased leverage they entail, a moneyness interaction term is included in the regression. Moneyness is assumed to be significant in explaining future stock returns to such an extent that the predictive ability for options with lower levels of moneyness is higher than that of options with higher levels of moneyness. The moneyness of options is calculated as:

$$moneyness_{(call)} = (\frac{S_t}{K})$$
$$moneyness_{(put)} = (\frac{K}{S_t})$$

S_t refers to the price of the underlying on the respective trading day t, and K to the predetermined strike price of the option. Call and put options are deemed out-of-the money if the calculated moneyness is smaller than 0.9, at-the-money if the moneyness is between 0.9 and 1.1, and in-the-money if it is larger than 1.1. The moneyness interaction term is then calculated for each trading day as the average of each option contract's moneyness multiplied by the respective mid-quote:

$$cm_i = (\frac{1}{J})\sum_{j}^{J} moneyness_{i,j} \cdot midquote_{i,j}$$
$$pm_i = (\frac{1}{M})\sum_{m}^{M} moneyness_{i,m} \cdot midquote_{i,m}$$

where cm and pm represent the moneyness interaction terms for call and put options respectively, i defines the underlying, $j = 1 \dots J$ the j different call option contracts per underlying per trading day and $m = 1 \dots M$ the m different put option contracts per underlying per trading day.

When the moneyness interaction term is included in the regression, the following models are estimated:

$$s_t = \alpha + \beta_0 \cdot c_t + \sum_{k=1}^{8} \beta_k \cdot c_{t-k} + \delta_0 \cdot cm_t + \sum_{k=1}^{8} \delta_k \cdot cm_{t-k} + \epsilon_t \tag{9.4}$$

$$s_t = \alpha + \gamma_0 \cdot p_t + \sum_{k=1}^{8} \gamma_k \cdot p_{t-k} + \varphi_0 \cdot pm_t + \sum_{k=1}^{8} \varphi_k \cdot pm_{t-k} + \epsilon_t \tag{9.5}$$

$$\begin{aligned} s_t = {} & \alpha + \beta_0 \cdot c_t + \gamma_0 \cdot p_t + \sum_{k=1}^{8} \beta_k \cdot c_{t-k} + \sum_{k=1}^{8} \gamma_k \cdot p_{t-k} \\ & + \delta_0 \cdot cm_t + \sum_{k=1}^{8} \delta_k \cdot cm_{t-k} + \varphi_0 \cdot pm_t + \sum_{k=1}^{8} \varphi_k \cdot pm_{t-k} + \epsilon_t \end{aligned} \tag{9.6}$$

The results of the regressions are presented in Table 9.4.

When the moneyness interaction term is included only for call options (model 9.4), none of the interaction terms is significant. Thus, this model is not

Table 9.4: Panel Least Squares regressions: Stock returns regressed on call and put returns and moneyness interaction terms

Regressors	(9.4)	(9.5)	(9.6)
α	-1.689094 (0.000160)	-1.809843 (0.000147)	-2.127401 (0.000167)
c(t)	23.30898*** (0.000885)	-	24.39741*** (0.000875)
c(t-1)	2.532855** (0.000885)	-	2.843135*** (0.000875)
c(t-2)	1.176350 (0.000885)	-	1.221838 (0.000876)
c(t-3)	-0.417249 (0.000886)	-	0.004661 (0.000876)
c(t-4)	1.505594 (0.000701)	-	2.513568** (0.000695)
cm(t)	0.422738 (4.35E-05)	-	0.809195 (4.30E-05)
cm(t-1)	-1.351980 (5.90E-05)	-	-1.526714 (5.82E-05)
cm(t-2)	0.275036 (5.89E-05)	-	0.275885 (5.82E-05)
cm(t-3)	1.085279 (5.93E-05)	-	0.800624 (5.85E-05)
cm(t-4)	-0.109467 (4.31E-05)	-	0.092279 (4.26E-05)
p(t)	-	-15.74959*** (0.000792)	-17.84346*** (0.000780)
p(t-1)	-	0.068019 (0.000793)	-0.636207 (0.000781)
p(t-2)	-	-0.596034 (0.000786)	-0.824600 (0.000774)
p(t-3)	-	-1.049094 (0.000776)	-1.283856 (0.000765)
p(t-4)	-	-3.017267*** (0.000648)	-3.928775*** (0.000639)
pm(t)	-	-6.743684*** (4.75E-05)	-6.161304*** (4.67E-05)
pm(t-1)	-	3.245192*** (6.73E-05)	3.113147*** (6.62E-05)
pm(t-2)	-	0.914011 (6.75E-05)	0.617091 (6.64E-05)
pm(t-3)	-	1.846350* (6.78E-05)	1.883249* (6.67E-05)
pm(t-4)	-	-1.442603 (4.86E-05)	-1.539844 (4.78E-05)
R^2	0.250457	0.242681	0.268961
Adj. R^2	0.242352	0.234492	0.260740
S.E. of regression	0.019872	0.019975	0.019629
N.obs.	23255	23255	23255

