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Reference Price Formation Under Reverse Market Conditions: Evidence from IPO Trading Volume

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ABSTRACT OF THE
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This thesis studies the reference price formation under reverse market conditions, determined by the prevailing bull and bear sentiment trends. I investigate the turnover changes after initial public offering (IPO), which forms a natural reference point for the investors, to which they compare all forthcoming price movements. The results imply that a stock is traded more when its market price exceeds the offer price, that the investor has initially paid to obtain the asset. Additionally, the IPO stocks that begin trading at a gain, tend to be traded more, as they fall below their initial purchase price for the first time. However, the initially losing stocks are not found to be traded more when their market price surpasses the initial offer price, which is not consistent with previous research. Regarding the effect of the market trends, investors seem to be more optimistic in the formation of their reference prices during bull markets, than during bear conditions. Moreover, new stock price maximums and minimums seem to strongly influence the reference point formation across different market conditions. Under bull circumstances, investors are also more quicker in reacting to new price maximums and minimums, when compared to the bear conditions, under which the reference prices do not seem to be updated as strongly, if at all, to new price crossings. Therefore, it can be interpreted that investors do adapt their notions on winnings and losses based on new information gained from the stock's current market performance, as they tend to wait longer to sell a losing stock and are also more eager to sell the winning stock before it rises any further. Finally, investors seeming to react faster during bull trends can be due to more frequent follow-up of their assets, which has been found characteristic for bull market investors.

Keywords: Reference Price Formation, Disposition Effect, Prospect Theory, IPO Underpricing, Market Trends, Investor Sentiment, Pooled Regression

Contents

List of Figures

List of Tables

1 Introduction

1.1 Background and motivation

The history of the stock markets has experienced both times of great booms as well as periods of volatile turmoil. The recent financial crisis has acted as a forceful reminder of the fluctuating nature of the market conditions into two reverse directions. Vast market bubbles, followed by sudden market crashes, form recurring anomalies that cannot be extensively explained through traditional finance theory. It would be therefore of great importance to understand the main drivers behind the market, namely the investors and their behavioral patterns under different market conditions.

Moreover, finance models, such as the efficient market hypothesis, are based on the premise that investors act rationally. However, recent studies in the field of behavioral finance have proven several inconsistencies in investor behavior, that conflict the traditional view on rational investors. These behavioral biases produce trading deviations that contradict the implications of economic rationality.

In fact, investors have been empirically found to estimate plausible decisions relative to a distinct mental reference level, namely some subjective reference point, when faced with uncertain situations. When it comes to losses, investors tend to seek risks, as opposed to avoiding risks when faced with a likely positive outcome (Gneezy, 2005). These are determinants of the disposition effect, which represents a well identifiable bias, that yet so far lacks evidence on the level of market-wide effects, but has been widely studied and recognized as a true phenomenon.

One of the greatest challenges to the field of finance is the exceptionally large degree of trading activity in the financial markets (Grinblatt and Keloharju, 2001). For this purpose, it is necessary to analyze market-wide data, which describes the whole equilibrium of the system. However, until recently, studying investor behavior based only on stock exchange data has been proven difficult, because of lack of unbiased and effective methods.

The difficulty in studying the reference prices as a market-wide effect has been the in lack of information on the reference prices of the traded assets. Therefore, studies conducted so far have mainly employed particular databases based on individual investor behavior. As the study of Kaustia (2004), which acts as the methodological framework for this paper, shows, this issue is however surmountable by studying the behavior of investors after initial public offering (IPO). In fact, initial public offerings provide a prominent aid for investigation, as a typical reference price would be the initial purchase price, as the offering price is shared by all investors. This enables me to research the market-wide data on the disposition effect by studying initial public offerings.

Moreover, there exists but a few studies incorporating the market conditions in the investor sentiment analyses, especially concerning the use of market-wide information. One reason behind the lack of significant results lies in the precondition of efficient market hypothesis, according to which all information should be incorporated within the prices in the market. However, as research has shown, this hypothesis is not always empirically consistent. The studies so far concentrating on the market conditions and disposition effect, have focused on either on the demand of individuals or the relation between market conditions and IPO returns, rather than the underlying behavioral determinants. None is performed by analyzing the whole market as one model and testing whether the trends influence the reference price formation of the investors. Motivated by this, my analysis draws the main focus beyond the sole purpose of investigating the post-IPO trading volume changes, and incorporates the effects of the market conditions prevailing at the time of the offering.

1.2 Existing literature

Prior empirical research has found evidence on investors having a lower propensity to sell stocks, that are trading at a capital loss. At the same time, investors have been found prone to sell off their winning stocks. This phenomenon is characterized as the disposition effect. Furthermore, this effect has been documented to depend on distinct reference points, held inside individual investors' mental accounts. These reference points are influenced by new information facing the investor. Therefore, the logical way to investigate the reference price formation is to study its effects via the disposition effect framework, by considering it as a precondition.

The disposition effect has been well documented in studies using aggregate market-wide data (Lakonishok, 1986; Ferris and Haugen, 1988; Bremer, 1996), data on individual investors (Grinblatt and Keloharju, 2001; Odean, 1998), as well as based on experimental questionnaires (Weber and Camererb, 1998). However, disposition effect based on aggregate market data has not been comprehensively studied by incorporating market conditions into the analysis.

Reference point formation studies have established a firm connection between the disposition effect and investors' tendency to hold separate mental accounts for different investments (Arkes *et al.*, 2008; Baucells and Weber, 2011; Kliger and Kudryavtsev, 2008). There is nevertheless some dispute over which is the correct reference price: purchase price, maximum/minimum price, or some other adjustable price. While the initial purchase price has accomplished its ground as a considerably reliable reference point, it opens up an intriguing research subject on testing the reference point formation based on initial public offerings' returns. Moreover, this thesis studies other plausible reference points that can be derived from the results of the post-IPO trading volume changes.

Additionally, this study will expand the research of Kliger and Kudryavtsev (2008) and Kaustia (2004) by incorporating the market condition analysis into the IPO data. Existing literature suggests that for negative initial return IPOs turnover seems to be significantly lower when the stock is trading below the offer price. Furthermore, when the stock price for the first time surpasses the offer price, the turnover is evidenced to increase significantly, which is recorded to last for a period of two weeks. Stock price minimums and maximums are also found to be followed by trade volume increases (Kaustia, 2004). Whether these effects occur following the same pattern both during bull markets, where the sentiment is high, and bear markets, where the sentiment lies lower, is the major concern within this thesis. The effects are hypothesized to differ according to the prevailing market trend, as investor behavior has been found as one of the key determinants behind market behavior. Thus, reference price formation under different market conditions should be further studied in order to understand the behavioral biases behind market price formation.

1.3 Research Problem and Purpose

The aim of this paper is to study, whether market conditions have an effect on the reference point formation of investors. Therefore, my research problem is the following:

Do stock market conditions affect the aggregate market reference price formation?

The magnitude of the disposition effect is studied both through the effect of bullish/bearish markets and through trading volume succeeding the IPO offer date. Additional variables, such as the market trend at the time of the offering and the size of the underpricing, are introduced in the preliminary analysis on the trading volume. In light of understanding the reference price formation even more deeply, the results suggest a need for further analysis, which is conducted by dividing the data groups based on both these significant results yielding variables, motivated by the effect the variable seems to have on both research groups. Evidence in any of the empirical analyses showing strong disposition effect would suggest some form of market inefficiency, as there might arise windows of opportunities for arbitrage.

1.4 Structure of the Study

Understanding the purpose of this study requires knowledge on both behavioral finance and its mechanisms as well as the basics on the pricing of initial public offerings. Moreover, investor sentiment is linked to market conditions.

The theoretical background including prior empirical research is described thoroughly in Section 2, which begins with an introduction to the key concepts and theories. This serves as the frame of reference for the later empirical analysis. Furthermore, there exists several approaches into examining the disposition effect based on different data sources, which are described in more detail.

Section 3 introduces the main hypotheses presumably leading to the answer of the research question, that are generated on the basis of the previous section's literature review. The logical continuum from this leads to Section 4, where the methodology, that will be applied in the data analysis, is introduced. Consequently, Section 5 describes the characteristics of the data sample used in this study.

Section 6 represents the specific empirical results of the data analysis and the validation for the hypotheses. Finally, Section 7 includes a summary of the study as a whole, as well as the final conclusions drawn from the results.

2 Theoretical background

This section introduces important concepts and theories essential for understanding the background of this study. Initial public offerings and their underpricing occurrence are discussed briefly, mainly concentrating on their effect on the post-IPO trading volume, which forms the basis for the later forthcoming analysis. Moreover, behavioral finance is discussed in more detail by introducing the main behavioral theories interconnected to the subject of this study. The focus is kept particularly on prospect theory, which forms the basis for disposition effect, the key concept for understanding the reference price formation.

2.1 Initial public offerings and the underpricing phenomenon

Initial public offerings are considered underpriced when they exhibit positive first-day returns. Several studies, such as (Ibbotson and Jaffe, 1975; Ritter, 1984; Levis, 1990), have provided empirical evidence on the determinants of IPOs average underpricing. Prior empirical studies provide several different reasons for underpricing. These include theories such as information asymmetry (Baron, 1982; Rock, 1986), second signaling (Allen and Faulhaber, 1989; Grinblatt, 1989) third legal liability and litigation risk (Tinic, 1988), information cascade effects (Welch, 1992), and finally investor behavior (Derrien, 2005; Ljungqvist, 2003). For the purpose of this thesis, at this point there is no need to characterize these in more detail, as the focus is kept on the trading volume effects.

IPO stocks tend to exhibit large initial returns but poor long-term performance and can therefore be considered to be overpriced in the after-market (Ljungqvist, 2003). In other words, empirical research has shown that large initial return firms tend to underperform the negative initial return firms in the long run. Because these IPO return patterns have been proven to vary in time, there exists so called hot and cold periods of IPO volume in history (Ritter, 1984).

Regarding the existing studies focusing on the market conditions and IPO markets, significant results are obtained by Derrien (2005). He finds, that if there exists a bull market at the time of the IPO offering, shares on average tend to be overpriced. Overpricing of IPOs is found to be affected by both the noise traders bullishness and by the IPO fees. Under both circumstances (high bull markets and high fees) the underwriter has an incentive to set an aggressive IPO price. Correspondingly, as the intensity of noise trader sentiment at offering increases, so does the IPO price and the level of initial return. Hence, (Loughran, 2002) argues, that positive initial return is not anymore the consequence of underpricing, but rather occurs (despite of overpricing) because of partial adjustment to public information. Also Long *et al.* (1990) developed theories on noise trading. They argue that as some investors trade based on a noisy signal that is unrelated to fundamentals, the asset prices will deviate from their intrinsic value. In bullish market conditions the issuer will eventually raise more money, which is one of the main reasons why IPOs tend to cluster in hot issue markets. Furthermore, according to Ljungqvist (2003) initial returns are negatively correlated with the recent number of offerings in the same industry, even though they are overall higher at hot issue markets.

Most studies focus on analyzing only the hot issue periods, because there are significantly more IPOs during those periods, which enhances the validity of the results. Hot issue market is defined as a month in which the average first-day return is above the median month's average first-day return (Ibbotson and Jaffe, 1975). According to Loughran (2002), there is strong positive serial correlation in the monthly average first-day returns, which cannot be explained consistently with rational behavior of investors. Essentially they claim, that according to prospect theory, market rises are followed by an increase in IPO underpricing in all IPOs within the selling period (nevertheless the date of going public), which can explain the correlation. Therefore, high average first-day returns will be observed for one to two months after market rises, because this is typically the range within which the issuers anchor their price range.

Loughran (2002) and Lowry and Officer (2010) argue underpricing stemming from indirect compensation to underwriters. Namely, investment bankers benefit from a lower offer price firstly because it makes it easier to find buyers for IPOs (reducing their marketing costs), and secondly because investors will engage in rent-seeking behavior in order to get priority over the allocation of hot IPO shares (which also increases the underwriters revenues in terms of gross spread). Moreover, overallotment options are not generally taken into account. During strong demand, overallotment options are much more likely to be exercised, thus affecting the trading volume. Furthermore, as there are overallotment options in 15% of all IPOs, their exercise would affect all the results. Loughran (2002) argues that in IPOs, gains and losses are computed relative to the price that the issuing firm's executives have anchored on. According to them, the IPO reference point offer price is the midpoint of the file range.

While the before mentioned studies find that high initial returns go together with hot IPO markets, Lowry and Officer (2010) argue that these hot markets also possess extraordinary high variability of initial returns. Over time, there exists a strong correlation between the mean and the volatility of initial returns. They suggest, that the level of uncertainty and the underwriter's ability to value the firms varies over time. In fact, one of the main problems facing issuers in IPO pricing is the aggregate demand uncertainty. There is an asymmetry of information between the issuing firm and the market, which is resolved through the initiation of trading, as the market participants' information is reflected in the prices.

Furthermore, it is found that IPO initial return variability is significantly higher when there are more difficult-to-value firms going public. These firms include young, small and technology firms. Lowry and Officer (2010) also find that the high variability of initial returns goes hand in hand with hot issue markets, stating that there is a strong positive correlation between the mean and the volatility of initial returns. The most important contribution of their study in terms of this thesis is the finding that the pricing problem is also sensitive to market-wide conditions. In other words, as uncertainty is higher in the market, it makes it harder for both investors and underwriters to value IPOs. The study does not however address the formation mechanism of reference prices, which is my main focus. Still, motivated by these results, I will incorporate initial return volatility into the empirical analysis by high tech industry and microcapitalization variables, in addition to a lock-up period variable.

Information extraction theory states that IPO underpricing is the cost of obtaining private information. Public information on the other hand is available costless before IPO price has been set. Bradley and Jordan (2002) find that more than 35% of initial returns can be predicted using public information available at IPO date, which cannot be explained by existing theories on IPO underpricing. Derrien (2005) studies, why the impact of market conditions on the aftermarket price of IPO shares is only partially incorporated into IPO prices. In his model, the aftermarket price of IPO shares depends on both private information of the intrinsic value of the firm as well as on noise trader sentiment. He finds that at the time of the offering, public information on noise trader sentiment seems to be partly included in the IPO price. This study further assumes that the noise traders are bullish, as the study period is a hot issue period. However, this assumption leaves out the effect of noise traders during bear markets, which I intend to incorporate in my own analysis.

2.1.1 Underwriter price support

Underwriters buy shares from the aftermarket for the purpose of covering a short position when allocating the shares. This is called underwriter price support in its principal form (Kaustia, 2004). This means that the underwriter oversells the issue to have a short position by e.g. exercising the overallotment option or by making aftermarket purchases.

Aggarwal (2000) finds underwriter support in half of the IPOs under investigation. According to him, the most probable IPOs to be price supported are the ones with initial returns equaling zero. Firms that exhibit higher initial returns are less likely candidates for price support, whereas half of negative initial return IPOs seem to be price supported in the study of Aggarwal (2000). In addition, price support has been found most frequent in larger issues and higher offer prices.

Additional findings from Aggarwal (2000) concern the price support period, which provides evidence against the previous literature of a price support period during only the first few days after the issue. In fact, most price support activities are found to last from 10 to 15 days with 16% still being supported after 20 days of issue, as well as 6% that have support even past 30 days.

The study of Ellis *et al.* (2000) finds that the underwriters accumulate inventory for the first 21 trading days when the IPO trades at or below the offer price during the first 20 days, and after a few days the inventory is actively reduced.

Therefore, underwriters have been found to affect the overall liquidity of the stock, though no price bidding has been evidenced. Several other studies also contribute to this phenomenon, sharing the observation of 20 days of price support period (Ellis *et al.*, 2002; Hanley *et al.*, 1993; Boehmer, 2002). As most support activity has been found to occur at somewhat below the offer price, it is likely to affect the trading volume e.g. when a positive initial IPO falls below its offer price for the first time. According to Kaustia (2004), this kind of support can increase the trading volume especially in the range of 95-100% below offer price, thus distorting the results of the possible disposition effect.

Guided by these previous studies, the guideline of only considering the trading volume period after the first 20 post-IPO trading days, is executed in this thesis. Also, for reasons stated above, the firms with zero initial returns are excluded from the empirical subsample.

2.1.2 Lock-up periods

Related to underwriter price support, the role of lock-up periods is addressed, because it may influence the turnover patterns in the later analysis. The reasoning behind the lock-up agreements is, that the owners of the firm going public typically sell about 15-20% of the company, while the remaining shares tend to be subject to a lock-up period, under which the buyers of these shares cannot sell their shares for a pre-specified time. The usual length for this time period is 180 days. As the lock-up period expires, there is an observable change in the number of shares in the market. Effectively, the event of lock-up period ending is not information-based, but rather subject to a pre-determined agreement. (Brav and Gompers, 2003)

As the lock-up period expires, Ofek and Richardson (2000) find a permanent drop in the stock price while at the same time the volume of shares traded jumps an average of 38%. This means that even though the price drop would be anticipated, the markets are not complying to this. They mean that the price drop should have been incorporated in the price as early as even on the first day after the IPO, because the lock-up period is known in advance. In reality, the evidence on bid-ask spreads, short interests and tax considerations suggest no arbitrage opportunities. Exemplary of this is the decline of the price that is larger for stocks harder to short and those with larger bid-ask spread. They also find that the price drop relates to the stock's volatility, which could act as a proxy for the owners of these shares wanting to diversify their risks.

The role of lock-up agreements is assessed later by incorporating a lock-up variable in the regression. It is beneficial to investigate, whether this agreement affects the total turnover of a firm, because even one large enough shareholder can have a decreasing effect on the stock return, if she is trying to remove all her holdings at one time. This may then cause further implications for the trading volume.

2.2 Investor sentiment

Investor sentiment forms the roof for the later reference price formation analysis of this thesis. Investor sentiment can be described as a belief on investments' future returns and risks, that cannot be explained by facts at hand. Modern behavioral finance suggests there are limitations to arbitrage. Moreover, rational investors (or arbitrageurs) have been found to be less aggressive, than the standard model would imply, in forcing market prices to their fundamentals. This can be due to a fear of betting against sentimental investors, which can turn out both risky and costly. (Baker, 2007)

The question is no longer pointed on whether investor sentiment affects stock prices but rather on how to measure its effects and correctly quantify them. The study of Baker (2007) states two ways of examining investor sentiment. The first approach is called the bottom up way which is executed using investor psychology biases, including overconfidence and under- or overreactions to past returns. Barberis *et al.* (1998) among others have developed models like this concentrating on predictions on market-wide investor sentiment patterns as well as their relation between stock prices and volume. The other approach by Baker (2007) proceeds in a macroeconomic top down way, which assumes that real investors and markets are too complicated to be analyzed and characterized by a few biases. This approach aims to explain which stocks are most likely to be affected by investor sentiment. These are the same stocks as the right-hand side stocks of Figure 1. I intend to combine both approaches by incorporating under- and overreactions, as driven by the market conditions, as well as firm-based characteristics in evaluating what creates the market anomalies.

The behavioral model developed by Long *et al.* (1990) divides investors into two types that set the prices in the market. The first are sentiment-free rational arbitrageurs and the second are exogenous sentiment -prone irrational investors. Even the rational investors suffer from short time horizons as well as costs and risks of trading and short selling. Therefore, both types are subject to restrictions, which leads to stock prices differing from their fundamental values.

In this model, mispricing in the market can be either due to an irrational investor sentiment change and/or to the rational investor arbitrage limits. Baker (2007) takes this model further by constructing a setting on the hypothesis that while sentiment-based demand varies from firm to firm, arbitrage is always equally difficult with any firm. According to him, sentiment increases are connected to speculative stocks with higher return expectations. E.g. during a market bubble, speculative stocks that are difficult to value are more sensitive to investor sentiment. Additionally, these speculative stocks tend to be overall more costly to buy and sell short, i.e. harder to arbitrage and the rational arbitrageur will withdraw. (Shleifer and Vishny, 1995) Therefore, these speculative stocks tend to be the most affected by investor sentiment.

As stated in the beginning, various regularities in investors' behavior have been documented to dispute with the traditional theories on rational investors. On of the most surprising evidence comes from the tendency of investors to sell winning stock too early whilst holding on to losing stocks, called the disposition effect (Shefrin and Statman, 1985). There are four behavioral elements in the disposition effect: prospect theory, mental accounting, regret aversion and self-control. Prospect theory explains the disposition to sell winners and keep losers when the gains are held and not rolled over into another gamble. Mental accounting addresses the conditions under which the disposition effect holds when the gains from realization are reinvested. Aversion to regret provides an explanation into why investors sometimes have difficulties in realizing both gains and losses. Self-control is exercised when investors force themselves to realize losses.