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Standard errors in parantheses

able to detect any sign that informed investors prefer to trade out-of-the money options. However, the estimation output of model 9.5 shows contemporaneous significance for the moneyness of put options, as well as for the first and third lag. The positive sign of lag 1 and 3 indicates that, given an increase in put-options' moneyness, controlling for the variation in mid-quotes, the return of stocks increases one day and three days later. Since the significant coefficients of the lagged put mid-quote returns are all negative, the overall relationship between moneyness and stock return predictability is negative as well. Hence, put-option moneyness is significant in explaining future stock returns, with lower option moneyness predicting higher stock returns. When the significance of call and put returns, and call and put moneyness interaction terms, for explaining stock returns, is tested in one single regression (model 9.6), the results for the moneyness interaction term in principle remain the same. The call return now also appears significant at lag 4.

The explanatory power of the regression models presented so far is rather high with an Adjusted R^2 exceeding 23% in each regression. However, call and put returns might incorporate the effect of other factors. Thus, it is necessary to add various control variables to the model in order to disentangle the impact of the return of options from the influence of other factors.

As discussed in the theoretical part of this paper, investors take into account the liquidity of assets when making their trading decision. They want to be compensated with a higher expected return for acquiring assets with a lower level of liquidity. Thus, the liquidity of assets is assumed qualified to predict future returns. The Amihud illiquidity measure (Amihud 2002) is included in the regression model so as to control for the effect of liquidity of stocks and options and in order to separate the predictive power of put and call option returns from the predictive power of (il)liquidity. Given that investors want to be remunerated for buying assets which exhibit higher illiquidity, the illiquidity measure is assumed to have a positive impact on the stock return, implying that investors require a higher expected return for buying illiquid stocks. The regression output is presented in Table 9.5.

ILLIQ_stock, ILLIQ_call and ILLIQ_put represent the illiquidity of stocks, calls and puts respectively. The results of Table 9.5 reveal that neither call nor put option illiquidity has a significant impact on the return of stock options. The illiquidity measure for stocks however, is highly significant up to lag 3. While the contemporaneous coefficient is negative, indicating that the actual return for illiquid stocks is lower, the coefficient of the lagged illiquidity measure is positive. Thus, consistent with the literature, this result illustrates that investors demand higher required returns for trading illiquid stocks. By observing a stock's liquidity, one is capable of predicting future stock returns up to three days in advance.

Table 9.5: Panel Least Squares regressions: Stock returns regressed on call and put returns, moneyness interaction terms and illiquidity

Regressors	t-statistics	standard errors
α	-0.679400	0.000177
c(t)	24.41882***	0.000872
c(t-1)	2.970206***	0.000870
c(t-2)	1.203466	0.000870
c(t-3)	0.140673	0.000871
c(t-4)	2.419763**	0.000699
cm(t)	0.779678	4.34E-05
cm(t-1)	-1.257071	5.83E-05
cm(t-2)	0.613109	5.78E-05
cm(t-3)	0.423913	5.82E-05
cm(t-4)	0.522462	4.24E-05
p(t)	-18.07437***	0.000775
p(t-1)	-0.374485	0.000776
p(t-2)	-0.776659	0.000770
p(t-3)	-1.396194	0.000761
p(t-4)	-3.948533***	0.000636
pm(t)	-5.990125***	4.64E-05
pm(t-1)	3.034580***	6.57E-05
pm(t-2)	0.648183	6.59E-05
pm(t-3)	2.268285**	6.62E-05
pm(t-4)	-1.558941	4.75E-05
ILLIQ_stock(t)	-18.28428***	40436.01
ILLIQ_stock(t-1)	3.287302***	40121.41
ILLIQ_stock(t-2)	3.589802***	40091.73
ILLIQ_stock(t-3)	2.805677***	40436.07
ILLIQ_stock(t-4)	-0.388776	5786.235
ILLIQ_call(t)	0.634870	0.016003
ILLIQ_call(t-1)	0.855315	0.015999
ILLIQ_call(t-2)	0.847443	0.015976
ILLIQ_call(t-3)	-0.713960	0.015984
ILLIQ_call(t-4)	-0.358069	0.015956
ILLIQ_put(t)	0.590867	0.013685
ILLIQ_put(t-1)	1.323957	0.013704
ILLIQ_put(t-2)	-0.676311	0.013633
ILLIQ_put(t-3)	1.400575	0.013653
ILLIQ_put(t-4)	-0.585874	0.013550
R^2	0.279701	
Adj. R^2	0.271134	
S.E. of regression	0.019491	
N.obs.	23651	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 9.6: Panel Least Squares regressions: Stock returns regressed on call and put returns, moneyness interaction terms and log of size

Regressors	t-statistics	standard errors
α	-3.280229	0.000832
c(t)	8.762420***	0.000418
c(t-1)	3.828279*	0.000419
cm(t)	4.309001***	1.98E-05
cm(t-1)	-3.279616***	2.68E-05
p(t)	-2.242655**	0.000367
p(t-1)	-2.414361**	0.000369
pm(t)	-7.238357***	2.15E-05
pm(t-1)	4.833637***	3.05E-05
Size(t)	294.2251***	0.002999
Size(t-1)	-211.5204***	0.004227
R^2	0.845184	
Adj. R^2	0.843410	
S.E. of regression	0.009034	
N.obs.	23651	

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Another opportunity to control for liquidity is to measure liquidity of the underlying asset as firm size. The size of the firm is supposed to be positively correlated with the liquidity of the traded securities. According to the size effect, reported in the literature, investors demand higher required returns for stocks of small sized corporations. This might be explained by the lower liquidity of securities issued by small sized firms. Therefore, the firm size, proxied by a firm's market capitalization[2], is included in the study instead of the illiquidity measure. The results are presented in Table 9.6[3].

When the firm size is included in the regression, all the variables appear significant with the predicted sign, for the first lag. The effect of the firm size is similar to the effect of the illiquidity measure, but the Adjusted R^2 increases to 84%. The firm size appears to be significant contemporaneously and on the first lag. However, only the negative coefficient of lag 1 supports the assumption that investors demand higher required returns for buying stocks of small sized firms.

The results of the regressions presented in Table 9.3 to Table 9.6 provide evidence that the return of call options leads stock returns for at least one

[2]In the regression analysis the variable for firm size enters the model as the logarithm of a firm's market capitalization.

[3]The results are only reported up to lag 1 since neither variable is significant at a higher lag.

lag. The positive sign of the significant coefficients indicates that an increase in the call return is followed by an increase in the stock return. This might reflect the existence of information based trading in call options, resulting in information being, at least one day, earlier incorporated in call options than in stocks. The return of put options is shown to be negatively significant at lag 4, unless for the regression in which the size effect is included as a control variable. The sign of each significant coefficient is negative, implying that an increase in the put return is followed by a decrease in the stock return 4 days thereafter. When put and call returns are estimated together in one regression and when the firm size is included in the model, the put return additionally appears significant at the first lag. Altogether the results provide evidence for *Hypothesis 1*, even though only the results for call options are stable when changing the model. Why the put return is observed to be significant at lag 4, and only when controlling for liquidity by firm size, at lag 1, can't reasonable be explained.