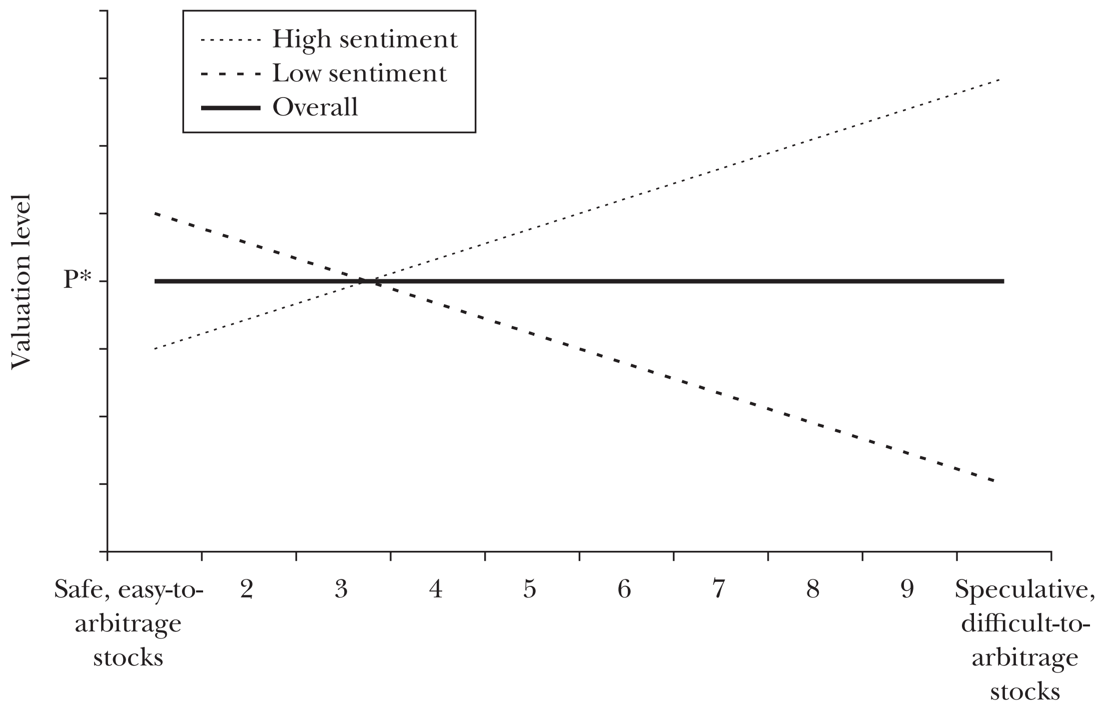


Figure 1: **Theoretical Effects of Investor Sentiment on Different Types of Stocks**
Baker (2007) has divided investor sentiment based on different types of stocks. The X-axis represents the level of difficulty in valuating the stocks, whereas the Y-axis marks the prices of the stocks in terms of their fundamental values. The lines represent the degree of investor sentiment in the market.

In Figure 1, bond-like stocks such as regulated utilities are included in the left-hand side, while the right-hand side includes newer, smaller, more volatile, distressed or extreme growth stocks. Accordingly, when sentiment is high, speculative stocks will be exposed to higher relative valuations. Correspondingly, as sentiment is low, safer stocks are valued more than the riskier ones.

According to the classical theory of decision under risk, individuals tend to consider risk as increasing with the magnitude and probability of potential losses. Decision theorists argue, that as the variance in the probability distribution of possible outcomes increases, so does the experience of a greater risk. According to Mongin (1997), instead of individuals viewing options by their objective value, options are valued by their utility or "moral value".

This all bases on the fact, that decision makers are prone to choose the option that offers them the highest expected value. Accordingly, if an individual is indifferent in her decision between a gamble and its expected value, she is considered risk neutral. The preference for a sure outcome as opposed to a risky possibility of equal or higher expected value describes the attributes of a risk averse person. Finally, a risk-seeking investor would rather take the risk of uncertain outcome than to take a sure outcome. (Mongin, 1997)

2.2.1 Sentiment proxies

There exists several ways to measure investment sentiment. Possible proxies, as listed by Baker (2007), include trading volume, IPO first-day returns, IPO volumes, mutual fund flows, surveys, investor mood, retail investor trades, premia on dividend-paying stocks, closed-end fund discounts, option implied volatility, insider trading and new equity issues. As retail investor trades, surveys and investor mood concentrate on analysis of individuals, these will not be further discussed in this paper. Instead, proxies that can be built on aggregate market data are characterized briefly.

Trading volume has been used by several studies in describing sentiment effects. Baker (2007) finds that when irrational investors are optimistic, and when short-selling is costlier than long positions, investors are more likely to trade and add liquidity. Additionally, the ratio of trading volume to the number of shares outstanding can act as a proxy for market turnover, which has been used to measure aggregate market sentiment swings. This method is applied in my analysis as well, and further discussed in Section 4.

Initial public offerings' first day returns have been found to be highly correlated with IPO volume and the relation between IPO underpricing and volume have been studied by e.g. Ljungqvist *et al.* (2006) and Ritter (1984) Furthermore, IPO volume has been documented to be sensitive to market fluctuations, as there exists hot and cold IPO periods. Several studies, such as (Lee *et al.*, 1991), (Neal and Wheatley, 1998), report evidence on closed end funds' average discount acting as a sentiment proxy, as the discount seems to increase as retail investors are bearish.

According to standard finance theory, as the expected volatility of the underlying security increases, so do the prices of options. The market volatility index "VIX" measures the options' implied volatility on the S&P100 index. The VIX has can be used as a sentiment proxy as it moves up as the market volatility, or uncertainty and fear, increases. (Whaley, 2008) This index is applied for the benefits of my study and discussed more in the Section 4.3.2.

Mutual funds can be used as a sentiment proxy in measuring how investors move between e.g. safer government bonds and riskier growth stock funds. Frazzini (2006) use mutual fund flows as a proxy for sentiment towards individual stocks and find that a relation between the funds' inflows and the performance of the individual stocks within the fund.

2.2.2 Prospect theory

Prospect theory, first introduced by Kahneman and Tversky (1979), is the leading behavioral model of decision making under risk. The theory has been successful to explain a vast range of empirical regularities such as market equity premiums, disposition effect, and the attractiveness of participating in state lotteries. According to prospect theory, the marginal impact of a change in probability decreases as the distance from relevant reference points diminishes.

According to prospect theory, investors are inclined into a disposition to sell winners and ride losers when standard theory would suggest otherwise. Before making the decisions, investors are prone to an editing stage, under which they mentally frame all their choices in terms of potential gains (losses) relative to a fixed reference point. After this, investors experience the evaluation stage, when an S-shaped valuation function, reflecting the risk aversion of gains and risk seeking of losses, is employed. (Kahneman and Tversky, 1979) Figures 2 and 3 represent the visualization of the valuation function.

In this model, the function for gains takes a concave form, whilst the loss function is of a convex nature. Generally, the status quo stands as the reference point that separates gains from losses. Furthermore, the value function is steeper for losses than for gains, which characterizes loss aversion. In other words, individuals typically require a larger compensation to give up a possession than the initial purchase payment would have been.

Loss aversion occurs as, relative to a common reference point, the utility decline for a loss

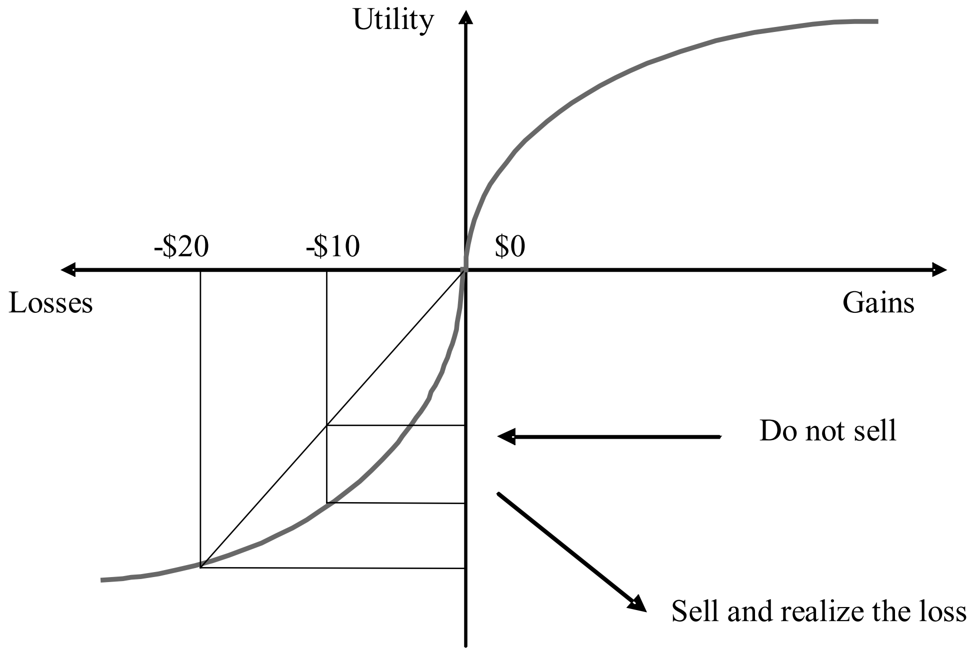


Figure 2: **Underreaction to Losses Explained by Prospect Theory**
The utility-gain(loss) of keeping a stock versus selling it. Eg. if the price drops from 30$ to 20$, next it could equally go up by 10$ or down by 10$. The dilemma lies between realizing a paper loss of 10$ now or keeping the losing stock. (Frazzini, 2006)

exceeds the increase in utility for a gain of same size. The other occasion where loss aversion exhibits itself is when the gamble, that is determined always a loss relative to the reference point, exceeds the utility of a certain loss of same mean, and vice versa for gains. Therefore, an investor might be more likely to replace their risk-free asset with a risky asset as the utility is locally concave (gain situation) than when the utility is locally convex (loss situation), assuming a hypothetical market of a single risky asset. In a multi-asset market however, reference prices do change and lead to replacement of a risky asset into a realized gain or loss. (Grinblatt, 2002)

The term additionally incorporates the bias towards status quo by the tendency for relative disadvantages of alternatives to attract more than the relative advantages (Samuelson, 1988). This results in an inverse S-shaped weighting function, which describes the tendency to over-weight low probabilities and underweight moderate to high probabilities. In other words, it implies risk aversion for gains and risk seeking for losses.

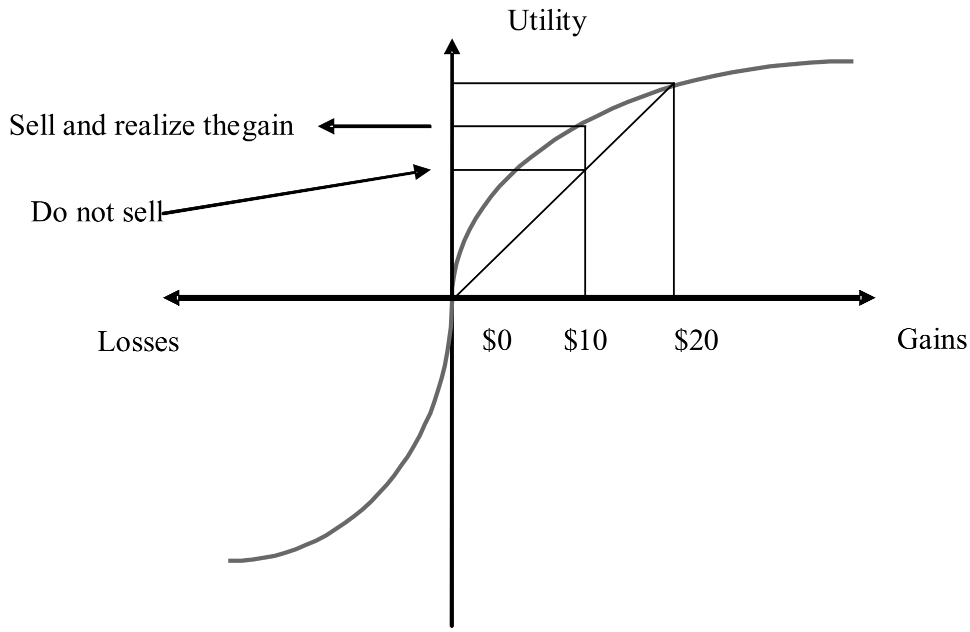


Figure 3: **Overreaction to Winnings Explained by Prospect Theory**
The utility-gain(loss) of keeping a stock versus selling it. Eg. if the price rises from 30$ to 40$, next it could equally go up by 10$ or down by 10$. The dilemma lies between realizing a gain of 10$ now or keeping the winning stock. (Frazzini, 2006)

According to prospect theory, when an individual is faced with two related outcomes, he can evaluate them either separately or integrated as one outcome. Because the value function for gains is concave, this results to the segregative treatment of two gains. (Loughran, 2002) In other words, the investor gets a stronger winning feeling on two gains instead of one larger gain.

When considering a gain and a loss, it depends on their magnitude, whether the investor tends to segregate or integrate the two (Frazzini, 2006). This phenomenon is illustrated in Figure 4. For example, when there is a high net worth increase after a small amount of dilution, this information is integrated and the investor feels better about the overall net gain. The y-axis represents the amount of the underpricing magnitude, while the x-axis stands for the change in market value between the filing date and the first closing market price. Thus, underpriced issues, that are followed by an upward revision in the offer price, are situated in the lower quadrant on the right of Figure 4. Therefore, even though there is money left on the table, the integrated benefit to the investor is associated into a winning feeling.

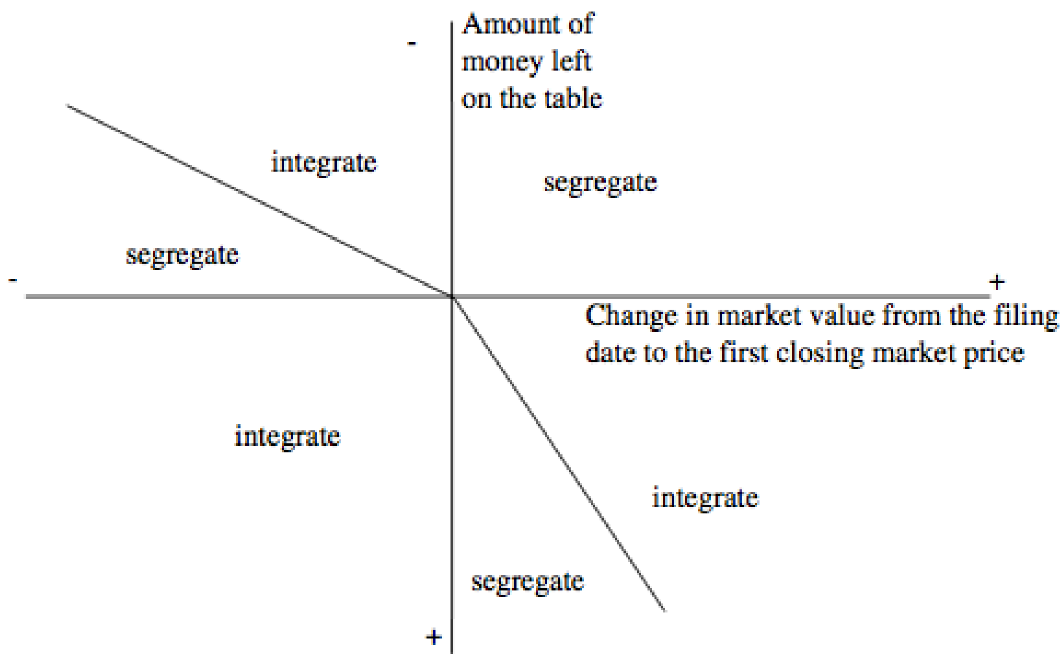


Figure 4: **Segregation vs. Integration in Financial Gain Experience**
The regions of integration and segregation for an investor that receives both gains and/or losses based on the fluctuations in valuation from the filing date to the first-day closing price and on the amount of money left on the table. A large change in market value belongs to the right-hand corner of the graph, while a large amount of money left on the table belongs to the lower-case region of the graph. (Loughran, 2002)

2.2.3 Disposition effect

Decision making under uncertainty has been explained by expected utility theory, which states that people are believed to behave according to the the axioms of rational choice (Neumann *et al.*, 1944). However, Kahneman and Tversky (1979) found empirical evidence that suggested people behaving irrationally, which lead them to develop prospect theory. According to prospect theory, individuals take gambles inconsistent with the expected utility maximization.

Investors have been reported to be inclined to preserve stocks which are not performing well, even though market information would suggest otherwise. At the same time, reactions to bad news concerning long-time well performing stocks cause investors to sell these winning stock more easily. Therefore, disposition effect can be described as the tendency of individual investors to hold on to losing stocks for too long, while realizing gains too early. The other aspect includes investors avoiding risks when there exists a possible certain gain, and on the other hand seeking risks when they are faced with possible losses.

This theory was further developed by Shefrin and Statman (1985) into disposition effect, thus linking it to investor behavior. Accompanied by unquestionable empirical evidence, disposition effect suggests prospect theory to prevail over expected utility maximization as an explanatory model. By studying trading data during 1964-1970, Shefrin and Statman (1985) found that approximately 40% of all transactions represent losses, regardless of the holding time, which is inconsistent with tax advantage theories.

Lakonishok (1986) investigates tax-motivated investor behavior, and finds that the tax predictions are not consistent as the turnover seems to be higher for winners than losers, as the disposition effect suggests. Still, at year-ends, the motivation for tax-related gains succeeds over other reasons for turnover increase. It would be beneficial to be able to distinguish the difference between information-motivated trading and tax-motivated trading because this is helpful to investors who invest based on trading patterns as a information source.

Disposition effect has been studied in three different methods: based on individual data, such as socioeconomic background, experimental data attained from laboratory conditions or through questionnaires, and finally by examining market-wide aggregated data, which will be the basis for the empirical section of this thesis.

2.2.4 Overconfidence

One element explaining the disposition effect has been suggested investor overconfidence. Statman *et al.* (2006) describe the overconfidence hypothesis as a perception of the investor's ability to compete in the general marketplace for stocks.

Odean (1998) study suggests that investors are overconfident because they are incapable of matching their investing skills to the realized gains. High market-wide returns make investors overconfident on their own abilities. As the market turns down, losses reduce the trading volume and overconfidence level.

Statman *et al.* (2006) use a vector autoregressive and impulse-response function methodology in investigating the trading volume implication of the overconfidence hypothesis. They find significant evidence supporting the overconfidence hypothesis as well as the disposition effect of Shefrin and Statman (1985). They find that NYSE/AMEX stocks' trading activity is positively correlated to past shocks in market return and the turnover response last for months or even years. There is therefore an increase (decrease) in market-wide trading activity after bull (bear) markets. In other words, the overconfidence of noise traders increases as they attribute high returns in bull markets to their trading skills. Statman *et al.* (2006) additionally discover that individual security trading responds even more to past shocks, which they interpret arising directly due to overconfidence hypothesis. Fama (1998) however describes the market efficiency as still valid and declines several points about the lack of efficiency stemming from over- and underreaction of investors to new information.

2.2.5 Attention hypothesis

Another explanation for holding losers too long and realizing winners early is the attention hypothesis. According to Barber and Odean (2007), investors are prone to give attention selectively to upcoming new information. Corroborate attention hypothesis states that as individuals are faced with numerous alternatives, they tend to prefer those that have caught their attention.

2.2.6 Mental accounting

Thaler (1985) introduced the concept of mental accounting in order to explain the behavioral consumer choice theory. Mental accounting uses the notion of a value function, first used in prospect theory (Kahneman and Tversky, 1979), and incorporates price straight in the function, which leads to the concept of reference price. The disposition effect describes how investors keep a separate mental account for each stock whilst maximizing their reference-level based value function within that account. (Kliger and Kudryavtsev, 2008)

Shefrin and Statman (1985) study the effect of emotions such as pride and regret on trading. According to them, investors hold separate mental accounts associated with each stock they hold. In this setting, the realization of gains is accompanied by pride whereas the realization of losses is followed by emotions of regret. Investors as human beings logically prefer feeling pride, which leads to a quicker sell of winners, while the realization of losers is postponed to avoid the feeling of regret.

2.3 Investor sentiment and market conditions

Investor sentiment has been empirically documented to be affected by market conditions. Under a bear market, investor sentiment is typically low, while the market conditions are quite volatile. Under these circumstances, earnings visibility is also lower, which causes difficulties in estimating the fair value of stocks. (Arkes *et al.*, 2008)

According to Brown and Cliff (2004), there are two types of traders in the market, the fundamentalists and the speculators. Fundamentalists have unbiased expectations of an asset's value, whereas speculators valuate assets with a bias. When the speculators value the intrinsic value greater (smaller) than the current price, they are bullish (bearish). Consequently, bullish investors expect, in addition to a positive return, a greater return than the fundamentalists' required rate of return. Measuring these deviations from the intrinsic value is not easy. Therefore, Brown and Cliff (2004) employ the bullish term when the expected price increases and bearish as it declines, which acts as the framework for my analysis as well.