The results for the impact of moneyness are inconclusive. While the moneyness interaction term of put options appears significant for at least one lag, for call options it only is observed to be significant when the firm size is included in the regression. *Hypothesis 2*, claiming that informed investors prefer to trade out-of-the money options, is proved when the regression model controls for the firm size.

The liquidity of call and put options is not found to be significant in explaining future stock returns. This finding somehow contradicts the Kyle model which predicts that informed investors prefer to trade in liquid assets in order to hide behind uniformed investors and to conceal their informational advantage. However, the liquidity of stocks is observed to be significant.

The trading volume of stocks and options is not included in the regression models as an independent variable, because the provided dataset does not allow to distinguish between buying and selling trading volume. Hence, it would not be possible to draw a meaningful conclusion about any information, potentially reflected by trading volume.

The regressions presented so far, test whether it is possible to predict future stock returns with the return of call and put options. However, there might also be a feedback effect, suggesting that there is no unidirectional impact but that stock returns also contain information about future option returns.

Option returns regressed on stock returns

In order to identify any feedback effect, the return of call options and put options is regressed on the return of stocks while controlling for liquidity of stocks and options. The following models are estimated:

$$
\begin{aligned}
c_t = \alpha + \eta_0 \cdot s_t + \sum_{k=1}^{8} \eta_k \cdot s_{t-k} + \vartheta_0 \cdot ILLIQ_{s,t} + \sum_{k=1}^{8} \vartheta_k \cdot ILLIQ_{s,t-k} \\
+ \beta_0 \cdot ILLIQ_{c,t} + \sum_{k=1}^{8} \beta_k \cdot ILLIQ_{c,t-k} + \varepsilon_t
\end{aligned}
\tag{9.7}
$$

$$
\begin{aligned}
p_t = \alpha + \eta_0 \cdot s_t + \sum_{k=1}^{8} \eta_k \cdot s_{t-k} + \vartheta_0 \cdot ILLIQ_{s,t} + \sum_{k=1}^{8} \vartheta_k \cdot ILLIQ_{st-k} \\
+ \beta_0 \cdot ILLIQ_{p,t} + \sum_{k=1}^{8} \beta_k \cdot ILLIQ_{p,t-k} + \varepsilon_t
\end{aligned}
\tag{9.8}
$$

$ILLIQ_s$, $ILLIQ_c$ and $ILLIQ_p$ represent the illiquidity control variables (the illiquidity ratio for stocks, call and put options), included in the regression. The results of the regressions are illustrated in Table 9.7 and Table 9.8. Again, only the results up to lag 4 are presented.

Table 9.7 shows that lagged stock returns are highly significant for explaining variations in call returns. The positive sign of the coefficient of the contemporaneous and the one day lagged coefficient represents the positive news communicated by an increase in the stock return. Thus, uninformed investors can extract the information incorporated in stock prices and buy call options in order to profit from the increase in the value of the underlying. However, the impact of stock returns on call returns for higher lags is negative. This would not have been predicted. It implies that an increase in the value of the underlying induces investors to sell call options and market makers to lower their quotes.

The results of Table 9.8 reveal a similar picture. The stock return leads the put return for at least two days. But again, only the results for the contemporaneous and the one day lagged variable are consistent with the idea of why investors trade options. The negative sign of the significant coefficients demonstrates that a decrease in the return of stocks discloses bad information about the underlying which encourages investors to buy put options, resulting in an increase in put options' quotes[4].