There is some supporting evidence of market conditions-driven impact on reference point formation in the field of psychology. Recent studies, including Arkes *et al.* (2008), Karlsson *et al.* (2009), Arkes *et al.* (2010), have modeled this effect through vast questionnaire experiments by simulating a real investment decision. These studies measure, what magnitude of utility an individual experiences from recent stock price changes, while given distinct information on the historical stock prices. These studies do not however provide evidence on a aggregate market level reference price formation.

Arkes *et al.* (2008) finds that reference point adaption is found to be occurring more with rising stocks than the falling ones, which makes it asymmetric. This study also suggests that, as the investors on average have more winning stocks than losing ones during rising markets, their reference point adaption is also faster.

Derrien (2005) examines the impact of favorable investor sentiment on the pricing, initial return and long-term performance of IPO stocks. The study bases on a particular data source, comprising 62 offerings in the French stock exchange. The focus is kept knowingly on the demand of individual investors, and the study finds that IPOs tend to be priced over their long-run intrinsic value, but yet do exhibit positive initial returns. Additionally, it seems that the demand of the individual investors is positively correlated with initial return and turnover, and strongly correlated with market conditions. He explains the underpricing phenomenon therefore as a consequence of the noise trader sentiment. Still, the specific consequences the market conditions cause on the reference prices are not characterized, as Derrien (2005) focuses more on the relation between the demand curves of individual investors and the pricing of IPO shares.

Investors are more likely to experience success in bull markets as the attribution bias exhibits an asymmetric property and is more present in the bull conditions (Odean, 1998). In other words, the self-enhancing attribution for success is more significant than the self-protective attribution for failure. Different market conditions can therefore provide a natural experiment to measure the disposition effect and whether bull markets cause investors to trade excessively, over selling the losers.

It has been found that when investor sentiment increases, the offer size of IPOs grow at the same time (Ljungqvist, 2003). In addition, the quality of the average issuer decreases as companies are increasingly more likely to get listed on non-investment purposes such as financing previous debt. Ljungqvist (2003) also argues that lock up-provisions are demolished earlier for corporate insiders in case of unexpectedly high investor sentiment, after the excess inventory of regular investors has been unloaded, or at the turning point of the hot market into a cold direction.

2.4 Reference point formation

According to the disposition effect, investors' tendency to sell winners and hold losers is due to the concept of a reference point which determines the losses from gains (Shefrin and Statman, 1985). Kliger and Kudryavtsev (2008) were the first to be able to empirically prove the mechanism of reference point formation. According to their study, salient events during a stock's holding period do affect their investors' perceptions, which causes them to update the stock's reference point.

Reference prices in behavioral finance are considered to be a function of past purchase prices of a financial asset (Shefrin and Statman, 1985). Studies such as Odean (1998) and Grinblatt and Keloharju (2001) have used the weighted average price as a proxy for the reference price. Other studies have applied the first purchase price or the most recent purchase price as a reference point. (Weber and Camererb, 1998; Frazzini, 2006) Finally, some studies, mostly those that do not have the information on the initial purchase price, use historical peaks as reference prices (Kliger and Kudryavtsev, 2008). Gneezy (2005) studies the effects of prior losses and gains on the formation of reference prices, and on the contrary finds that historical peaks tend to be the most descriptive reference prices that investors base their decisions on.

One could argue that there is a considerable amount of investors who do not follow the price movements of their investments. Still, the market trading volume is so large, that even if a percentage of all investors changed their reference points according to these news, it would affect the trading volumes. (Kliger and Kudryavtsev, 2008) Additionally, after IPOs, investors are expected to follow the events even more closely. Kliger and Kudryavtsev (2008) also find, that events in firms with a higher beta cause more reference point formation. Higher beta implies higher exposure to market volatility. Therefore, the relation between turnover and market volatility could be one determinant of the reference price formation.

Investors may update their reference prices more easily with smaller firms, as they possess low information flow and analyst coverage (Kliger and Kudryavtsev, 2008). Smaller firms are also more difficult to value, which is due to the fact that they demonstrate more idiosyncratic variance, plus they are more costly to buy and sell short, which makes them harder to arbitrage

(Shleifer and Vishny, 1995). How the disposition effect is connected to all this is through the fact that in the beginning the smaller firms may experience even long periods of negative earnings, but still have a potential for future larger returns. If the investors are conscious of this, they may keep the losing stocks in waiting for the future price peaks.

2.5 Methods used in previous studies

The existing past research on prospect theory and disposition effect can be divided into three categories based on the source of their data: *aggregate market data*, *individual data*, and *experimental data*. Studies based on each are linked to the IPO underpricing and explained the relevance and the need for further research.

2.5.1 Aggregate market data

The study of Lakonishok (1986) was the first to use aggregate market data as a basis for the disposition effect analysis. They find significant evidence from historical stock prices on winners having a stronger abnormal trading volume than losers.

Kliger and Kudryavtsev (2008) discovered, that firms' quarterly earnings announcements influence reference point formation when the analysts' earnings forecasts are unable to predict the prices accurately. Additionally, they found that market price reactions followed the earnings announcements, and that smaller sized firms with higher betas caused a stronger reaction in the reference point formation. Therefore, it seems reference point formation process is more reactive to company-specific events when there is less information on the market and as the prices are more sensitive to market fluctuations.

Kaustia (2004) studies the disposition effect through IPO trading volume. He is able to point out that turnover is significantly lower for negative initial IPOs when the stock trades below the offer price. Additionally, it increases profoundly on the day the price exceeds the offer price for the first time. This increase is documented to last for two weeks. Furthermore, new maximum and minimum stock prices seem to affect reference point formation as they increase the trading volume significantly. Additionally, Kaustia (2004) did not find a significant asymmetry observable at zero initial returns, which would support the disposition effect during the first trading day. This can be due to price support, which is described in further detail in Section 2.1.1.

A stock's fundamental value is unpredictable because it follows a random walk. Still, it is found that the stock's equilibrium price tends to underreact to information. Because of the disposition effect, there is a spread between a stock's fundamental value and its market price. The fundamental value is here referred to the stock price that would exist in the absence of a disposition effect. (Grinblatt, 2002)

Barberis *et al.* (1998) studies the effect of a positive earnings shock. Underreaction means that on average the stock price does not react sufficiently to this shock, leaving the price below fundamental value. In this model, it is assumed that investors base their decisions on two alternative models. The first model implies that investors are mean-reverting and are expecting the returns to deviate from the previous announcement. The other model suggests that after consequtive announcements into the same direction (positive/negative) investors are inclined to make their forecasts based on a trend they think of observing. Barberis *et al.* (1998) argue in their model that firms' earnings announcements represent information of low strength but possesses high statistical weight. This is one explanation into why stock prices underreact to earnings announcements (and other similar events). Furthermore, their study implies that series of consistent patterns of news are experienced more strongly but actually possess low statistical weight. Thus, patterns of good or bad news are argued to lead to stock price overreactions.

According to Lee and Jiang (2002), the magnitude of the changes in how the noise traders perceive the asset's risk impacts expected returns via shifts in their sentiment. Accordingly, noise traders usually have poor market timing, as they are inclined to transact together with other noise traders. The greater the misperception, the greater the capital losses. Lee also finds, that excess returns are positively correlated with shifts in sentiment. Furthermore, bullish shifts in sentiment lead to downward revisions in return volatility and implies higher future excess returns.

Lowry and Officer (2010) find evidence on the interconnectedness of the IPO pricing problem and market-wide conditions. Market-wide uncertainty makes it harder for underwriters and investors to value IPOs. Market conditions can also drive firms' decisions to go public (Pástor and Veronesi, 2005). What is yet to be determined however, is whether market conditions affect the behaviour of the aggregate market in terms of turnover changes. In other words, is investors' behaviour dependent on the prevailing market conditions. This is addressed in my study.

Ljungqvist (2003) study the relation of IPO long-run performance and investor sentiment primarily in a hot market. They find that underpricing and long-run performance are negatively correlated as in Ritter (1984), but their study contributes the correlation to only hold when the probability of the hot market ending soon remains small. While an interesting finding regarding the effect of the market conditions on the long-run performance of an IPO, this aspect will be left out of this thesis because of concentration on the effects of market conditions on the short-run market trading.

Finally, as Statman *et al.* (2006) states, several studies on individual investor transactions have found evidence of disposition-prone individual behavior. In fact, this suggests a specific behavioral attitude towards the stock market in general. Therefore, these investors under inspection are likely to overestimate their abilities in active buying and selling of securities of stocks in general, rather than only on the specific holdings under research. Therefore, the best way to measure overconfidence or the disposition effect would be to use aggregate trading volume data.

2.5.2 Data on individual investors

Odean (1998) studied the disposition effect by analyzing the trading records of 10,000 accounts of a large discount brokerage house. According to this study, investors are found to demonstrate a significant preference for realizing winning stocks rather than the losing ones. Moreover, they prove that investor behaviour is also strongly affected by tax-motivated selling especially in the end of each year.

Additionally, the motivation of the investors was found unrelated to both avoidance of trading costs of low priced stocks and to the desire to rebalance portfolios. Moreover, many investors engage in tax-motivated selling, which occurs especially in December. Shefrin and Statman (1985) also note this effect and explain it by the fact that investors sell their losers in the end of the year because of a self-control measure. In other words, they hypothesize that investors recognize the tax benefits of selling losers, while without a similar kind of reasoning are reluctant to realize the losses.

Frazzini (2006) finds that when the investors have a tendency towards disposition effect, there is a post-event price drift because the prices underreact to news. When the stock price appreciates as a result of good news, investors want to sell it to lock in the paper gain, which on its turn pushes down the price, assuming a downward-sloping demand curve. This study was done by investigating fund managers and discovered that the lower-performing professional investors were as prone to the disposition effect as the individual investors. According toTversky and Kahneman (1992), people pay too much attention to the strength of information (evidence) exposed to them and too little attention to its statistical weight when making forecasts about the future performance of their investments.

Ranguelova (2001) studies the daily trading records 78,000 clients of a discount brokerage house. The results indicate that the disposition effect concentrates primarily on large capitalization stocks. In fact, she finds that the stocks which are trading at the smallest 40% of the market capitalization actually exhibit effects of the reverse kind to the disposition effect, as investors keep winners and sell the losers.

Grinblatt (2002) argue the disposition effect creates a spread between a stock's fundamental value and its market price. In this case, the fundamental value is the stock price that would exist if there was no disposition effect. Their study finds that the disposition effect may empirically affect the tendency of past winners to outperform past losers. They base their research on the hypothesis that if some investors are prone to disposition effect, the stocks with aggregate unrealized capital gains correspondingly outperform the stocks that posses aggregate unrealized capital losses. Furthermore, their study finds that the correlation between past returns and variables related to the disposition effect might be the drivers of stock returns' momentum.

According to attribution theory, individuals too strongly attribute events justifying their actions to high ability whilst the opposite events are seen to arise from external noise or sabotage factors. Daniel and Hirshleifer (1998) argue that investors may be trading based on private signals which they afterwards reflect to public signals. In this case, good news raises investors' confidence but bad news only modestly decrease it. In other words, the public signals are on average considered as confirming the validity of the investor's private signal. Therefore, public information may trigger further overreaction. Their study finds that this kind of continuing overreaction causes momentum in security prices, but in the long-term the price is drawn back closer to fundamental value as more public information occurs.

2.5.3 Experimental tests

As general in finance empirical research, there are less studies made based on the experimental design. This does not however mean, that these studies present controversial results, but they are rather laborous projects with many considerations.

Bloomfield (2002) finds empirical evidence on the model developed by Barberis *et al.* (1998), according to which investors use the past trend reversals of stock prices when determining their estimates of future reversals (regime-shifting). They find that investors tend to overreact to a price reversal when there has been but a few reversals prior to the last. On the other hand, when the number of reversals has been high, the investors seem to underreact to recent price reversal.

Weber and Camererb (1998) conducted a multi-stage experimental test to determine whether individuals under an imaginary investing setting act according to the hypotheses of the disposition effect. The subjects of the experiment were tested on buying and selling shares in six risky assets, with the prices fluctuating throughout the experiment. Their results evidenced that the subjects did sell winning and keep losing stocks, which is in contrast with the Bayesian optimization theory.

Arkes *et al.* (2008) studies the reference price formation through an experimental design. He conducted a laboratory study for undergraduate students and tested whether the asymmetric adaptation after gains or losses holds when faced with monetary incentives and also whether the incentives influence the reference point adaptation. Their results indicate that reference point adaptation applies more completely to gains than to losses. They also find that the adaptation (upwards) is done more quickly, if a stock is repurchased at the same price at which it was sold before. They hypothesize this stems from the closing of the prior mental account.

3 Hypotheses

The methodology of this thesis bases itself on the work of Kaustia (2004). Initially motivated by the study of Kliger and Kudryavtsev (2008), who use earnings surprise as a proxy and compare the stock market reaction accordingly to the observed earnings level versus analytics' forecast levels, I have replaced the earnings announcements with initial public offering's first trading date returns and the analysts forecasts with the offer price. Therefore, the initial offer price to the investors acts as a reference point, to which investors compare all forthcoming price movements.

Based on the existing literature described in the previous sections, there is not enough significant evidence on the effect of market conditions on the reference price formation of the aggregate market.

My research question is therefore the following:

Do stock market conditions affect the aggregate market reference price formation?

In order to investigate this, I firstly intend to study the impact of the disposition effect on the post-IPO turnover. Regressions are run to determine the variables that represent the most significant implications for reference price movements. To find out the solution for the ultimate research question, I have formed the following pre-conditioning hypotheses, which will be researched to first identify the model as valid.

I start by examining the reaction of the aftermarket on IPO pricing. This part is based on the changes in trading volume after the underwriter support period has ended. Thus, IPO trading volume is used as a proxy for investor sentiment. My analysis lies on the much studied assumption of the investors' reference price being the initial purchase price, i.e. the offering price of the IPO. The results of the further regressions will however incorporate other options for reference prices, which will be explained in Section 6.1.1. Before that, I will next go through the hypotheses.

As the disposition effect states, investors tend to hold on to losing investments and sell winners.

Hence, trading volume should be lower when the price is trading below the offer price and higher when the price surpasses the offer price for the first time. According to Kaustia (2004), this would represent a strong enough behavioral bias. Moreover, investors that are disposition-prone and have not sold their shares previously, tend to delay their decision to sell. IPO shares that have not previously traded above the offer price should exhibit this effect at its strongest.

Moreover, when investors are reluctant to trade losers, trading volume should be higher when the stock is trading above the offer price vs. below it (Kaustia, 2004). This is because investors are prone to realize winners. If the offer price is indeed a reference price, the disposition effect should lead to a higher trading volume when the stock is trading at a higher price level in relation to its initial offer price. This leads to the first set of four hypotheses, that serve as a precondition of the market condition based analysis:

H1: *Post-IPO trading volume is higher in the price levels above the offer price*

H2: *Trading volume for negative initial return IPOs increases when the offer price is surpassed for the first time*

H3: *Trading volume for positive initial return IPOs increases when the offer price is surpassed for the first time*

H4: *When new price maximums (minimums) are reached, trading volume increases*

When the IPO market price with a negative initial return exceeds the offer price for the first time, there should be an immediate effect in terms of trading volume. This will answer the question, whether disposition effect is significant enough to affect asset pricing. Moreover, due to price support reasons, as explained in Section 2.1.1, trading volume should increase slightly below the offer price for winners, and then again decline. Furthermore, other reference prices are considered in addition to the offer price, in order to detect the implications the new maximum and minimum prices have on the total turnover of the stock.

A counter-argument could suggest that the more time it takes to surpass the offer price, the less initial investors there are left, and thus the effect might not be as strong because of fewer investors share a common purchase price anymore. However, Kaustia (2004) argues that the initial investors' disposition might be even stronger within more time as they want to sell to realize their winnings.

After these first hypotheses, I test the market condition induced effects on the reference price formation via the shifts in the post-IPO trading volume. These two hypotheses are designed to provide the answer for the research problem:

H5: *Market conditions (bullish/bearish trends) affect the reference price formation*

H6: *Reference price formation is more frequent under bull markets*

As stated before, trading should occur less in bear markets because of valuation difficulties. This reasoning is backed-up by Derrien (2005), who argues, that noise traders (individuals) only participate in the aftermarket when they are bullish. When they are bearish, higher transaction size implies institutional investors to be responsible for aftermarket trading. Accordingly, I hypothesize that investor sentiment is less observable under bear markets, as there are fewer noise traders. Therefore, the active adaptation of reference prices should be faster and more volatile during bull markets, than during bear conditions. Naturally, hypothesis number 5 acts as a presumption for hypothesis number 6, as the testing of the latter gains meaning only on the verification of the fact that reference price formation indeed varies according to market trends.

Finally, as per the research of Barber and Odean (2007), Kliger and Kudryavtsev (2008) and Frazzini (2006), there should be more reference point updating with stronger surprises. Moreover, reference points tend to be adapted more after rising stock news rather than declining (Arkes *et al.*, 2008). Therefore, I test whether the size of the underpricing, which acts as the surprise element for the investor, has implications on the trading volume.

H7: *Large initial returns cause more reference point adaptation*

Now that the hypotheses are stated, the means to resolve them are characterized thoroughly in Section 4.

4 Methodology

In this section, I discuss the methods applied in the empirical analysis. Essential methods include both individual daily firm regression analysis and pooled regression analysis. The purpose of the first regression is to develop a model for a normal turnover. The residuals from this regression represent the abnormality of the daily turnovers of individual firms. These residuals are then further analyzed by the pooled regression method, to determine the main factors that cause the total turnover to deviate from its normal values.

4.1 Regression analysis of daily turnover

The first-stage regression will be performed for each firm individually. The characteristics for these are described in Section 5. Before this, the methodology and variables of the regressions are explained.

To estimate the turnover behaviour of the subsamples, I first form a model of normal turnover for each firm. The turnover is estimated from post-IPO dates between 160 and 484 according to the following equation:

$$V_i = \alpha 1 + X_i \beta_i + e_i \tag{1}$$

where,

V_i= T_i x 1 vector of log of firm i daily turnover
α_i= regression constant for firm i
1= T_i x 1 vector of log ones
X_i= T_i x m_1 matrix of first step explanatory variables for firm i
β_i= m_1 x 1 vector of regression coefficients for firm i
e_i= T_i x 1 vector of error terms for firm i

Abnormal turnover for each firm is determined by controlling for market turnover, previous days' turnover, contemporaneous and lagged returns and seasoning effects. Abnormal trading volume is measured according to Kaustia (2004), in accordance with Tkac (1999), by dividing the number of shares traded by the number of shares outstanding (V_i in the above equation). This turnover ratio data is extracted from the Center for Research in Security Prices (CRSP) database files separately for each firm. The regression variables following the methodology of Kaustia (2004) and their explanation are displayed in Table 1.

Following the study of Lakonishok (1986) and Ferris and Haugen (1988), market turnover is measured by a simple average of all the companies turnover presented within the analysis. In the first regression, turnovers serve as the dependent variable and the market turnover is one of the independent variables, with disturbance terms representing the abnormal turnovers. According to the below regression equation, the daily data of each individual firm is used to determine the coefficients of the turnover market model.

Tkac (1999) determines the market model turnovers as follows:

$$VT_{it} = \alpha_i + \beta_i VTM_t + e_{it}$$

where,

VT_{it} = the turnover of security i in month t

VTM_t = the relevant market turnover in month t

e_{it} = the disturbance term for company i in month t

This formula is then further developed to identify the abnormal turnovers, which are defined after the following equation:

$$AVT_{it} = VT_{it} - (\alpha_i + \beta_i VTM_t)$$

In the analysis, these residuals are divided according to the sign of the initial return and thus belong to either the winning stocks or the losing stocks. Whereas the above-mentioned studies employing this method use a dataset of four years of stocks already listed for several years, my study concentrates instead on newly-listed companies over a period of two years

Table 1: **Regression Variables for the Dependent Variable of Daily Logarithmic Turnover**
Explanatory variables used in individual firm regressions. The objective is to model the normal turnover of each firm, with the dependent variable being the logarithm of daily turnover (number of shares traded/ number of shares outstanding).

Variable	Description
Volume variables	
Market turnover	Log of Aggregate number of shares traded divided by the aggregate number of shares outstanding
Turnover	Log of Number of firm i shares traded divided by the number of shares outstanding
Turnover (-1)	Log of Turnover at day $n-1$ relative to observation day
Turnover (-2)	Log of Turnover at day $n-2$ relative to observation day
Seasoning variables	
Time	Time in months relative to offer date
Time^2	Time in months squared
Stock return variables	
R	Daily log stock return
Max [R,0]	If positive, the return, otherwise zero.
-Min [R,0]	If positive, zero, otherwise absolute value of return.
Volatility	The daily stock return squared
R (-1)	Stock return at day -1 relative to observation day
R (-2)	Stock return at day -2 relative to observation day

following the study of Kaustia (2004). The motivation as explained comes from the known offer prices of IPOs, which act as the first anchoring point for the disposition effect.

The estimation periods of the individual firms can overlap to some extent. However, following the research design of Kaustia (2004) should mitigate against any cross correlation effects. Even if volume is correlated with both contemporaneous and lagged returns, the model should remove most systematic effects because it already includes the return based variables in addition to market volume. The return variables take in all the market information affecting the distinct firm. Therefore, as the signals to the IPO market specific trading volume are correlated with the contemporaneous and lagged returns, or market volume, the cross-sectional impact on the residuals should be minimal.

Furthermore, my analysis does not take the model of the study of Kaustia (2004) only as a given, but tests other variables before the first regressions, that may be affecting the normal turnover. These variables are explained in more detail in Section 6.1.1.

4.2 Pooled regression analysis

In this section, the method of pooled regression analysis is described and its fit is justified for the later forthcoming empirical analysis. First, the panel data method is explained and based on its implications, the pooled OLS method of the second-stage regressions is accounted for.

4.2.1 Panel data regression

A panel data consists of i number of individuals, each with n sets of observations. According to Matyas and Sevestre (2008), the panel is said to be balanced if every individual is observed equally many times. Analogously, an unbalanced panel may contain individuals that are observed different numbers of time. Furthermore, the panel is fixed, if for the whole duration of the study, there is the same set of individuals. Therefore, the panel data for this study is an unbalanced one.

Panel data method is applied in this study, because it takes into account the time varying nature of the data. Broadly determined, panel data can be regressed in three main methods: pooled, fixed and random effects. Pooled regression should be used when the individual effects contain only observable features that can be determined to represent the constant.

If there are some possibly unobservable features that are correlated with the model, the least squares estimator will be biased and inconsistent, and one should use the fixed effects regression model instead. This model estimates the constant as a group-specific term within the regression model. Fixed refers to the non-stochastic correlation of the individual effects and the constant with the whole model. Time-invariant variables cannot be estimated by the fixed model, as they will mimic the individual specific constant term. (Matyas and Sevestre, 2008)

If however, the unobserved individual heterogeneity is uncorrelated with the model variables, the regression model should be based on a random constant term, taking into account the random effects. Whether the unobserved individual effect of the firms have features that are correlated with the regressors in the model is the key distinction between fixed effects and random effects models. The Hausman test can be performed to test whether the variables are correlated with the constant or not. (Matyas and Sevestre, 2008)

There are no time-invariant variables in the second-stage regressions of this study, so the random effects estimator is not considered. Furthermore, as the data ought to be unaffected by any underlying unknown variables, as I am measuring only the relation between return and turnover, the proper model should be the pooled OLS-regression. Also, the intercepts at the pooled model are assumed to be identical, which fits the analysis in this paper, as the residuals should represent the abnormal deviations from the normal turnover. Therefore, the analysis is done in the same way as the one conducted by Kaustia (2004).

4.2.2 Pooled OLS

As mentioned, I use Ordinary Least Squares (OLS) regression on the residuals obtained from the previous regressions. This enables me to detect the size of behavioral effects. Following Kaustia (2004), the individual error terms e_i form the dependent variable Y as follows:

$$Y = Z\beta + \epsilon \tag{2}$$

$$Y = [e_1 e_2 ... e_N], \quad Z = [Z_1 Z_2 ... Z_N]$$

where,

Y= vector of stacked error terms e_i

Z= matrix of second step explanatory variables

Z_i= T_i x m_2 matrix of second step explanatory variables

β= m_2 x 1 vector of regression coefficients

ϵ= m_2 x 1 vector of error terms

To determine important reference prices, I will measure the total turnover after IPO. Initial return is measured as the percentage change from the offer price to the first closing price. The turnover is measured from the twenty-first day of trading onwards. This procedure is followed according to Kaustia (2004) and Lowry and Officer (2010) in order to avoid the effects of price support. I use the exceeding prices in relation to the offer price, by describing the events as follows: A crossing of the offer from below at a level of 1.10 corresponds to the stock price yield of more than 10% to initial investors.

A set of dummy variables is used to indicate crossings of specific stock price levels, new high and low prices and trading within specific price ranges. All variables for the pooled regression are displayed in Table 2. The variable that indicated the first crossing of the offer price, gives losers the value of 1 when the stock price crosses the offer so that it surpasses above it. Correspondingly, winner stocks have to cross below the offer price to get a value of 1. Furthermore, other price levels are initiated for the purpose of control variables. These dummies represent levels of 0.95, 1.00,...,1.50 for the losers and 1.20,1.15,...,0.80 for winners. Additional dummies include variables, which indicate the new maximum and minimum stock prices over the previous 20 trading days.

There might be an additional distorting factor that has to be taken into consideration, namely, the new investors who buy the initial investors' increased supply of shares at offer price and sell them only above the offer level. In other words, when the trading increases close to the offer price, this may lead to an increase in volume at the corresponding price. Therefore, a dummy indicating the crossing after the first crossing is introduced both at the same price levels as described before as well as further levels of 0.70, 0.75,...,0.90.

Table 2: **Explanatory Variables of the Pooled Regression.**
Pooled regression is run to determine the magnitude of the behavioral effects. Dependent variable is obtained from the residuals of the first regression.

Variable	**Description**
Record High 1M	Previous -month -high dummy indicating 1 if the highest value occurred during past 20 trading days, otherwise 0
Record Low 1M	Previous -month -low dummy indicating 1 if the lowest value occurred during past 20 trading days, otherwise 0
First Crossing Above Level X	Dummy variable indicates 1 if the stock return index crossed the level xx relative to offer price from below for the first time, otherwise 0. E.g. First Crossing 1.10 contributes the value of 1 on the day the stock price for the first time crosses the level of 1.10 in relation to the offer price, thus surpassing *above* the initial price
First Crossing Below Level X	Dummy variable indicates 1 if the stock return index crossed the level xx relative to offer price from above for the first time. E.g. First Crossing 0.90 contributes the value of 1 on the day the stock price for the first time crosses the level of 0.90 in relation to the offer price, thus surpassing *below* the initial price
Second,...,Nth Crossing of Level X	Dummy variable indicates 1 if the stock return index crossed the level x relative to offer price from below, or above, otherwise 0
Range [X_1, X_2]	Dummy variable indicating 1 if the stock price is inside the price range, otherwise 0. E.g. Range [1.10, 1.15[gets the value of 1 every day the stock return index is trading at a gain between 10% and 15% in relation to the offer price, and a value of 0 otherwise.
Record High 1M ($R \geq 5\%$)	Interaction dummy between the record high price and ($R \geq 5\%$), indicating 1 whenever the return is equal or larger than 5%.
Record Low 1M ($R \leq 5\%$)	Interaction dummy between the record low price and ($R \geq 5\%$), indicating 1 whenever the return is equal or smaller than -5%.

The abnormal volume of the stock's trading range is also measured without considering the crossing of any of the price levels. For this purpose I include dummies of a particular range relative to the initial offer price. Exclusions in the ranges include the class of [1.00,1.05[for both the winners and the losers, as this range serves as a benchmark.

4.3 Pooled regression based on market conditions

Market conditions on each firm going public will be tested within this second regression with an additional segmentation of the firms, the dividing basis indicating for bull and bear markets. The methods and variables correspond to the afore-mentioned ones, only differing in the segmentation preassumptions. To determine the bull and bear markets, I use both the VIX-index and a means of technical analysis called the MACD method, which are described next.

4.3.1 Moving average convergence-divergence (MACD)

MACD is a form of technical analysis and is one of the most simple and effective momentum indicators. It is constructed by calculating moving averages of different-lengths. Chong and Ng (2008) study daily closing prices using the relative strength index and the MACD.

$$EMA_t = [\frac{n}{2} \cdot (P_t - EMA_{t-1}] + EMA_{t-1}$$

where,

EMA_t = exponential moving average at time t
n = number of periods for EMA

In this formula, the initial EMA is the n-day simple moving average (SMA) of the series. The most common time periods used in this analysis are 12 and 26 days. (Chong and Ng, 2008) However, because of the brief nature of these periods, I will extend the periods in my analysis to better represent the longer periods of my study. I will use periods of 2 years and 230 days, which correspond to the same relation as the 12 and 26 day periods.

Essentially, these moving averages are considered as trend-following indicators which the MACD then turns into a momentum oscillator. This indicator is particularly good in identifying past market signals, and should be investigated by following the signal line crossovers and divergences. Figure 5 represents the MACD graph, modeled on data on the S&P500 index extracted from Thomson One Datastream.

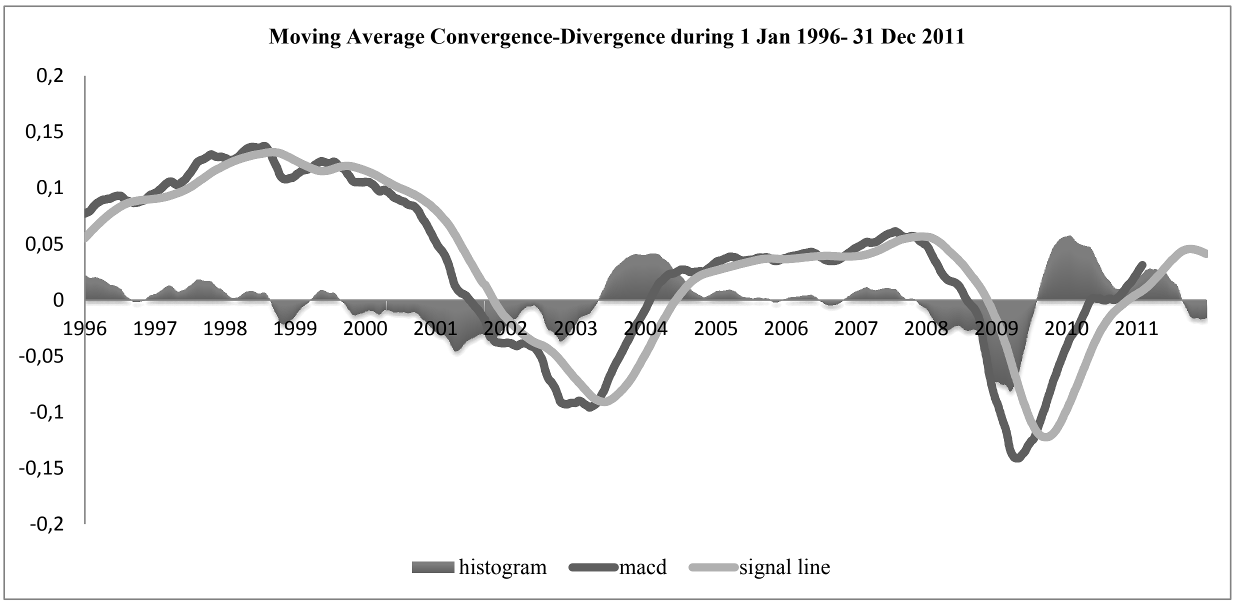


Figure 5: **S&P500 Modeled with the MACD Method**
Convergences and divergencies of the S&P500 index. As the moving averages cross, converge and diverge, the MACD fluctuates on both sides of the zero line. The zero line detects the market trend reversals. Data is extracted from Thomson One Banker. Time window runs from 1 January 1996 to 31 December 2011

Convergence is said to occur as the moving averages move towards each other, whereas divergence means the averages moving away from each other. The zero line is called the center line, which detects the trend reversals. As the MACD line moves above and below the center line, it means the shorter moving average has crossed the longer moving average, positive values indicating the shorter being above the longer average and vice versa. As the shorter moving average diverges further up, it indicates an increase in upside momentum. Correspondingly, downside momentum occurs as the shorter moving average diverges down from the longer moving average. (Campbell *et al.*, 1998)

The MACD analysis also entails a signal line, which is typically calculated the 9-day EMA of the MACD-line, or in my analysis, the 174-day EMA of the MACD-line (calculated keeping the same overall relation between the time periods). Because the signal line is a moving average of the indicator, it facilitates the follow-up of MACD turns. In fact, the most imporant contribution of this analysis to my study is its capability to detect bullish (bearish) crossovers of the MACD as it crosses the signal line from below(above). (Chong and Ng, 2008)

The MACD line can be calculated both on individual securities as well as on indices. Following the study of Chong and Ng (2008), I model MACD based on the S&P 500 index, because it best describes the market conditions of my base sample. Furthermore, the motivation behind the 2-year longer moving average lies in the idea, that the initial volume data on the individual firms in my sample has the same length.

4.3.2 VIX-index

The Chicago Board Options Exchange (CBOE) Market Volatility Index (VIX) is implied from the S&P500 index options on a real-time basis each trading day (Whaley, 2008). It serves as an estimate for the short-term expected return volatility. The index is not backward-looking but rather represents the volatility that has only recently been realized. VIX can be considered as a fear index in a way that it reflects the anxiety in the markets. Whaley (2008) explains that the VIX tends to peak during market turmoils, and as the volatility increases the investors demand higher returns for their stocks which cause the prices to fall. He also finds that when the stock market falls, the VIX tends to rise at a higher absolute rate as opposed to the situation where the market rises.

As investors become bullish it raises the market risk as they are holding riskier assets, which also increases expected returns. The converse effect happens in bear markets. (Lee and Jiang, 2002) This explains why the index that describes the volatility in the market can be a sign of bull/bear markets. Such an index is the VIX-index, which measures the volatility of options.

VIX is used in this study as a benchmark sign on the prevailing market trends, or market shifts,

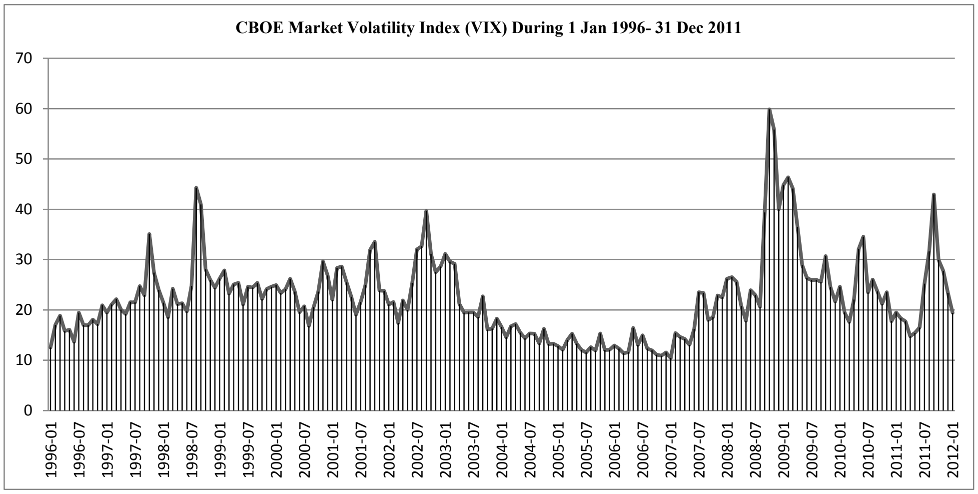


Figure 6: **CBOE Market Volatility Index**
VIX index estimates the short-term expected return volatility within the market. Peaks in the index can be considered signs of increased market anxiety. VIX is modeled based on the S&P500 data extracted from Thomson One Banker. The time period runs from 1 January 1996 to 31 December 2011.

if you will. As it has been empirically tested to represent the sentiment shifts, it provides a proper estimate for especially the downturn points in the markets. Figure 6 illustrates the VIX index for the time period under inspection.

In this study, VIX is compared to the MACD-line as a reassuring measure of the validity of the MACD-method. The two give a coherent and non-concurring estimate on the past market shifts. These shifts are then used to determine the prevailing market conditions on each day of the following period of each firm. In fact, these estimates are used to divide the firms of subsamples into “Bull” and “Bear” categories later in the pooled regressions in Section 6.3.

4.4 Regressions based on the size of the initial returns

The last regressions are run based on the size of the initial returns. These regressions comply with the same variables and methods as with the second-stage regressions described before. The only difference is, the winners and losers are further divided based on the size of the initial returns. Accordingly, the winner firms of the largest 40 percent difference between the offer price and the first-day closing price are marked as the largely underpriced and the rest are put in the average underpricing category. The segmentation is done in accordance with Ranguelova (2001). For the losers, this procedure is performed in the same way, but accounting the first group for the largest 40% in overpricing and the rest belonging to the average overpricing category.

5 Data

In this section I describe the data retrieval process along with the main characteristics of the full and the subsamples, as well as the prevailing market conditions during the IPOs of these firms. The full dataset consists of 2849 US IPOs, which are then further divided into a subsample of 1527 firms for the regression analysis purposes.

5.1 Description of the data retrieval process

The full data comprises U.S. initial public offerings listed in the Thomson One Securities Data Corporation (SDC) database. The time period continues directly from the ending of data period of Kaustia (2004) and spans effectively from 1 January 1996 to 31 December 2011. All data on offer dates and prices, in addition to gross proceeds are matched both with data in the Center for Research in Security Prices (CRSP) and Thomson One Banker.

The data retrieval process goes as follows. Initially the SDC data retrieval gives 10,674 IPOs in the US during the time period under inspection. The data is next sorted to better fit for the purposes of this study. Following the study of Loughran (2002), exclusions include unit offerings, closed-end funds, real estate investment trusts (REITs), partnerships, and American depository receipts (ADRs). Additionally, only original IPOs are considered, so later issues made by the same firms under the same period have been excluded. After these eliminations, the amount of IPOs drops to 4,732 firms. Furthermore, all IPOs under an offer price of $1 a share (263 firms) have been excluded.

In measuring the reference price formation, I use Thomson One Banker as a primary source for extracting the stock price and volume data following the post-IPO 2-year period. The sample firms are matched with Thomson by tickers and are all tracked over a maximum period of 484 trading days, which corresponds to two years on both stock return and trading volume. The number of shares outstanding after the issue are gathered from CRSP database. To match the information of the sources I employ the CUSIP numbers to identify the issuer. Because the time period ends in December 2011, for an amount of 322 firms going public in 2011, the stock data is truncated at 1 September 2012, leaving out about 84 days amount of observations for the last IPO of 2011. Firms that have less than 160 trading days tracking data available, have been excluded, as well as firms, which lack more than 15 days of information on trading volume. After all eliminations, the data consists of 2,849 IPOs

5.2 Sample characteristics

Following the study of Kaustia (2004), the sample is divided into three categories based on the sign of the initial return of the first public offering. Accordingly, the categories representing the full sample are called “winners”, “losers” and “neutrals”. The winners correspond to IPOs of positive initial returns, losers to negative initial returns and logically the neutral sample exhibits no difference in the first trading day’s return relative to the offer price.

5.2.1 Full sample

The yearly number of IPOs is displayed in Figure 7. First observations can be made by comparing this e.g. to the MACD Figure 5: IPOs do indeed seem to be clustered in hot and cold periods, which follow market fluctuations.

As mentioned, the final sample includes 2,849 firms. Out of these, 2281 have positive initial returns, 523 negative initial returns and 45 trade at zero return. This corresponds to 18.3% of IPOs having negative initial returns, which are labeled as “losers”. Correspondingly, 80.1% have positive initial returns and will be marked as “winners”. The remaining 1.6% of firms had a zero initial return (*i.e.* they are trading at offer price at first closing). Zero return can be due to price support, which was described in 2.2. On average, the full sample losers are smaller with a median market capitalization of \$288.2 million, as the figure for all firms is \$348.5 million.

Additionally, the relation between losers’ gross proceeds and all firms’ proceeds is about the same as the market capitalization relation. Average number of IPOs of the full sample firms per day during the 15 year period is 1.64, with a median of 1. Maximum number of IPOs per

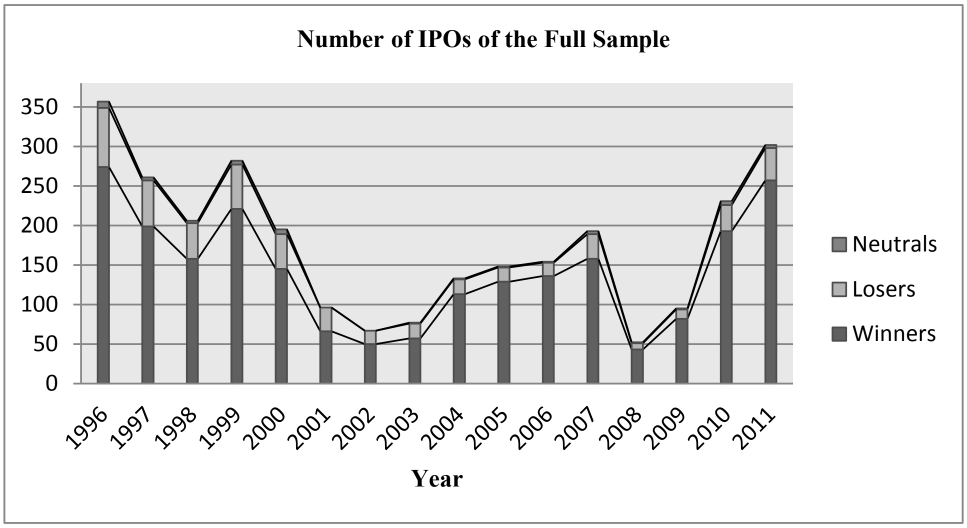


Figure 7: **The Full Sample Distribution of IPOs**
The aggregate number of initial public offerings divided by the sign of the initial return and by the occurrence between 1 January 1996 and 31 December 2011.

day was 11, while the minimum was 1. The mean and median market capitalization for all subsamples is presented in Table 5.