These results illustrate that the lead of option returns at some lags is not unidirectional. There is evidence of a feedback effect, indicating that mutual learning between stock and option markets can be observed. Uninformed investors can extract information from options about future stock price movements, but they can also use the information impounded in stocks to

[4]Similar results are obtained when liquidity is measured as firm size instead of the illiquidity ratio.

Table 9.7: Panel Least Squares regressions: Call option returns regressed on stock returns and illiquidity ratios

Regressors	t-statistics	standard errors
α	0.993616	0.001384
s(t)	26.63582***	0.053830
s(t-1)	31.81310***	0.053836
s(t-2)	-4.111335***	0.053785
s(t-3)	-1.948722*	0.053730
s(t-4)	-2.873297***	0.054874
Illiq_stock(t)	-1.108995	360625.8
Illiq_stock(t-1)	1.225152	359742.9
Illiq_stock(t-2)	-2.207372**	360670.2
Illiq_stock(t-3)	1.226373	360688.8
Illiq_stock(t-4)	-0.784479	386899.8
Illiq_call(t)	-3.909743***	0.134297
Illiq_call(t-1)	0.191875	0.133899
Illiq_call(t-2)	0.889865	0.133789
Illiq_call(t-3)	1.722451*	0.133871
Illiq_call(t-4)	1.727002*	0.133897
R^2	0.230486	
Adj. R^2	0.221582	
S.E. of regression	0.163915	
N.obs.	23255	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

predict future price movements of options. Thus, with the regression models and data applied in this study, it was not possible to find clear evidence for the hypotheses of a unidirectional lead of options.

Table 9.8: Panel Least Squares regressions: Put option returns regressed on stock returns and illiquidity ratios

Regressors	t-statistics	standard errors
α	1.806968	0.001536
s(t)	-20.73151***	0.058103
s(t-1)	-23.58966***	0.058112
s(t-2)	2.261708**	0.058054
s(t-3)	1.476142	0.057996
s(t-4)	-0.446829	0.059230
Illiq_stock(t)	-4.184010***	389228.9
Illiq_stock(t-1)	-5.319399***	388340.7
Illiq_stock(t-2)	1.992750**	389366.9
Illiq_stock(t-3)	1.323297	389397.8
Illiq_stock(t-4)	1.987850	417697.3
Illiq_put(t)	4.578004***	0.126780
Illiq_put(t-1)	0.576117	0.124058
Illiq_put(t-2)	0.400400	0.124084
Illiq_put(t-3)	0.663861	0.124068
Illiq_put(t-4)	0.373592	0.124038
R^2	0.256413	
Adj. R^2	0.247808	
S.E. of regression	0.176932	
N.obs.	23255	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

CHAPTER 10

Conclusion

The analysis presented in this paper is developed to investigate the informativeness of stock and option markets and to identify the preferred trading venue of informed investors. One aspect that motivates the analysis of options' informativeness and their impact on underlying assets is the importance to understand, how and when information is incorporated in assets and how asset pricing models should be designed in order to appropriately reflect the process of producing and incorporating information. The two fundamental option pricing models, the Binomial Tree and the Black-Scholes model, both assume that capital markets are perfect and that options are redundant securities, implying that no additional information, which is not already disseminated by the underlying, is reflected in options. However, if investors with superior information about the underlying choose to trade options rather than stocks, then options can no longer be considered as being redundant since they reflect new information which is not yet incorporated in the underyling asset. If this propostion is supported by real data, option prices should lead stock prices. In this paper this potential lead is tested by the means of lead lag regressions. The results of the study, however, do not allow to draw an unambiguous conclusion.

The analysis does not provide clear evidence that the preferred trading venue of informed investors is the option market, since no unidirectional lead could be identified. The result of an option as well as a stock lead indicates that informed investors do not have an absolute preference for either market, but instead trade both assets. Thus, option and stock markets seem to influence each other and mutual learning occurs. Nonetheless, with this study it can be shown that options can no longer be regarded as redundant securities, since at some lags, they lead stocks.

The relatively weak results of the analysis might, to some extent, be derived from the deficiency of the available dataset. One decisive shortcoming of the dataset is that it consists of daily data and does not provide intra-day data. Nowadays though, due to a substantial increase in high frequency trading volume, learning most likely occurs by observing intra-day price changes and not as a result of daily price changes. Prices change within seconds and if the frequency, by which the data is observed, is too low, initial price changes in one market and the respective reaction in another market appear to occur contemporaneously. Therefore, a study based on daily data is not able to appropriately capture the correct price discovery process. Future research on the informativeness of options should be based on intra-day data instead of daily data. If such a study is able to identify an unidirectional lead of options, the anlysis should encompass a simulation desgined to identify whether it is actually possible to earn a positive return by applying a trading strategy which is based on the information contained in option prices.

Furthermore, in order to appropriately investigate the effect of trading volume on the informativeness of options, it is essential for future research to base the study on a dataset which enables to distinguish between buyer and seller initiated trading volume. With total trading volume it is not feasible to separate the effect of positive and negative news, which might be reflected in the trading volume. When put and call trading volume is used in this analysis as a measure of liquidity, it is found to be insignificant. This finding, though, is not consistent with the Kyle model, which predicts that informed investors prefer to trade in markets with ample liquidity. If information is first incorporated in options, uninformed investors have access to new information by merely observing the price movements of options without being required to direct additional funds to an in-depth search of information. Informed investors, on the other hand, have no interest in supplying uninformed investors with easily accessible information given that they intend to maximize the value of their informational advantage at the expense of uninformed investors. Therefore, they have an incentive to camouflage their identity, which is easier to achieve in markets and assets with a higher level of trading volume. However, the results presented in this paper suggest that informed investors do not factor in the trading volume of options when deciding where to trade. This might be regarded as an evidence that, when trading options, informed investors are attracted by the increased leverage of options, even though the lower level of liquidity and trading volume might incur additional costs.

APPENDIX A

Appendix

Figure A.1: Structure of option data

						Data structure				
obs	UNDERLYING	UNDERLYIN...	EXPIRY	TYPE	STRIKE	LAST	BID	ASK	VOLUME	OPENINTER...
1	A	36.48	20120121	C	15.00	24.00	20.05	23.10	0	18
2	A	36.48	20120121	P	15.00	0.05	0.00	0.04	0	255
3	A	36.48	20120121	C	17.50	0.00	18.45	20.00	0	0
4	A	36.48	20120121	P	17.50	0.17	0.00	0.05	0	181
5	A	36.48	20120121	C	19.00	0.00	17.05	17.80	0	0
6	A	36.48	20120121	P	19.00	0.16	0.00	0.05	0	193
7	A	36.48	20120121	C	20.00	27.25	16.05	16.80	0	120
8	A	36.48	20120121	P	20.00	0.05	0.00	0.05	0	349
9	A	36.48	20120121	C	21.00	0.00	15.05	15.80	0	0
10	A	36.48	20120121	P	21.00	0.19	0.00	0.05	0	51
11	A	36.48	20120121	C	22.50	10.90	13.55	14.55	0	23
12	A	36.48	20120121	P	22.50	0.03	0.01	0.02	0	335
13	A	36.48	20120121	C	24.00	0.00	12.25	12.75	0	0
14	A	36.48	20120121	P	24.00	0.13	0.01	0.04	0	37
15	A	36.48	20120121	C	25.00	16.00	11.40	11.75	0	81
16	A	36.48	20120121	P	25.00	0.05	0.02	0.06	0	987
17	A	36.48	20120121	C	26.00	0.00	10.40	10.65	0	0
18	A	36.48	20120121	P	26.00	0.06	0.03	0.05	0	111
19	A	36.48	20120121	C	27.00	8.45	9.40	9.70	0	1
20	A	36.48	20120121	P	27.00	0.06	0.03	0.06	33	340
21	A	36.48	20120121	C	28.00	8.49	8.45	8.60	2	708
22	A	36.48	20120121	P	28.00	0.19	0.03	0.08	0	313
23	A	36.48	20120121	C	29.00	9.40	7.45	7.65	0	74
24	A	36.48	20120121	P	29.00	0.19	0.05	0.08	0	177
25	A	36.48	20120121	C	30.00	6.75	6.50	6.60	210	400
26	A	36.48	20120121	P	30.00	0.08	0.07	0.10	7	1408
27	A	36.48	20120121	C	31.00	6.05	5.55	5.65	8	625
28	A	36.48	20120121	P	31.00	0.38	0.11	0.13	0	1337
29	A	36.48	20120121	C	32.00	4.63	4.60	4.70	6	116
30	A	36.48	20120121	P	32.00	0.15	0.16	0.18	19	2180
31	A	36.48	20120121	C	33.00	3.96	3.70	3.80	343	496
32	A	36.48	20120121	P	33.00	0.25	0.25	0.28	10	1045
33	A	36.48	20120121	C	34.00	3.10	2.86	2.92	228	1102
34	A	36.48	20120121	P	34.00	0.44	0.40	0.42	46	2616
35	A	36.48	20120121	C	35.00	2.47	2.09	2.15	4	1660
36	A	36.48	20120121	P	35.00	0.69	0.63	0.66	41	1455
37	A	36.48	20120121	C	36.00	1.52	1.45	1.49	172	1202
38	A	36.48	20120121	P	36.00	0.93	0.97	1.01	48	1201
39	A	36.48	20120121	C	37.00	1.00	0.93	0.97	15	1096
40	A	36.48	20120121	P	37.00	1.46	1.45	1.50	5	704
41	A	36.48	20120121	C	38.00	0.65	0.56	0.59	343	1697
42	A	36.48	20120121	P	38.00	2.14	2.07	2.13	129	918