5.2.2 Subsample

For the purpose of reference price effects, I form further subsamples from the full sample. This segmentation is done by tracking the fluctuations of the stock prices in terms of the offer price. In other words, losers which stock price crosses the offer price from below for the first time only after four weeks (20 trading days), form one subsample. Correspondingly, I form a subsample from winners by the stock price that crosses the initial offer from above since the 21st trading day. Effectively, the crossing of the offer level occurs on any date between 21 and 484 days after the listing date. Zero effect group is assumed to be under price support, which is why it is not included in the further analysis.

Figure 8 illustrates the distribution of the subsample data. Out of the 2849 firms, 449 meet the requirements of the loser subsample, whereas 1028 are chosen for the winner subsample.

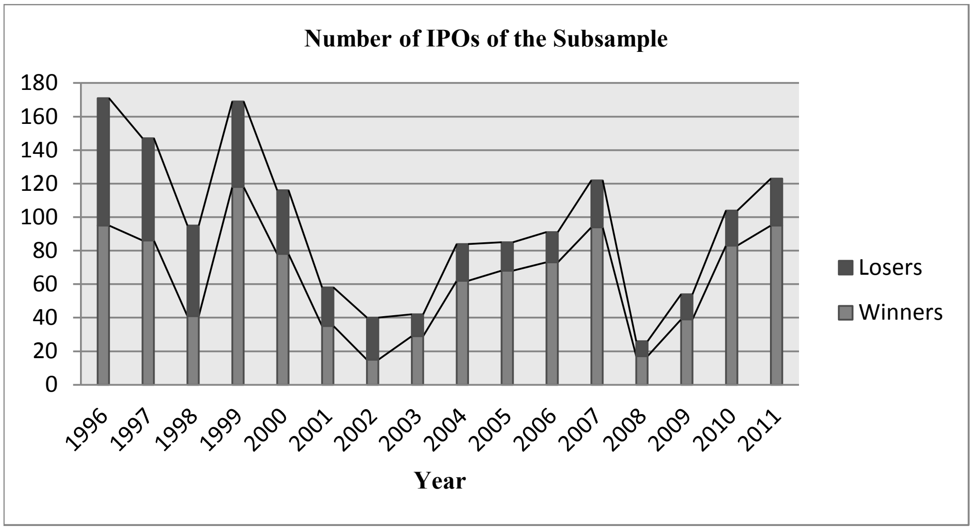


Figure 8: **The Subsample Distribution of IPOs**
The aggregate number of initial public offerings divided by the sign of the initial return and by the occurrence between 1 January 1996 and 31 December 2011.

As it can be seen, the subsample graph resembles the aggregate distribution of the full sample quite closely. Therefore the subsample should be adequately formed in relation to the initial sample. The only difference is, the relation of losers to the aggregate number of IPOs is somewhat larger for the subsample. This is, however, a benefit for the purposes of this study, as there is more data available for the losers, which balances the results in terms of number of observations.

Table 3: **Statistics for the Subsample under Lock-up Agreement**
Descriptive statistics for the winners and losers of the subsample, that are subject to a lock-up arrangement. Information has been gathered from SDC database.

Winners	**mean**	**median**	**stdev**	**min**	**max**	**all**
No. of lock-up days	200.0	180.0	104.8	30	730	731
% of shares under lock-up	63.1	68.0	23.0	2	100	273
Losers	**mean**	**median**	**stdev**	**min**	**max**	**all**
No. of lock-up days	98.8	90.0	101.8	36	540	275
% of shares under lock-up	64.0	67.0	21.7	3	100	89

An additional input to the study brings the incorporation of information on lock-up agreements, market trends, firm size and belonging to a high tech industry. I have gathered data from the SDC on lock-up days and on relative amount of shares under lock-up provision. As described in Section 2.1.2, lock-ups may affect the turnover of the individual firms, which justifies their incorporation into the analysis. As it can be seen from Table 3, the mean and median number of lock-up days seems to be substantially larger for winner firms (mean 200, median 180) as opposed to the losers (mean 99, median 90). As stated in Section 2.1, in a longer time period, the initial losers tend to overperform the winners. Therefore, these figure suggest that having longer lock-up agreements may essentially hinder the performance of the firm. This is however, a question of long-run performance, which is not within the scope of this paper. The purpose of this variable is instead to act as a part in determining the normal volume for each firm in the first regression in Section 6.1.1.

Table 4: **Statistics of the Supplementary Variables**
Statistics on firms that belong to a hightech industry and on firms that are smaller than $200M in market capitalization, divided by the prevailing market trend at the time of their first public offering. The variables are used in the preliminary regression in Section 6.1.1

Additional variables	**Winners**			**Losers**		
	Bull	Bear	All	Bull	Bear	All
Hightech	173	105	278	66	29	95
MicroCap	116	44	160	60	22	82
Market trend at issue	712	316	1028	332	167	499

Moreover, I have used the market capitalization data retrieved from the SDC to identify microcapitalization enterprises, because, they may be potentially reversing the disposition effect, as suggested by Ranguelova (2001). Table 4 describes the characteristics for both the winner and loser subsamples in different market conditions. The relative amount of winners during a bull period corresponds to the relative amount of both hightech and microcap firms under bull markets, when compared to the whole amount of winners during this period. The same applies to the losers as well, so there are no surprises in these ratios.

From SDC, I also got information on the firms' industries, which I used to identify high-tech firms. This was done by sorting the firms under the SIC-codes registered under the high-tech category. The stock market trends I have estimated using the VIX index together with the MACD method, as described in Section 4.3.2.

Initial returns of the subsample are displayed in Table 5 together with other descriptive statistics. The initial return equals the percentage difference between the aftermarket price on the 1st day of trading and the offer price. The tracking of trading volume, which is used in the second regressions, on the other hand begins at day 21, strongly due to price support bias. This adjustment is consistent with the studies of Kaustia (2004), Lowry and Officer (2010), Grinblatt and Keloharju (2001).

Table 5: **Descriptive Statistics of the Samples Divided by Initial Return Type**
Statistics are given for both the full sample of 2849 firms as well as for the subsample of 1527 firms. Full sample is divided based on the sign of the initial return into winners, losers and neutrals, and the subsample correspondingly into winners and losers (excluding the zero effect firms). The time period runs from 1 January 1996 to 31 December 2011

Full Sample	Offer year	Initial return	Proceeds, $M	Offer price	Market cap, $M	% shares offered
Winners (n= 2281)						
Mean	2002	23.21 %	193.07	14.03	2 545.65	44.73 %
Median	2001	7.24 %	69.20	14.00	402.56	40.00 %
St. Dev	5.1	25.01 %	403.05	8.13	609.75	18.06 %
Losers (n= 523)						
Mean	2001	-6.46 %	95.24	15.88	1 573.83	44.47 %
Median	1999	-3.52 %	50.10	17.00	288.18	42.12 %
St. Dev	4.7	14.33 %	141.88	9.39	651.60	21.07 %
Neutrals (n= 45)						
Mean	2002	0.00 %	84.49	15.59	1 121.30	47.66 %
Median	2000	0.00 %	50.00	11.63	227.48	44.21 %
St. Dev	5.4	0.00 %	93.02	5.55	385.89	27.44 %
All (n= 2849)						
Mean	2002	10.63 %	147.09	14.45	1 821.10	45.05 %
Median	2000	6.99 %	57.50	13.00	348.45	41.19 %
St. Dev	5	20.70 %	359.11	7.79	403.56	28.99 %
Subsample						
Winners (n=1028)						
Mean	2003	23.14 %	162.16	13.24	2 534.51	46.67 %
Median	2004	15.45 %	64.00	13.00	361.60	43.07 %
St. Dev	5	24.20 %	307.29	7.80	347.17	16.76 %
Losers (n=499)						
Mean	2001	-9.68 %	65.84	15.59	1 567.21	41.64 %
Median	2000	-5.50 %	37.05	17.00	267.58	34.05 %
St. Dev	4.8	6.81 %	101.64	8.16	270.40	29.25 %

6 Empirical results

In this section, the results of the methodology driven regressions are assessed. First, the results of the descriptive data analysis are characterized. This is followed-up by the pooled preliminary analysis, which assesses the fit of additional variables into the first-stage regressions. Based on the results of the preliminary regression analysis, the base case first-stage and second-stage regressions are performed. The base-case regressions are run according to the framework of the study conducted by Kaustia (2004). After this come the regressions based on the prevailing market trend during the time of the issue. Finally, the size effects of the initial returns are measured and reported through the same regression methods.

6.1 Descriptive analysis

Before the first regressions, the statistics for the variables are calculated. These are displayed in Table 6, which represents the pooled firm days of 1028 winners and 499 losers. Notable is, that the average absolute trading volume of the winners is over twice as large as the losers, which could imply that losers are traded less, in line with the disposition effect. In estimating the market turnover, the firms overlap 173 days on average, with a median of 170 days. The maximum number of days for the firm observations is 484.

Table 6: **Summary Statistics of the Daily Return and Turnover Variables of the Subsample**
Summary statistics on the daily return and turnover are calculated from the pooled firm days of 1028 winners and 499 losers in the subsample. The volatility variable is proxied by squared returns, following the methodology of Kaustia (2004). Each firm contributes to the statistics covering the first two years of trading data (excluding the first 20 days). Observation time period runs from 1 January 1996 to 31 December 2011.

	Winners			**Losers**		
Variable	Mean	Median	St. Dev	Mean	Median	St. Dev
Turnover	0.64 %	0.42 %	2.55 %	0.54 %	0.39 %	1.91 %
Turnover, R>0	0.77 %	0.85 %	0.38 %	0.75 %	0.94 %	1.03 %
Market turnover	0.40 %	0.90 %	0.2097 %	0.44 %	0.34 %	0.28 %
$-trading volume	1,067,089.36	130,800.00	2,078,044.05	409 066.94	67 673.50	2,193,555.09
$-trading volume, R>0	1,397,339.10	167,300.00	5,406,721.70	1,078,711.01	130,291.00	5,676,810.70
R	0.13 %	0.00 %	6.05 %	0.17 %	0.00 %	4.40 %
R, R>0	3.42 %	1.90 %	5.41 %	4.87 %	1.79 %	6.75 %
R, R<0	-3.47 %	-2.02 %	5.67 %	-3.09 %	-1.80 %	6.97 %
Volatility	0.37 %	0.02 %	1.47 %	0.19 %	0.02 %	1.93 %

Figure 9 represents the initial returns and first-day median turnovers divided by initial return category. As it can be seen, for winners the turnover seems to increase with large positive initial returns. The losers' turnover on the other hand seem to increase both below the offer price and above it, which would be inconsistent with the disposition effect. However, this is only the first day turnover. It could be, that some noise investors drop the loser shares immediately, which would mean the disposition effect is not a good fit for the first-day investor behavior when it comes to the losers. Furthermore, the price support activities may influence the total turnover, as explained before.

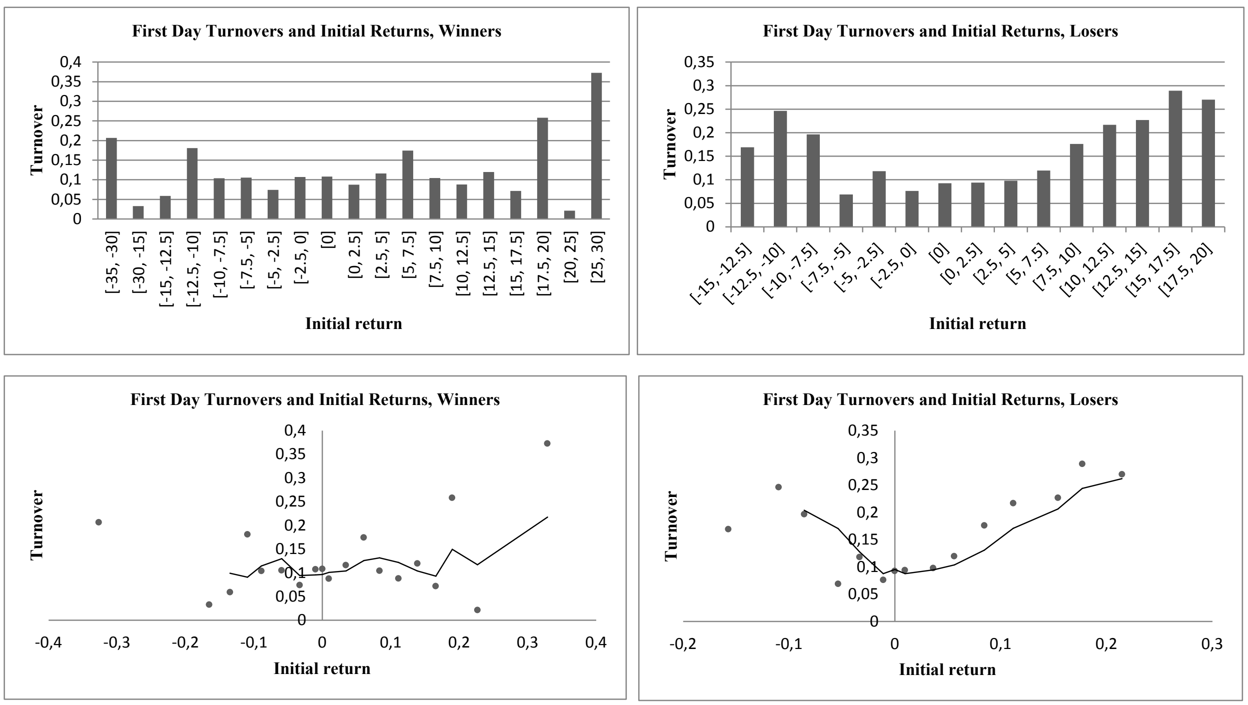


Figure 9: **Initial Returns and Turnovers of the Winners and Losers**
First trading day turnovers divided by initial return size, estimated separately for the positive initial return firms (1028 winners) and the negative initial return firms (499 losers). The lower graphs illustrate the average turnovers with an added 3-period moving average calculated from the turnover values. Time period runs from 1 January 1996 to 31 December 2011.

Figure 10 illustrates the whole subsample together, with a polynomial trend line attached. Here the line does support the disposition effect theory, as the overall trading seems to decrease below the offer price, and increase above it. Therefore, at first glance it would seem that the offer price does act as a reference price, steering the turnover at both sides of it.

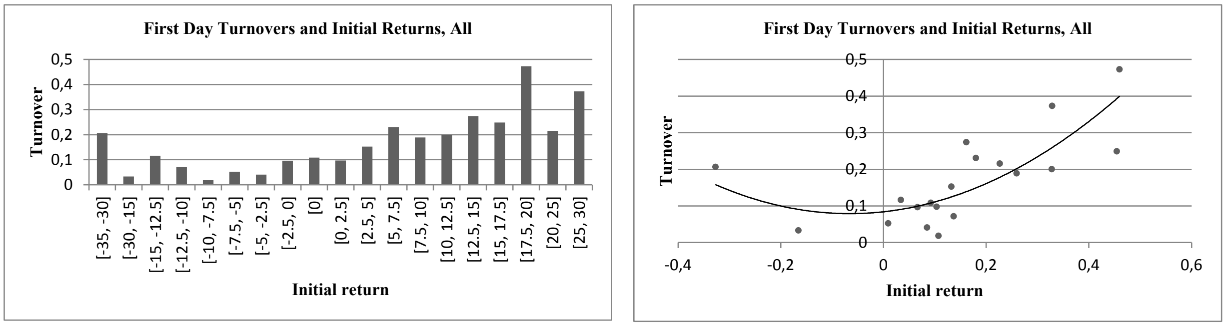


Figure 10: **Initial Returns of the Whole Subsample**
First trading day turnovers divided by initial return size, estimated for the whole subsample of 1527 firms combined. The lower graph illustrates the average turnovers with a polynomial trend line attached. Time period runs from 1 January 1996 to 31 December 2011.

In order to learn more about the relation between the initial return size and the reference point formation, these issues are returned to in Section 6.4, where the groups are further divided based on the size of the initial returns and regressed accordingly.

6.1.1 Preliminary regression

Before the individual regressions, I run a random estimator regression for both groups in order to perform a supplementary first-stage analysis. The analysis is not performed on the pooled OLS estimator, as there are categorical variables present at this stage. Moreover, this model assumes there can be additional unknown factors that are not observable but affect the total outcome. As I am intending to estimate the determinants of normal turnover, this is a suitable estimator for these purposes. The results are displayed in Table 7.

This analysis provides more insight into what variables are statistically significant in terms of the turnover. As it can be seen, significant impact is made on behalf of market turnover, time since offer, time squared, maximum and minimum prices, and volatility. The determinants of previous days' returns do not seem to significantly impact the turnover, but are however incorporated into the model in order to keep the variables coherent with the study of Kaustia (2004).

To find out, whether more factors affect the turnover of shares, I have incorporated 4 additional dummy variables: *Hightech*, *Market trend at issue*, *Microcap*, and *Lock-up expiration.*

For example, underwriters tend to have difficulties in valuing small, young and high-tech companies. Motivated by this, I incorporate a variable pointing out the hightech companies to the preliminary regression, which describes the riskiness effect that this variable has on turnover. As hypothesized before, these firms are expected to possess more risks and can therefore affect the total turnover. The data is collected from Thomson Financial SDC and is matched by hightech SIC-codes. Other variables include the micro-capitalization variable, detecting the effects of firms smaller than $200 million. The Microcap variable follows the same logic as the Hightech variable, as small firms are expected to be riskier. Additionally, market capitalization can have an effect on reference point formation: low market capitalization stocks may induce a different effect on the reference point formation updating. The lock-up period variable measures the possible turnover effect of an expiring lock-up agreement, and finally the market trend variable tests, as a preliminary measure, whether the market conditions have significant implications on the overall turnover and can act as a segmentation basis for the second-stage regressions.

Out of the categorical variables, hightech, microcap and market trend at issue seem to have a strong statistically significant effect on the turnover of the winners. However, for the losers, there are no statistically significant differences, except for the market trend effect. Accordingly, the additional variables cannot be further utilized in the first-stage regression in the following sections. Still, the losers results can be interpreted by the magnitude of the probabilities, even though not statistically significantly. This way, it can be seen that the maximum return, time since offer, volatility and market trend at issue time represent smaller probabilities of finding these results in a random distribution. What is most important, the variable of market trend is significant at a 95% level, which suggests a good fit for the segmentation basis in the market trend generated regression sections.

In order to determine the normal turnover for winners and losers, I will not however incorporate the market trend variable in the first-stage regression. One reason is that, as explained in Section 4.1 on the cross correlations, the variables of the normal turnover model should detect any market movements and reflect them into the prices. Therefore, the base model for

Table 7: **First-stage Random Estimator Regression Results for Individual Firms**
Regression coefficients are calculated based on the random estimator regression on the firms pooled in the winner (1028 firms) and loser (499 firms) subsamples. Coefficients represent the sign and magnitude of the effect on the normal turnover of the firms. Sample period runs from 1 January 1996 to 31 December 2011.

	Winners			**Losers**		
	Coefficient	t-value		Coefficient	t-value	
Market turnover	0,23851	15,49670	***	0,63632	0,51820	
Turnover -1 day	0,00000	-0,36220		0,00001	0,11330	
Turnover -2 days	0,00000	0,09900		0,00000	0,05400	
Time since offer	-0,00004	-2,90940	**	-0,01903	-0,62150	
Time sqrt	0,00107	2,67040	**	0,00117	0,99030	
Maximum return	0,20001	18,20520	***	1,40810	1,52040	
Minimum return	0,25637	23,38750	***	0,37003	0,40030	
Volatility	-0,03540	-11,46070	***	-0,19764	-0,81300	
Returns -1 day	0,00020	0,85050		0,00739	0,35790	
Returns -2 days	0,00003	0,08770		-0,00004	-0,00480	
Hightech	1,37000	18,10400	***	140,90000	0,50800	
Market trend, day 1	1,61000	21,22400	***	717,20000	2,58600	**
MicroCap	1,01000	13,40400	***	103,60000	0,37300	
Lock-up period	0,00573	0,47620		-0,00239	-0,00190	
Adj. R^2	19,50 %			18,20 %		
No. of firms	1028			499		
Max no. of firm observations: 484						

the normal turnover will follow the one employed by Kaustia (2004). Still, the preliminary model does offer significant implications for the different market trends. Hence, the effect of the market conditions cannot be left without attention, as they seem to impact both winners and losers turnover. To investigate this more, I will later in Section 6.3 divide the winners and losers based on the prevailing market trend at issue and run the second-stage regressions based on these groupings, to investigate whether the conditions play a role in the reference price formation.