Table A.1: List of companies included in the study

Symbol	Company name	Symbol	Company name
AA	Alcoa Inc.	JPM	JPMorgan Chase & Co.
ABT	Abbott Laboratories	KGC	Kinross Gold Corp.
ABX	Barrick Gold Corp.	KMI	Kinder Morgan Inc.
ACI	Arch Coal, Inc.	KO	The Coca-Cola Co.
AIG	American International Group Inc.	LLY	Eli Lilly and Co.

Table A.1: List of companies: continued

Symbol	Company name	Symbol	Company name
AMD	Advanced Micro Devices Inc.	LNKD	LinkedIn Corp.
ANF	Abercrombie & Fitch Co.	LOW	Lowe's Companies Inc.
ANR	Alpha Natural Resources Inc.	LVS	Las Vegas Sands Corp.
APC	Anadarko Petroleum Corp.	MA	MasterCard Inc.
AXP	American Express Co.	MCD	McDonald's Corp.
BA	Boeing Co.	MCP	Molycorp Inc.
BAC	Bank of America Corp.	MET	Metlife Inc.
BBY	Best BUY Co Inc.	MGM	MGM Resorts International
BHI	Baker Hughes Inc.	MMR	McMoRan Exploration Co.
BMY	Bristol-Myers Squibb Co.	MO	Altria Group Inc.
BP	BP p.l.c.	MON	Monsanto Co.
BTU	Peabody Energy Corp.	MOS	Mosaic Co.
C	Citigroup Inc.	MRK	Merck & Co. Inc.
CAT	Caterpillar Inc.	MS	Morgan Stanley
CF	CF Industries Holdings Inc.	NEM	Newmont Mining Corp.
CHK	Chesapeake Energy Corp.	NKE	Nike Inc.
CLF	Cliffs Natural Resources Inc.	NLY	Annaly Capital Management Inc.
CMG	Chipotle Mexican Grill Inc.	NOK	Nokia Corp.
COP	ConocoPhillips	OXY	Occidental Petroleum Corp.
CRM	Salesforce.com Inc.	PBR	Petroleo Brasileiro Petrobras SA
CTL	CenturyLink Inc.	PCS	Platinum Communications Corp.
CVS	Cvs Caremark Corp.	PEP	PepsiCo, Inc.
CVX	Chevron Corp.	PFE	Pfizer Inc.
DAL	Delta Air Lines Inc.	PG	Procter & Gamble Co.
DD	E. I. du Pont de Nemours and Co	PM	Philip Morris International Inc.
DE	Deere & Co.	POT	Potash Corp. of Saskatchewan Inc.
DIS	Walt Disney Co.	RIG	Transocean Ltd.
DOW	Dow Chemical Co.	S	Sprint Nextel Corp.
EMC	EMC Corp.	SD	SandRidge Energy Inc.
F	Ford Motor Co.	SLB	Schlumberger Ltd.
FCX	Freeport-McMoRan Copper & Gold Inc.	SLW	Silver Wheaton Corp.
GE	General Electric Co.	T	AT&T Inc.
GG	Goldcorp Inc.	UPS	United Parcel Service Inc.
GLW	Corning Inc.	USB	U.S. Bancorp
GM	General Motors Co.	V	Visa Inc.
GS	Goldman Sachs Group Inc.	VALE	Vale SA
HAL	Halliburton Co.	VLO	Valero Energy Corp.
HD	Home Depot Inc.	VZ	Verizon Communications Inc.
HES	Hess Corp.	WAG	Walgreen Co.
HLF	Herbalife Ltd.	WFC	Wells Fargo & Co.