6.2 Base case regressions

After defining the determinants of the normal turnover model, the next step is to run the regressions accordingly for each firm in both subsamples. This analysis contains individual first-stage regressions, that serve as the basis for the second-stage pooled OLS regressions, following the methodology of Kaustia (2004), as explained in Section 4.

6.2.1 First-stage daily regressions

Table 8 represents the average regression coefficients with t-values for initial winner and loser firms. The residuals that are obtained from these individual regressions are used later as the dependent variables for the pooled regressions. The idea behind the first regressions is to model the normal turnover model, by taking into account the lagged and seasonal effects.

The results of the individual regressions mostly follow previous research. As it would be expected, the turnover for the winners seems to grow, whereas the turnover for the losers declines, when they are unaffected by all other variables. This is a first sign of the disposition effect as winners are realized but losers kept, ceteris paribus. These first-stage regression results also show that the variables increasing share turnover the most seem to be market turnover, the previous days' turnover, and new price maximums and minimums. Significant relations lie between turnover, stock return, market turnover and the volatility. This is coherent with previous research.

As the time since the offer increases, the turnover seems to decline, which is in line with the study of Kaustia (2004). Further similarities include the volatility seeming to decrease the turnover of losers, however differing in the increasing nature of winners turnover in my study and decreasing in his results. In his model, volatility decreased both winners and losers turnovers, and this was discussed to be fighting with the results of previous research on evidence of a strong positive correlation between turnover and volatility. Still, following the instructions of Kaustia (2004), I will keep the volatility as a part of the first model, even if it is negative for losers. After all, as this variable is proxied by squared returns in both

Table 8: **Average Results of the Individual Firm Daily Turnover Regressions**
First-stage regressions use the logarithm of daily turnover as the dependent variable. The sample consists of winners (1028 firms) that cross the offer price level from above and of losers (499 firms) that cross the level from below for the first time between 21 and 484 days during the sample period from 1 January 1996 to 31 December 2011.

	Winners		**Losers**	
	Average	t-values	Average	t-values
Turnover (Constant)	0,0705	0,117	-0,5046	-1,110
Market turnover	0,6304	0,189	0,5799	0,871
Turnover -1 day	0,0001	0,703	0,0000	2,176
Turnover -2 days	0,0001	0,859	0,0003	0,478
Time since offer	-0,0001	-0,640	-0,0739	-1,027
Time sqrt	0,0019	0,666	0,0028	1,029
Maximum return	0,2470	0,000	2,1611	0,968
Minimum return	0,2657	0,211	1,1548	0,803
Volatility	1,3202	0,749	-2,1204	-3,496
Returns -1 day	0,0147	0,710	-0,1262	-1,438
Returns -2 days	0,0187	0,582	-0,1502	-0,736
Adj. R^2	28.9 %		30.1 %	
No. of firms	1028		499	
Max no. of firm observations 484				

studies, it can only be considered as a rough estimate on the underlying standard deviations. Still, as hypothesized in Section 3, under more volatile market conditions the turnover should decrease, as investors find it harder to value the assets. This provides an additional reason into, why the subsample will be later divided by the market conditions, in order to learn more about this potential influence, and whether the losers' turnover actually decreases more during the more volatile periods.

Furthermore, as the previous days' returns increase, the turnover of losers seems on average to decline, which can be due to investors wanting to wait for the actual crossing of the initial reference price. However, these lagged returns' effect is not of significant nature at this stage of the analysis. They are however kept for further purposes for the development of the next step model. With winners, the previous days' returns grow the turnover, which is consistent with previous research.

The seasoning variables, time and time squared, are not significant factors in the whole model, but are kept as a means of detrending the turnover series, in order to guarantee stationarity, a precondition in the regression analysis.

Because these are only average statistics, the results cannot be interpreted yet to an empirically reliable extent, but they provide a preliminary impression on the matter. Overall, according to the coefficients and their t-values, the parameters seem to be quite similar for both subsample groups, which would imply that the model can be well applied for further analysis.

6.2.2 Second-stage pooled regression for winner firms

Second-stage pooled regressions are used firstly to define the determinants of abnormal turnover, measured by the residuals of the first-stage regressions, and secondly to model the reference price formation. Each regression is performed separately for the winner and loser groups. The results of the base case and interaction incorporated pooled regressions for winners are displayed in Table 9.

Statistically significant factors affecting the abnormal turnover of winners are record high prices, as well as record low prices and low prices that decline more than 5%. In both models, the intercept itself is significant at a 90% level, and implicates a decline in turnover, if all other variables remain unchanged. The coefficient is nevertheless quite small, and therefore almost indistinguishable from zero, so no governing truths can be derived out of this result.

Surprisingly, record high prices larger than 5% do not seem to have a statistically significant effect, and the results suggest that beyond this threshold trading decreases, maybe due to positive expectations about further price rise. This could also imply that investors do realize winners faster when new record high prices are met, but if the rise is large enough, investors hold on to the winners. However, the coefficient is again quite small, so the interpretation is only speculation at this point. Record low prices on the other hand are not significant, until they fall beyond the 5% level. Taking this into account, investors seem to lay off realization when the price drops enough. This is logical in terms of the disposition effect, as the initially winning stock essentially loses with the fall.

Table 9: **Daily Pooled Turnover Regression Results for Winners**
The sample of 1028 firms consists of winners, that cross their offer price from above for the first time between 21 and 484 trading days. The residuals from regression 1 (see Table 8) are held as the dependent variable. The base case regression only accounts for the record high and low factors, while the second regression includes the interaction variables of the magnitude of the record high and low prices. The sample period runs from 1 January 1996 to 31 December 2011.

	Base Case			**HI/LO interactions**		
Variable	*Coefficient*	*t-value*		*Coefficient*	*t-value*	
Intercept	-0.0081	-16.9919	.	-0.0079	-16.843	.
Record High 1M	0.0396	35.8770	***	0.034	32.8091	**
Record Low 1M	0.0041	4.2970		0.0158	16.871	.
Record High 1M (R>5%)				-0.0087	-2.417	
Record Low 1M (R<5%)				-0.0705	-32.674	**
First Cross Below 1.20	0.0148	1.0420		-0.0014	-0.1020	
First Cross Below 1.15	0.0556	3.3460		0.0697	4.1910	
First Cross Below 1.10	-0.0856	-5.1990		-0.0643	-3.9000	
First Cross Below 1.05	-0.0764	-4.2690		-0.0629	-3.5130	
First Cross Below 1.00	0.0376	2.8040		0.0497	3.7060	
First Cross Below 0.95	0.1083	6.5000		0.1338	8.0200	
First Cross Below 0.90	0.0740	4.2910		0.0786	4.5510	
First Cross Below 0.85	-0.0961	-5.3980		-0.0825	-4.6300	
First Cross Below 0.80	-0.1066	-6.1280		-0.0754	-4.3290	
Second Cross Below 1.20	0.0491	4.4810		0.0495	4.5140	
Second Cross Below 1.15	-0.0412	-3.6900		-0.0202	-1.8090	
Second Cross Below 1.10	-0.0424	-3.7710		-0.0236	-2.0940	
Second Cross Below 1.05	-0.1217	-10.3910		-0.1048	-8.9350	
Second Cross Below 1.00	-0.0383	-3.3670		-0.0274	-2.4040	
Second Cross Below 0.95	0.0334	2.8390		0.0470	3.9940	
Second Cross Below 0.90	-0.0216	-1.8070		-0.0096	-0.8030	
Second Cross Below 0.85	-0.0864	-7.0780		-0.0652	-5.3360	
Second Cross Below 0.80	-0.0578	-4.5010		-0.0384	-2.9820	
RANGE [0.00, 0.70]	0.0914	7.3000		0.1284	10.2180	
RANGE [0.70, 0.75]	0.0171	1.3870		0.0394	3.1800	
RANGE [0.75, 0.80]	0.0183	1.0980		0.0112	0.6710	
RANGE [0.80, 0.85]	0.1219	7.2360		0.1280	7.5950	
RANGE [0.85, 0.90]	-0.0123	-0.7580		0.0039	0.2370	
RANGE [0.90, 0.95]	-0.0692	-4.3260		-0.0665	-4.1560	
RANGE [0.95, 1.00]	0.1600	12.5960		0.1586	12.4800	
RANGE [1.05, 1.10]	0.1769	12.5950		0.1679	11.9410	
RANGE [1.10, 1.15]	0.2126	20.6552	*	0.2211	21.5099	*

RANGE [1.15, 1.20[	-0.0138	-1.0960	-0.0082	-0.6550
RANGE [1.20, 1.25[	0.0063	0.6120	0.0021	0.1970
RANGE [1.25, 1.30[	0.0562	5.4120	0.0440	4.2330
RANGE [1.30[	-0.0338	-3.7270	-0.0262	-2.8890
R^2	0.62 %		0.82 %	
No. of observations	497552		497552	
No. of variables	33		35	

Although the results of the crossing variables do not seem statistically significant, I have assessed the directional and size of impact effects that the variables have on the turnover, *i.e.* are they increasing or decreasing the turnover and by how much comparing to other variables.

As the stock price for the first time declines below levels 1.10 and 1.05, it has a declining effect on turnover, which is not consistent with Kaustia (2004). In his study, the whole group of first crossings cause a positive movement on the turnover, whereas my results suggest that right before the price drops below its suspected reference price, the effect turns into an incentive for the investors to momentarily rather hold on to the declining stocks, than sell them. This could further imply that the reference price has changed upwards as the stock initially began trading at a new all-time high, and as the stock falls, investors are reluctant to realize it.

Crossing the offer price (level 1.00) changes the direction again, as the once winning stock trades below its offer price, which seems to increase realization. This is consistent with the hypothesis, that as the offer price is passed, the turnover increases, which was described to partly originate from the price support actions. Still, below level 0.85, the stock has fallen as much that it does appear to reduce the trading, which is consistent with the disposition effect.

The second crossings do not either provide statistically significant implications. However, the same pattern as in the first crossings can be seen from Figure 11. In the second crossings the decreasing nature of trading starts already at the level of 1.15 (i.e. at a gain of 15% in relation to the offer price), whereas the turnover decline in first crossings starts at the level of 1.10. Additionally, the level of 0.95 of the second crossings is the only level that results in increased realization of the stock. In fact, falling below the level of 0.95, and increasing the turnover could be a direct implication of price support activities, as described in Section 2.1.1. Furthermore, where Kaustia (2004) had all his second crossings variable coefficients negative, mine seem to move in the same manner as the first crossings, but remaining overall below the first crossings line. This would suggest that as the price crosses the reference price for the second time, the effect is rather a decline in turnover than an increase.

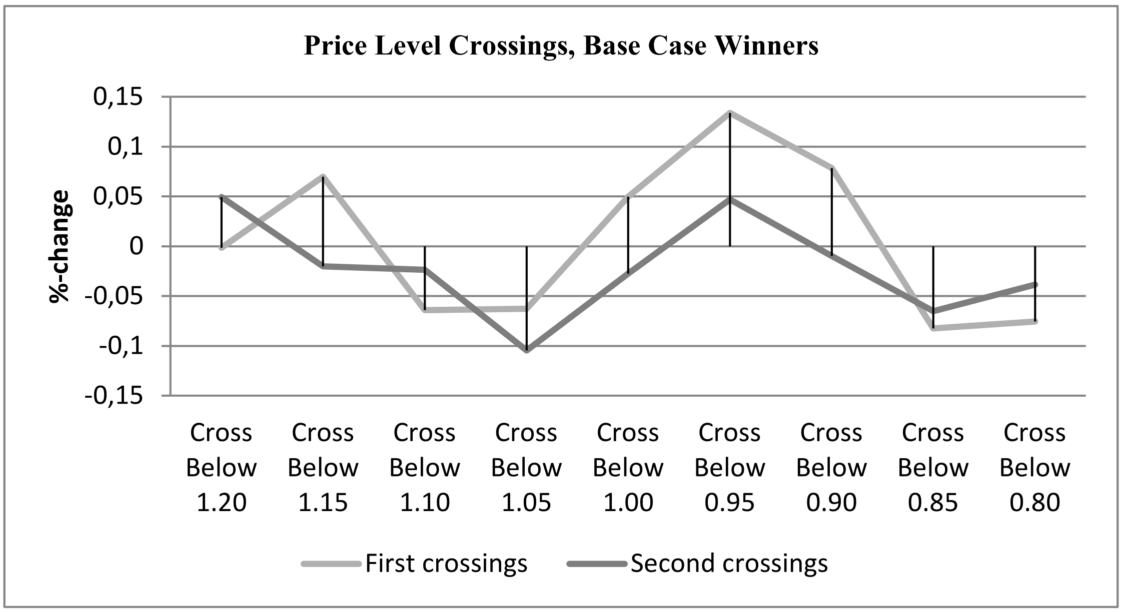


Figure 11: **Winners' Price Level Crossings**
First and second crossings of the offer price level represent the turnover effect of the coefficients of the winners' pooled regression. E.g. at the level of 0.95, the turnover is affected by a log increase of 0.1083, which is the coefficient value of the first crossing below level 0.95.

The ranges variables roughly follow the crossings' coefficients. Trading at the range of [1.10, 1.15] gives a statistically significant implication of an increase in trading volume. Below this, trading faces increasing effects, until the price is in the range between 0.90 and 0.95, after which it turns negative. This follows the initial hypothesis of keeping a losing stock. However, the ranges provide additional information below the following crossings, as it seems that stocks trading below 0.80 are in effect realized and not kept, not like the disposition effect would assume.

Furthermore, each time a first-time crossing occurs, it is at the same time a one-month low, which causes the price range to change. Therefore, to get the total effect from crossing the offer price level for the first time, one has to sum up the coefficients for Record Low 1M, First Cross Below 1.00 and the change that is caused from changing the price range from [1.00, 1.05[to [0.95, 1.00[. This yields to a 24.2% increase in total turnover. About 3% of the turnover increase is explained by the new record high price, 80% by the price range change and 17% from crossing the reference level for the first time.

6.2.3 Second-stage pooled regression for loser firms

The results of the pooled regression for losers are displayed in Table 10. Statistically significant results for the losers are obtained solely with the variable describing the effects of record high price over 5%. Unlike the study of Kaustia (2004), my results seem to decrease the turnover as this record high price is reached. It seems that investors are reluctant to realize the losers as they reach new record high prices. This result is somewhat controversy, for the disposition effect would suggest a realization of the better performing stock. The different results between these two studies can stem from the different time periods of the samples. For example, in my data, there exists the overheated hot IPO period of the late 1990's, which could have affected my results. Examining the correlations in Appendix D addtionally implies that the turnover of losers on average moves to the opposite direction to market turnover. Therefore, the reasons could lie behind large market movements, that have potentially affected the investor behavior into more cautious trading reactions, when faced with new price extremes.

Furthermore, the interpretation for my results could be, that as the stock begins trading as a loser, this mental account lingers in the investors minds, thus making its effect stronger than the suspected reference price, and eventually elevating the new reference price higher than expected. The effect of record low prices, though not significant, seem to decrease turnover, which would comply with the disposition effect.

Table 10: **Daily Pooled Turnover Regression Results for Losers**
The sample of 499 firms consists of losers, that cross their offer price from below for the first time between 21 and 484 trading days. The residuals from regression 1 (see Table 8) are held as the dependent variable. The base case only accounts for the record high and low factors, while the second regression includes the interaction variables of the magnitude of the record high and low prices. The sample period runs from 1 January 1996 to 31 December 2011.

	Base Case		**HI/LO interactions**		
Variable	*Coefficient*	*t-value*	*Coefficient*	*t-value*	
Intercept	0.00943	0.28516	0.01004	0.2348	
Record High 1M	-0.04689	-0.51467	-0.01515	-0.16338	
Record Low 1M	0.00231	0.02357	-0.00227	-0.02231	
Record High 1M (R>5%)			-0.53764	-1.84993	*
Record Low 1M (R<5%)			0.02810	0.10748	
First Cross Above 0.95	0.14247	0.06961	0.10949	0.05349	
First Cross Above 1.00	0.0499	0.0111	0.0782	0.0174	
First Cross Above 1.05	-0.03381	-0.0476	-0.05121	-0.0722	
First Cross Above 1.10	-0.0129	-0.0014	0.0420	0.0047	
First Cross Above 1.15	-0.27423	-0.02879	-0.30541	-0.03206	
First Cross Above 1.20	0.37532	0.05406	0.39537	0.05694	
First Cross Above 1.25	-0.06827	-0.0863	-0.01516	-0.0192	
First Cross Above 1.30	-0.0429	-0.050	-0.1413	-0.0165	
First Cross Above 1.35	0.07048	0.0818	0.12578	0.01460	
First Cross Above 1.40	-0.09627	-0.0696	-0.08715	-0.0630	
Second Cross Above 0.70	-0.05979	-0.05604	-0.07869	-0.07374	
Second Cross Above 0.75	0.08594	0.08057	0.06558	0.06147	
Second Cross Above 0.80	-0.03086	-0.02944	-0.05170	-0.04932	
Second Cross Above 0.85	0.02424	0.02266	0.0295	0.0276	
Second Cross Above 0.90	-0.0888	-0.0834	-0.3038	-0.2851	
Second Cross Above 0.95	0.33060	0.30785	0.30590	0.28482	
Second Cross Above 1.00	0.4370	0.3786	0.0892	0.0773	
Second Cross Above 1.05	0.14817	0.12161	0.11168	0.9165	
Second Cross Above 1.10	0.18771	0.14616	0.14081	0.10962	
Second Cross Above 1.15	0.12615	0.9653	0.7702	0.5892	
Second Cross Above 1.20	0.10867	0.7946	0.6268	0.4582	
Second Cross Above 1.25	0.4545	0.3160	0.0490	0.0341	
Second Cross Above 1.30	0.3865	0.2537	-0.0273	-0.0179	
Second Cross Above 1.35	0.14693	0.9233	0.12976	0.8153	
Second Cross Above 1.40	0.17586	0.10605	0.14216	0.8572	
Second Cross Above 1.45	0.11329	0.6804	0.8761	0.5261	
Second Cross Above 1.50	0.27341	0.15471	0.23553	0.13327	
Second Cross Above 1.55	-0.6252	-0.3406	-0.9855	-0.5368	
RANGE [0.00, 0.10]	-0.10453	-0.5684	-0.8541	-0.4629	
RANGE [0.10, 0.20]	0.13144	0.9365	0.15455	0.10967	
RANGE [0.20, 0.30]	-0.58702	-0.49714	-0.56197	-0.47390	
RANGE [0.30, 0.40]	-0.29337	-0.28006	-0.23125	-0.21970	
RANGE [0.40, 0.50]	-0.18572	-0.18731	-0.10900	-0.10943	
RANGE [0.50, 0.60]	-0.33127	-0.33795	-0.26573	-0.26998	

RANGE [0.60, 0.70[	-0.50120	-0.51796	-0.42440	-0.43743
RANGE [0.70, 0.75[	0.10430	0.10584	0.19000	0.19246
RANGE [0.75, 0.80[	-0.16014	-0.16259	-0.6524	-0.6612
RANGE [0.80, 0.85[	-0.11251	-0.11383	-0.3845	-0.3887
RANGE [0.85, 0.90[	-0.3799	-0.3785	0.5911	0.5880
RANGE [0.90, 0.95[	-0.3745	-0.3548	0.6711	0.6348
RANGE [0.95, 1.00[	0.3350	0.3107	0.14086	0.13042
RANGE [1.05, 1.10[	0.10794	0.9203	0.26975	0.22933
RANGE [1.10, 1.15[	-0.4041	-0.3270	0.13399	0.10812
RANGE [1.15, 1.20[	-0.36112	-0.28261	-0.22114	-0.17276
RANGE [1.20, 1.25[	0.6020	0.4582	0.22718	0.17251
RANGE [1.25, 1.30[	-0.18893	-0.13374	-0.7235	-0.5117
RANGE [1.30, 1.40[	-0.31952	-0.22352	-0.8137	-0.5669
RANGE [1.40, 1.50[	-0.12832	-0.8297	0.8493	0.5477
RANGE [1.50, 1.60[	-0.22002	-0.13473	-0.2444	-0.1493
RANGE [1.60, 1.70[	-0.29926	-0.16920	-0.9639	-0.5440
RANGE [1.70, 1.80[	0.17385	0.8831	0.33576	0.17038
RANGE [1.80, 1.90[	0.2756	0.1380	0.19327	0.9668
RANGE [1.90, 2.00[	0.3805	0.1849	0.21561	0.10467
RANGE [2.00[	0.3087	0.1465	0.34692	0.16412
R^2	0.27 %		0.28 %	
No. of observations	241516		241516	
No. of variables	56		58	

Also regarding the crossing variables, the results are mixed compared to the study of Kaustia (2004). In line with his results is the observation that as the loser stock crosses its offer price for the first time, the volume increases. In my study, after this the pattern however seems to turn into a decrease in the trading behavior. In other words, the losers that become winners, are not realized but rather kept. At first crossing the 0.95 and 1.00 seem to increase the turnover, but after this it suddenly starts a declining pattern. This is not consistent with the disposition effect, but it does give additional weight to the observations above, that the "loser label" could follow the stock, thus lowering the new "break-even-point" or approvable reference level.