HPQ	Hewlett-Packard Co.	WFT	Weatherford International Ltd.
IBM	International Business Machines Corp.	WLT	Walter Energy Inc.
JCP	J C Penney Company Inc.	WMT	Wal-Mart Stores Inc.
JNJ	Johnson & Johnson	X	United States Steel Corp.
JNPR	Juniper Networks Inc.	XOM	Exxon Mobil Corp.

Zusammenfassung

Viele Modelle zur Bewertung von Finanzinstrumenten basieren auf der Annahme, dass alle im Markt agierenden Investoren über denselben Informationsstand verfügen. Empirische Studien haben jedoch gezeigt, dass Informationen ungleich unter Marktteilnehmern aufgeteilt sind. Das führt dazu, dass es Investoren gibt die einen Informationsvorsprung besitzen, welchen sie versuchen bestmöglich auszunutzen um ihren erwarteten Profit zu maximieren. Die Existenz heterogen verteilter Informationen beeinflusst die Preisfindung und Informationseffizienz des Marktes.

Diese Arbeit untersucht die Verarbeitung und Übertragung von Informationen in Aktien- und Optionsmärkten und welche Auswirkungen das Vorhandensein von Investoren, die über Insiderinformationen verfügen, auf das Zusammenwirken der beiden Märkte hat. Die Grundhypothese dieser Arbeit ist, dass informierte Investoren bevorzugt Optionen anstatt der zugrundeliegenden Aktien handeln. Es wird angenommen, dass der Hebel, welchen Optionen bieten, den informierten Investoren einen höheren Profit ermöglicht, ungeachtet der geringeren Liquidität und den höheren Handelskosten in Optionsmärkten. Es wird erwartet, dass Investoren mit positiven Informationen über die zugrundeliegende Aktie bevorzugt *out-of-the-money* Call Optionen und Investoren mit negativen Informationen *out-of-the-money* Put Optionen kaufen. Wenn ein Handel in Optionsmärkten auf Grund eines Informationsvorsprungs einiger Investoren stattfindet, hat das zur Folge, dass neue Informationen zuerst von Optionen wiedergespiegelt werden. Demzufolge wird in dieser Arbeit unterstellt, dass es möglich ist, mit aktuellen Optionspreisen zukünftige Aktienpreise zu bestimmen. Diese Annahme wird in dieser Arbeit anhand von Lead-Lag Regressionen überprüft. Die verwendeten Optionsdaten beziehen sich auf Optionen, die an der CBOE gehandelt werden, und die zugrundeliegenden Aktienwerte auf Aktien, die an der NYSE gelistet sind.

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