The second crossings' deviate from the first crossings pattern, which is illustrated in Figure 12. It seems that now after crossing the level of 0.95 results in increased trading, which continues up through the crossing levels. This could be a direct implication of a shifted reference price. It seems the loser stigma is not prevalent anymore, as the loser stock presents a recurring shift upwards. Moreover, the shift in turnover seems less volatile than with the first crossings, indicating a steadier response to the new price levels, perhaps a sign of a more adjustable reference price.

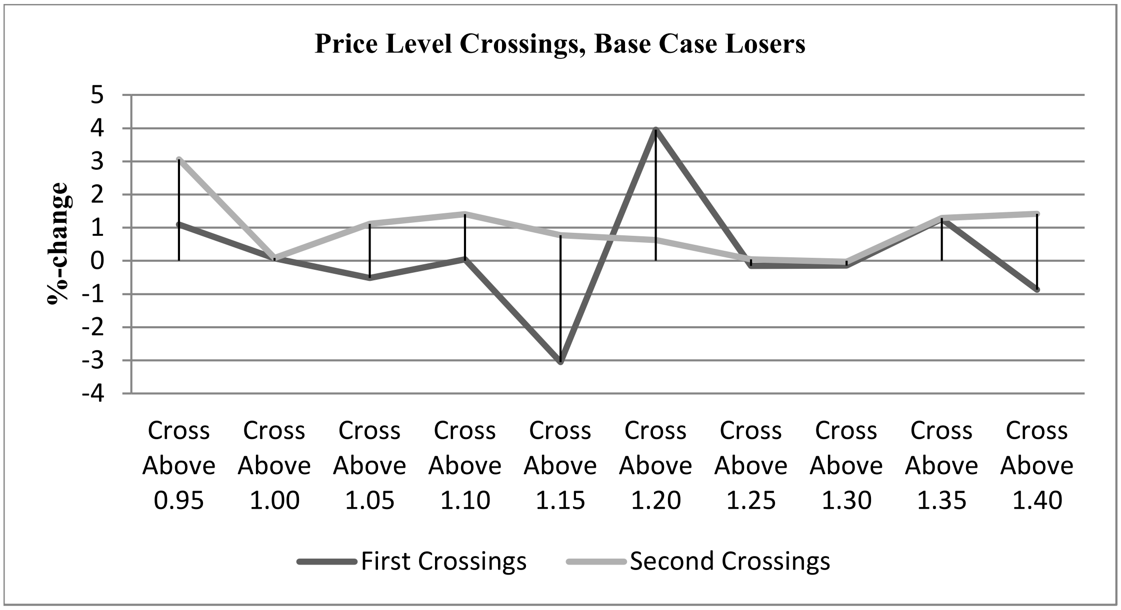


Figure 12: **Price Level Crossings, Losers**
First and second crossings of the offer price level represent the turnover effect of the coefficients of the losers' pooled regression. E.g. at the level of 1.05, the turnover is affected by a log decrease of -0.0338, which is the coefficient value of the first crossing above level 1.05.

Coming to the ranges' effects, the lower levels seem to have a consistent diminishing effect on the turnover, which is in line with the disposition effect of not wanting to realize losses. At the combined range between 0.95 and 1.10 the effect is however changed, as trading increases. This result is in line with the second crossings pattern. In other words, it seems that the trading increases already below the offer price, which on its part, could suggest a lower reference price for losers. The forming of the reference prices is therefore not straight-forward, which supports earlier research results.

Furthermore, each time a first-time crossing occurs, it is at the same time a one-month high, which causes the price range to change. Therefore, to get the total effect from crossing the offer price level, one has to sum up the coefficients for Record High 1M, First Cross Above 1.00 and the change that is caused from changing the price level from [0.95, 1.00[to [1.00, 1.05[. This yields a 8.9% increase in the turnover, which is quite low. About half of the turnover increase can be explained by the new record high price, one third by the price range change and about 5% from crossing the reference level for the first time.

6.3 Market trend regressions

In this section, the subsample groups are further divided into two groups based on the prevailing market trend at the time of the issue. The segmentation follows the determinants of a bull and a bear market period, as explained in Section 4. Furthermore, only the results of the interaction inhibited regression are displayed, as there was no significant difference between the results of the two variable interaction models.

6.3.1 First stage market regressions

The results of the first regressions are displayed in Table 11. The first-stage variables seem to comply in significance with the variables of the overall model at the same stage. Both maximum and minimum return seem to generate positive impact on the turnover, regardless of the prevailing market conditions. Moreover, volatility seems to increase the winners as well as the losers bull turnover. Conversely, during bear times the volatility seems to decrease the trading of assets for both groups.

Figure 13 describes the bull and bear market IPOs divided by their initial returns. As discussed before on the price support effects, in accordance with this figure, the zero return group indeed seems to distort the normality of the distribution, which further justifies the exclusion of this group from the regression analysis.

6.3.2 Second-stage market trend regressions for the winners

Table 12 represents the results of the pooled second-stage regressions for the winners. According to the hypotheses, the disposition effect should be more observable under a bull market, because there are more noise traders. Looking at Table 12, this seems to hold. The intercept is highly significant, indicating a decline in trade if all the variables remain unchanged. Other

Table 11: **Individual Firm Daily Average Turnover Regression Results Under Different Market Conditions**
Each firm is defined to belong to either winning or losing group by the sign of the initial returns. Both samples are then further divided into *Bull* and *Bear* groups defined by the market trend at the time of the offering. All variable results represent the daily firm-specific average values. The sample period runs from 1 January 1996 to 31 December 2011.

	Winners		**Losers**	
Variable	*Bull*	*Bear*	*Bull*	*Bear*
Turnover (Constant)	0,0858 (15,4475)	0,0398 (1,7309)	0,0983 (8,4565)	1,5373 (1,0187)
Market turnover	0,0656 (4,4107)	0,0525 (2,6111)	-0,0144 (-0,2963)	-1,4642 (-0,8852)
Turnover -1 day	0,0000 (-0,4208)	0,0003 (1,6503)	0,0001 (0,7890)	-0,0001 (-1,0918)
Turnover -2 days	0,0002 (0,9128)	0,0002 (0,9465)	0,0003 (1,6522)	0,0002 (2,2027)
Time since offer	0,0002 (0,2111)	0,0053 (1,4453)	0,0008 (0,4633)	-0,2197 (-0,9806)
Time sqrt	0,0000 (-0,9690)	-0,0002 (-1,3446)	-0,0001 (-1,1126)	0,0084 (0,9911)
Maximum return	0,1562 (4,2544)	0,5417 (2,7558)	0,1859 (1,8548)	6,0163 (0,9743)
Minimum return	0,1442 (4,0702)	0,4313 (2,7277)	0,4069 (1,5652)	2,6100 (0,9720)
Volatility	3,3110 (4,5298)	-2,5993 (-1,0014)	4,3193 (2,8748)	-14,6507 (-0,6766)
Returns -1 day	0,0151 (1,3424)	0,0032 (0,1579)	0,0565 (2,5701)	-0,4826 (-0,9044)
Returns -2 days	0,0021 (0,1878)	-0,0093 (-0,4473)	-0,0380 (-1,1106)	-0,3692 (-1,1551)
Adj. R^2	25.3 %	19.8%	21.1 %	17.6%
No. of firms	712	316	332	167
Max no. of obervations per firm 484				

variables displaying significant results during bull period include the price maximums and minimums, first crossing the levels 1.20, 1.05 and 0.90, as well as the second crossing of level 0.85. Therefore it seems that under bull markets, new record high and low prices increase the turnover, but as their magnitude crosses beyond 5% the effect turns into negative and

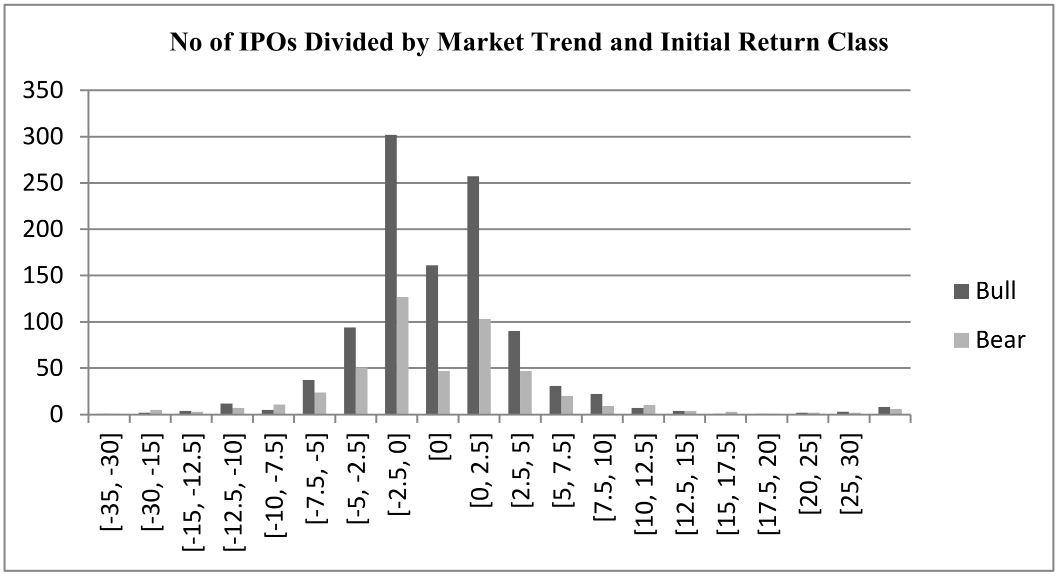


Figure 13: **Number of IPOs under Different Market Conditions**
Number of IPOs consists of the full sample divided by the market trend at the time of the initial public offer, and then placed in initial return class according to the relation between the offer price and first-day closing price of each firm. Sample period runs from 1 January 1996 to 31 December 2011.

the trading decreases. Especially the Record low 1M below 5% is highly significant implying that investors hold on to the (initially winning and) now losing stocks.

Figure 14 provides more insight into the relation between first and second time crossings during bull and bear markets. Intuitively it can be interpreted, that during the bull markets the second line crossings seem to foresee the movements of the first line. Obviously, because the first line crossings occur first, this suggest that the first reactions have influenced the second reactions so that the reference price seems to have moved upwards.

For example, if we follow the highest values on the winners market trend graphs, it can be seen that the highest peak for the bull period occurs at the level of 0.90, whereas the highest peak for the bear period (as well as for the overall period in Figure 11) occurs at the level of 0.95. These turnover peaks represent the new record low points for the winners. The latter is consistent with the disposition effect, because the price has just fallen below its offer price which is the pain spot for the investors. During the bull period, the same magnitude effect is triggered not until the 0.90 level, which could be interpreted as the new pain point, as it seems the investors are more optimistic and do not realize the share before this level. Moreover, because the level of 0.90 is significant, the logical explanation could be that during bull markets investors are more optimistic and therefore the notion of reference price allows for a lower break-even point than during bear markets.

Table 12: **Winners' Pooled Regression Results based on the Prevailing Market Trend**
The sample of 1028 firms consists of winners, that cross their offer price from above for the first time between 21 and 484 trading days. The residuals from regression 1 (see Table 8) are held as the dependent variable. The bull period regression accounts for firms issued under bull market conditions, while the bear regression describes the issued under bear market conditions. The sample period runs from 1 January 1996 to 31 December 2011.

	Bull period			**Bear period**	
Variable	*Coefficient*	*t-value*		*Coefficient*	*t-value*
Intercept	-0.0111	-46.0360	***	-0.003532	-2.4580
Record High 1M	0.0358	68.8270	***	0.0345	10.3750
Record Low 1M	0.0251	52.426	***	0.0037	1.3121
Record High 1M (R>5%)	-0.0290	-15.4180		0.0256	2.3944
Record Low 1M (R<-5%)	-0.0623	-51.7560	***	-0.0760	-12.6250
First Cross Below 1.20	0.1476	19.9260	*	-0.1905	-4.6070
First Cross Below 1.15	-0.0227	-2.6190		0.1579	3.2580
First Cross Below 1.10	-0.0705	-8.1610		-0.0212	-0.4450
First Cross Below 1.05	0.1243	19.9840	*	0.0711	1.3990
First Cross Below 1.00	0.0028	0.4050		0.0637	1.5910
First Cross Below 0.95	0.1217	13.7100		0.1740	3.7030
First Cross Below 0.90	0.1811	19.7010	*	-0.1469	-3.0150
First Cross Below 0.85	-0.0587	-6.1780		-0.1233	-2.4570
First Cross Below 0.80	-0.1338	-14.4200		0.0190	0.3890
Second Cross Below 1.20	0.0765	13.5590		0.0694	2.1130
Second Cross Below 1.15	-0.0799	-13.9260		-0.0859	-2.5410
Second Cross Below 1.10	0.0775	13.3070		-0.2314	-6.9500
Second Cross Below 1.05	-0.0839	-13.8100		-0.0888	-2.5930
Second Cross Below 1.00	0.0478	8.0740		-0.1088	-3.2640
Second Cross Below 0.95	0.0908	1.4940		0.1350	3.8500
Second Cross Below 0.90	0.0632	10.2760		-0.1327	-3.6780
Second Cross Below 0.85	-0.1265	-20.2820	*	0.0030	0.0810
Second Cross Below 0.80	-0.0623	-9.2690		0.0470	1.2580
RANGE [0.00, 0.70]	0.1276	19.1750	.	0.0593	1.6700
RANGE [0.70, 0.75]	0.0540	8.2760		0.0191	0.5410
RANGE [0.75, 0.80]	0.0671	7.5240		-0.0479	-1.0280

RANGE [0.80, 0.85[	0.0867	9.6000		0.1146	2.4440
RANGE [0.85, 0.90[	-0.1168	-13.3700		0.2251	4.9710
RANGE [0.90, 0.95[	-0.0914	-10.5660		-0.1095	-2.5040
RANGE [0.95, 1.00[	0.1064	19.618	*	0.0790	2.1500
RANGE [1.05, 1.10[	0.1388	26.1610	**	0.1736	4.3670
RANGE [1.10, 1.15[	0.3399	64.0919	***	-0.0103	-0.2550
RANGE [1.15, 1.20[	-0.0522	-8.0660		0.0448	1.1960
RANGE [1.20, 1.25[	-0.0320	-5.9980		0.0871	2.8080
RANGE [1.25, 1.30[	0.0915	17.0540	.	-0.0241	-0.7810
RANGE [1.30[	-0.0437	-9.4110		-0.0418	-1.5200
R^2	0.59 %			0.42 %	
No. of observations	344608			152460	
No. of variables	35			35	
No. of firms	712			316	

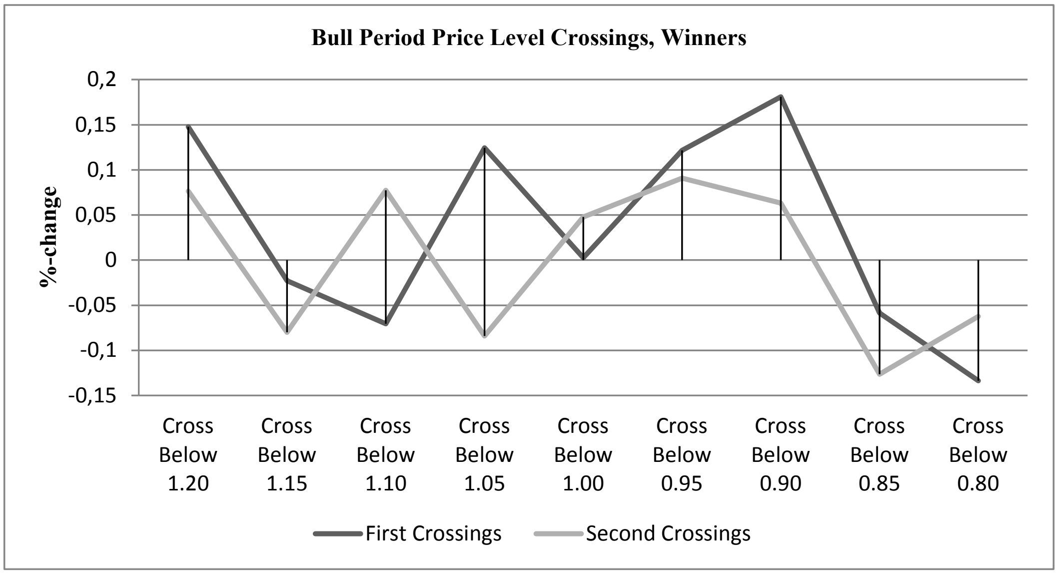
The same effect can be seen with the other peak in the figure at the bull level of 1.05 and the bear and normal levels of 1.15. This would imply that the market conditions do affect the reference price formation.

During bear markets, the second crossings seem to synchronize with the first crossings, the only difference being that the effect seems to be much more decreasing the trading. However, crossing below 0.95 momentarily increases the turnover, as the stock falls below its offer price. Still, the bear market turnover reactions act accordingly with the overall pattern.

Additional highly significant results during the bull period include the ranges of [0.95, 1.00[, [1.05, 1.10[and the range of [1.10, 1.15[. The results suggest that trading at these ranges compared to the offer price does increase the sale of the winning stock, in line with the disposition effect, whereas the preceding levels above and below these ranges seem to decrease turnover. At ranges below these, the effect continues to be positive, and suggests that during bull markets, winners are sold even at a loss.

As hypothesized, the effects of the individual variables are less observable under bear markets, as there are no statistically significant impacts. However, the coefficients most close to being significant are the record high price and record low price over -5%.

When assessing the total effect of the bull period first time cross below the offer price, the



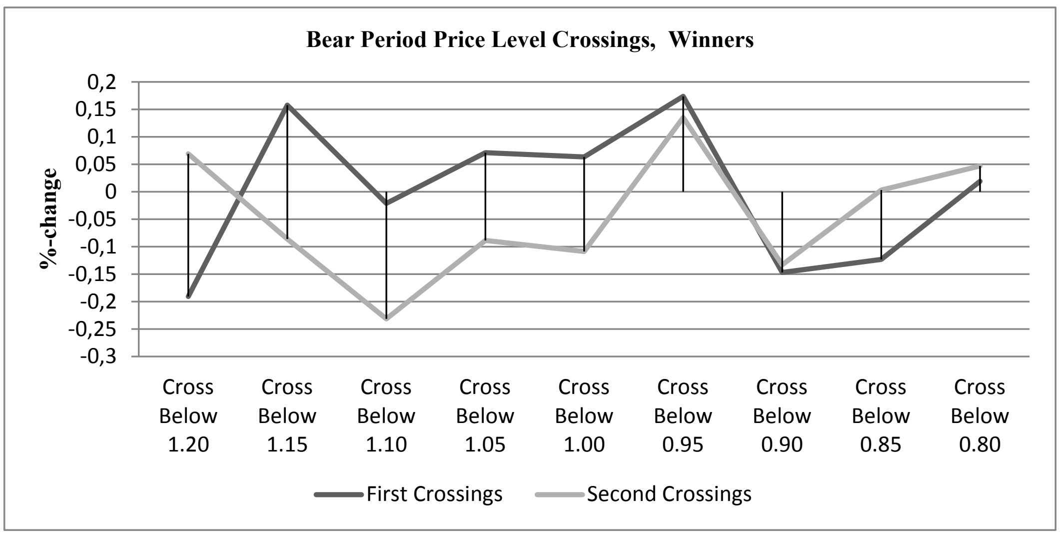


Figure 14: **Market Trend Adjusted Price Level Crossings, Winners**
First and second crossings represent the coefficients of the winners' regression. E.g. At Cross Below 1.15 during the Bull period, the first crossing of this level results in a log decrease of 0.0227 in the turnover, while the same level during Bear period results in a log increase of 0.1579 in total turnover.

combined log effect of Record Low 1M, First Cross Below 1.00 and the change in price ranges yields an 14.4% increase in the turnover as the level is surpassed. The corresponding figure for the bear period turnover increase is 15.8%, which is not consistent with the hypothesis that the disposition effect would be less observable under bear markets. In fact, this suggests, that the reaction during bear markets is somewhat larger. On the other hand, as observed above, the reference price seems to be lower for the bull period. This would further suggest, that there is no difference between the market conditions' total effect on the turnover, but it is indeed incorporated within the prices. What is however significant, is the finding, that the reference price seems to vary according to the prevailing market trend, at least for the winners. The losers are assessed similarly in the next section.

6.3.3 Second-stage market trend regressions for the losers

The results of the second-stage market trend regressions for the losers are displayed in Table 13. The significance of variables of the loser firms' bull period are more observable and strongly significant when compared to the bear market's results.

During bull markets, both the record high and low prices play a significant role in determining the size of the turnover. The bull intercept is highly significant, indicating a decrease in turnover if other variables remain unchanged. The bear market intercept however suggests an increase in turnover, although the result is not statistically significant.

Table 13: **Losers' Pooled Regression Results based on the Prevailing Market Trend**
The sample of 499 firms consists of losers, that cross their offer price from below for the first time between 21 and 484 trading days. The residuals from regression 1 (see Table 8) are held as the dependent variable. The bull period regression accounts for firms issued under bull market conditions, while the bear regression describes the issued under bear market conditions. The sample period runs from 1 January 1996 to 31 December 2011.

	Bull period			**Bear period**		
Variable	*Coefficient*	*t-value*		*Coefficient*	*t-value*	
Intercept	-0.0215	-25.8197	***	0.32341	2.5652	
Record High 1M	0.0593	33.2007	***	-0.5281	-1.8960	
Record Low 1M	0.0579	29.7098	***	-0.1329	-0.4275	
Record High 1M (R>5%)	0.0903	16.4536	.	-18.0363	-19.8048	*
Record Low 1M (R<-5%)	-0.0907	-17.4532	*	0.9845	1.3191	
First Cross Above 0.95	-0.2629	-7.1195		3.6056	0.4876	
First Cross Above 1.00	0.7684	8.4883		-3.1645	-0.2477	
First Cross Above 1.05	-0.6405	-5.5247		23.6072	0.4926	
First Cross Above 1.10	-0.2963	-2.5225		-9.7791	-0.4750	
First Cross Above 1.15	2.4132	14.7658	*	-10.1713	-0.4283	
First Cross Above 1.20	-0.4063	-1.9611		4.1753	0.1774	
First Cross Above 1.25	-0.4480	-2.1829		-5.6781	-0.2411	
First Cross Above 1.30	-0.7411	-3.3338		4.4522	0.1865	

First Cross Above 1.35	-0.3624	-1.6206		2.3081	0.0987
First Cross Above 1.40	0.1873	0.8386		-1.3237	-0.0556
Second Cross Above 0.70	-0.1337	-6.5427		-1.9152	-0.5888
Second Cross Above 0.75	0.0134	0.6560		1.9192	0.5938
Second Cross Above 0.80	-0.1759	-8.6814		-1.0578	-0.3370
Second Cross Above 0.85	-0.1239	-6.0121		0.2187	0.0677
Second Cross Above 0.90	-0.0551	-2.7051		-0.8001	-0.2453
Second Cross Above 0.95	-0.1215	-5.8862		9.6693	2.9693
Second Cross Above 1.00	0.2044	9.2612		0.3440	0.0973
Second Cross Above 1.05	0.2106	9.0029		3.0666	0.8334
Second Cross Above 1.10	1.3455	54.7480	***	1.9388	0.4913
Second Cross Above 1.15	-0.1813	-7.2355		2.8518	0.7149
Second Cross Above 1.20	-0.1037	-3.9707		1.7896	0.4253
Second Cross Above 1.25	0.2237	8.2336		-0.1688	-0.0373
Second Cross Above 1.30	-0.2947	-10.1057		0.7969	0.1701
Second Cross Above 1.35	0.2254	7.2649		3.5680	0.7550
Second Cross Above 1.40	0.0646	2.0045		4.3206	0.8759
Second Cross Above 1.45	-0.1408	-4.3743		3.0604	0.6128
Second Cross Above 1.50	-0.1000	-2.9147		7.2458	1.3807
Second Cross Above 1.55	0.0105	0.2932		-3.0954	-0.5753
RANGE [0.00, 0.10]	-0.1417	-3.8787		-1.9210	-0.3636
RANGE [0.10, 0.20]	0.3147	11.0390		2.9558	0.7590
RANGE [0.20, 0.30]	-0.1366	-5.9505		-16.9077	-4.7815
RANGE [0.30, 0.40]	0.3319	16.3155	*	-7.5236	-2.3895
RANGE [0.40, 0.50]	-0.1524	-7.9209		-2.9747	-0.9961
RANGE [0.50, 0.60]	-0.0062	-0.3262		-8.2402	-2.7505
RANGE [0.60, 0.70]	-0.1886	-9.9974		-12.1032	-4.2169
RANGE [0.70, 0.75]	-0.1554	-8.2167		6.0927	2.0270
RANGE [0.75, 0.80]	-0.1674	-8.8183		-3.2222	-1.0800
RANGE [0.80, 0.85]	-0.1702	-8.8861		-1.3280	-0.4496
RANGE [0.85, 0.90]	-0.1716	-8.8998		2.2923	0.7503
RANGE [0.90, 0.95]	-0.0831	-4.0872		3.1695	0.9899
RANGE [0.95, 1.00]	-0.2329	-11.1405		5.4734	1.6977
RANGE [1.05, 1.10]	-0.2164	-9.5876		10.3814	2.9047
RANGE [1.10, 1.15]	-0.0773	-3.2610		5.8573	1.5308
RANGE [1.15, 1.20]	-0.1830	-7.5755		-6.4131	-1.6196
RANGE [1.20, 1.25]	-0.0862	-3.4378		7.1096	1.7474
RANGE [1.25, 1.30]	-0.2672	-10.0655		-2.3020	-0.5069
RANGE [1.30, 1.40]	-0.0680	-2.4853		-1.6380	-0.3678
RANGE [1.40, 1.50]	0.4272	14.5117		3.0470	0.6320
RANGE [1.50, 1.60]	-0.2734	-8.7278		-2.0717	-0.4145
RANGE [1.60, 1.70]	0.0057	0.1663		-1.6378	-0.3120
RANGE [1.70, 1.80]	0.3160	8.3618		12.3098	2.0542
RANGE [1.80, 1.90]	0.0085	0.2217		6.5669	1.0729
RANGE [1.90, 2.00]	-0.0096	-0.2460		4.3783	0.6825
RANGE [2.00[	-0.0588	-1.4679		10.3701	1.5721
R^2	0.61 %			0.27 %	
No. of observations	160688			80828	
No. of variables	58			58	
No. of firms	332			167	

Under a bear market, only the variable of record high price over 5% is significant and causes the turnover to decline. This could be a sign of future expectations on the losing stock to grow, as it is not sold even at a record high price, whereas in the bull market the effect is of a positive kind leading to realization of the asset.

More differencies between the markets include the price drop below -5%, which leads to decreased trading in bull markets whereas during bear markets the effect is estimated to increase trading (even not statistically significantly). This could imply that the disposition effect does not apply well to bear markets, which could further be due to the fact that there are estimated to be more institutional traders during bear markets, as explained in Section 2.1.

Further implications of the results include the second crossing of the bull period 1.10 price level, which leads to a highly significant increase in trading. This is a direct implication of the disposition effect as the loser is realized after crossing the offer price level, which can therefore be considered as the dominating reference price. However, the reference level must have changed after the first crossing, since the same level at first crossing leads to a decrease in trading.

Looking at Figure 15 this can be seen even more clearly. The bull level of crossing 1.15 forms the maximum effect peak in the graph, which matches the bear level of 1.05. During bull markets, crossing the level of the offer price for the first time at 1.15 winnings, generates a highly significant increase in turnover, and the following first crossings do not. During bear markets, the highest increase in turnover is reached at the level of crossing the offer price at 1.05. This result is also significant, because it is at the same time a new record high price larger than 5%. It seems the pessimistic investors realize their shares quicker than the optimistic investors. Therefore, the same pattern that was observed with the winners, can be seen with the losers as well.

The second crossings overall seem to generate a steadier turnover effect without as high peaks or throughs as with the first events. Especially, the bear period seems to balance the reactions to almost a straight line. This could also be a sign of a flexible reference price as the price

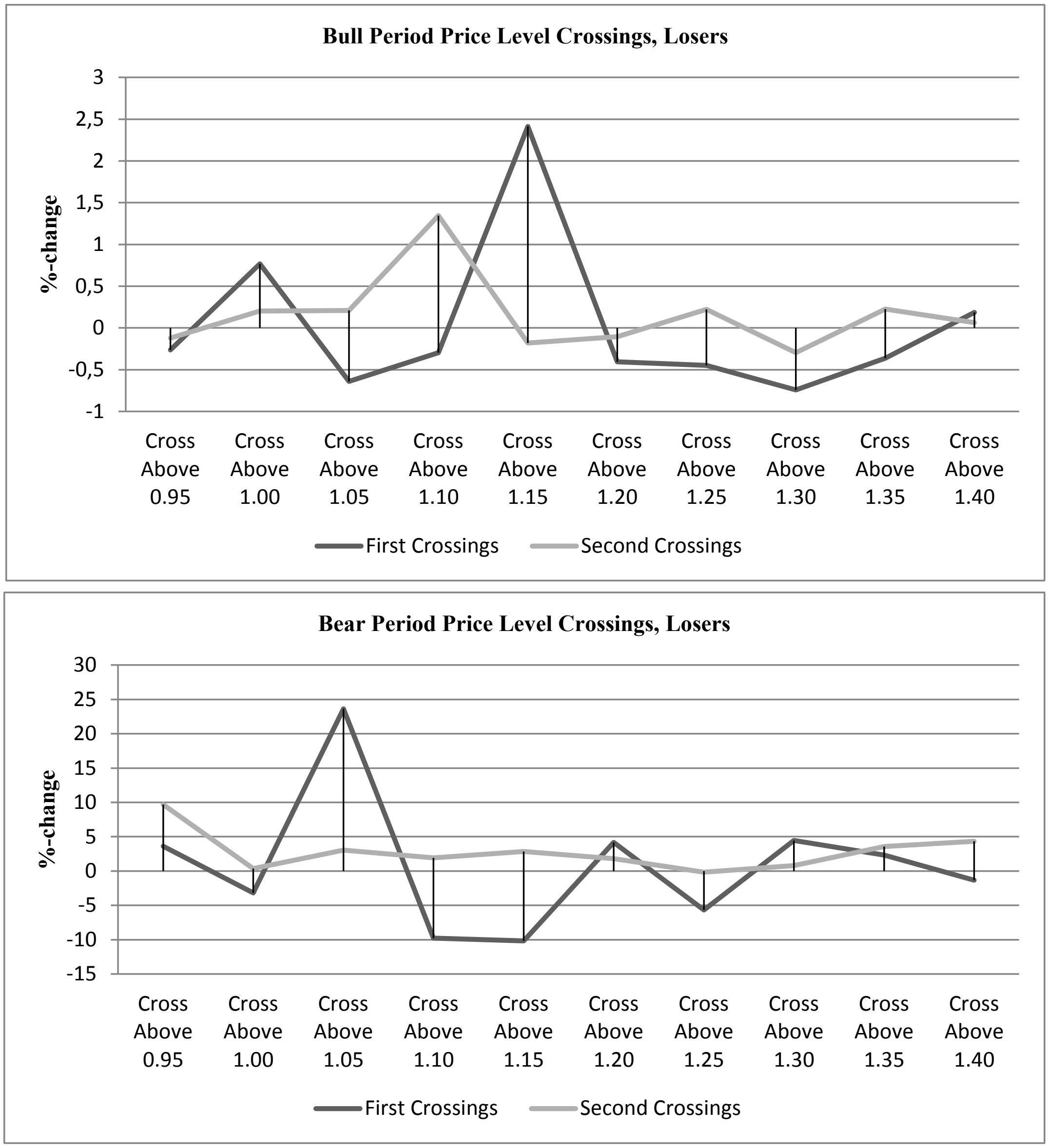


Figure 15: **Market Trend Adjusted Price Level Crossings, Losers**
First and second crossings represent the coefficients of the losers' regression. E.g. At Cross Above 1.15 during the Bull period, the first crossing of this level results in a log increase of 2.4132 in the turnover, while the same level during Bear period results in a log decrease of -10.1713 in total turnover.

movements do not effect the turnover as roughly anymore. On the other hand, investors may be more cautious in their movements and not as hasty to trade as in the bull markets, which could stem from less individual noise investors during the bear markets.

When assessing the effects to the total turnover, by summing up the coefficients of Record

High 1M, First Cross Above 1.00 and the change in price ranges, this yields a 79.2% increase in total turnover, which is relatively speaking quite high. The corresponding increase in turnover during bear period is 72.8%. Therefore, the total turnover does not seem to be affected by different market conditions, but rather the reference price is adjusted based on the prevailing market trend.

Overall, the crossings of the losers seem to generate much more stronger shifts in the turnover, as the coefficients are larger than the winners'.

6.4 Initial return size regression effects

In this final regression analysis I have divided the subsamples based on the magnitude of the initial returns separately for winners and losers. The size of the underpricing of winners is defined by the 40% largest initial return stocks making the upper group the "largely underpriced" firms, whilst the other represent the average and small underpricing levels. The losers have been divided in the same way based on the magnitude of the overpricing, respectively. The results of the winners are placed in Table 14 and the results of the losers in Table 15.

Table 14: **Winners' Regression Results for the Magnitude of the Underpricing**
Number of largely underpriced winners is 287 and number of average underpriced firms is 741. Large underpricing corresponds to the largest 40% i.e. above 17,3% initial return for the winners. The sample period runs from 1 January 1996 to 31 December 2011.

	Large initial returns		**Average initial returns**		
Variable	*Coefficient*	*t-value*	*Coefficient*	*t-value*	
Intercept	-0.0005	-0.380	-0.0066	-11.2570	
Record High 1M	0.0304	7.6500	0.0266	19.9680	*
Record Low 1M	-0.0027	-0.8980	0.0153	11.6530	
Record High 1M (R>5%)	-0.0142	-1.2930	-0.0486	-10.9940	
Record Low 1M (R<-5%)	-0.0565	-9.6250	-0.0761	-24.0340	*
First Cross Below 1.20	-0.0323	-0.6600	0.3418	20.7530	*
First Cross Below 1.15	0.0014	0.0250	-0.1210	-6.4030	
First Cross Below 1.10	-0.2059	-3.5680	0.0101	0.5590	
First Cross Below 1.05	0.0503	0.8460	-0.0020	-0.0940	
First Cross Below 1.00	-0.0472	-0.9140	-0.1224	-8.0390	
First Cross Below 0.95	0.2701	4.4740	0.0317	1.7180	

First Cross Below 0.90	-0.3004	-4.8990	0.4362	20.8070	*
First Cross Below 0.85	0.1890	3.1310	-0.5015	-23.7780	*
First Cross Below 0.80	-0.1406	-2.3140	0.0546	2.6760	
Second Cross Below 1.20	0.1561	4.0820	0.1471	12.2000	
Second Cross Below 1.15	-0.0294	-0.7560	0.1026	8.5300	
Second Cross Below 1.10	-0.0100	-0.2450	0.1186	10.0040	
Second Cross Below 1.05	-0.2022	-4.7120	-0.1101	-8.8450	
Second Cross Below 1.00	0.1823	4.2140	-0.0221	-1.7220	
Second Cross Below 0.95	0.1085	2.4980	-0.0371	-2.8870	
Second Cross Below 0.90	-0.0369	-0.8310	-0.2572	-19.6650	*
Second Cross Below 0.85	-0.1087	-2.4190	-0.0957	-6.9950	
Second Cross Below 0.80	-0.1002	-2.2670	-0.0682	-4.6760	
RANGE [0.00, 0.70[	0.3283	7.6370	-0.1428	-10.1190	
RANGE [0.70, 0.75[	0.0141	0.3290	-0.1033	-7.3340	
RANGE [0.75, 0.80[	0.0375	0.6810	-0.0994	-5.0450	
RANGE [0.80, 0.85[	0.0599	1.1510	0.5388	26.4210	**
RANGE [0.85, 0.90[	0.0782	1.4340	-0.0984	-4.9110	
RANGE [0.90, 0.95[	-0.2110	-3.8490	0.0976	5.5500	
RANGE [0.95, 1.00[	0.1993	4.2710	0.1294	8.8050	
RANGE [1.05, 1.10[	0.2591	5.1530	0.2403	21.675	*
RANGE [1.10, 1.15[	0.2372	4.9320	0.0785	5.6230	
RANGE [1.15, 1.20[	-0.1525	-3.4130	0.2416	21.038	*
RANGE [1.20, 1.25[	-0.0352	-0.9770	-0.1588	-13.6880	*
RANGE [1.25, 1.30[	0.1012	2.8260	0.2349	19.9350	*
RANGE [1.30[	-0.1287	-4.9480	-0.0933	-7.8280	
R^2	0.35 %		0.83 %		
No. of observations	138908		358644		
No. of variables	35		35		
No. of firms	287		741		

As explained in Section 2.3, larger underpricing should result in larger trading volume, as the reference point is updated more with stronger surprises. What can be seen from the Table 14 is that the firms of average or low underpricing seem to possess smaller turnover movement effects than the largely underpriced firms. Still, the only statistically significant effects are obtained with the average and small underpriced groups at record highs (positive) and lows (negative), first crosses below 1.20 (positive), 0.90 (positive) and 0.85 (negative), second crossings below 0.90 (negative) and trading at ranges [0.80, 0.85[, [1.05, 1.10[and between [1.15, 1.30[.

Table 15: **Losers' Regression Results for the Magnitude of the Overpricing**
Number of largely overpriced losers is 287 and number of average overpriced firms is 741. Large overpricing corresponds to the largest 40% losses over -8.62%. The sample period runs from 1 January 1996 to 31 December 2011.

	Large initial losses			**Average initial losses**		
Variable	*Coefficient*	*t-value*		*Coefficient*	*t-value*	
Intercept	-0.0167	-8.1829	.	-0.006889	-10.2542	*
Record High 1M	0.0564	17.9772	.	0.0394	23.1115	*
Record Low 1M	0.1002	20.7725	*	0.0110	7.7566	
Record High 1M (R>5%)	0.1153	12.1077		-0.0008	-0.1204	
Record Low 1M (R<-5%)	0.3212	32.7975	**	-0.7416	-22.4143	*
First Cross Above 0.95	0.4123	1.9936		-0.5228	-23.3126	*
First Cross Above 1.00	0.6785	2.6971		1.1138	27.5283	**
First Cross Above 1.05	-1.0718	-5.1966		-0.8175	-12.9022	
First Cross Above 1.10	0.3520	1.7039		0.8760	11.2930	
First Cross Above 1.15	0.6690	2.6540		-1.1331	-14.7860	
First Cross Above 1.20	-1.0098	-4.9010		0.7702	14.3952	
First Cross Above 1.25	-0.2428	-5.8515		0.0537	0.8420	
First Cross Above 1.30	-0.0241	-0.5604		0.2219	3.4686	
First Cross Above 1.35	0.0111	0.2497		-0.0898	-1.1463	
First Cross Above 1.40	0.0357	7.7385		-0.5436	-6.7750	
Second Cross Above 0.70	-0.2370	-5.7025		-0.1015	-6.6330	
Second Cross Above 0.75	0.0049	0.1136		-0.1526	-10.1887	
Second Cross Above 0.80	0.0453	1.0176		-0.0435	-3.1209	
Second Cross Above 0.85	0.2318	5.0111		-0.1445	-9.6242	
Second Cross Above 0.90	0.2732	5.7309		0.1851	12.8279	
Second Cross Above 0.95	-0.0556	-1.1285		0.1394	9.4175	
Second Cross Above 0.95	0.1251	2.4636		-0.1902	-11.6104	
Second Cross Above 1.00	0.0369	0.6565		0.0003	0.0168	
Second Cross Above 1.05	0.1641	2.8842		0.0834	4.2503	
Second Cross Above 1.10	-0.0799	-1.3056		0.1862	9.8266	
Second Cross Above 1.15	0.0149	0.2306		0.0387	2.0456	
Second Cross Above 1.20	0.2514	3.7695		0.1581	7.9068	
Second Cross Above 1.25	-0.1789	-2.5097		-0.3049	-13.9895	
Second Cross Above 1.30	-0.1155	-1.5212		-0.0263	-1.2092	
Second Cross Above 1.35	0.3532	4.5064		-0.0836	-3.4738	
Second Cross Above 1.40	-0.2323	-3.0446		0.2538	9.6948	
Second Cross Above 1.45	0.1016	1.2118		0.3571	12.8802	
Second Cross Above 1.50	-0.0334	-0.3591		-0.2329	-8.1661	
RANGE [0.00, 0.10]	-0.1267	-2.2831		-0.1682	-5.0206	
RANGE [0.10, 0.20]	0.2666	6.0391		0.0358	1.5073	
RANGE [0.20, 0.30]	-0.2262	-5.7981		0.1872	9.8072	
RANGE [0.30, 0.40]	-0.0789	-2.2850		-0.0194	-1.1208	
RANGE [0.40, 0.50]	-0.0114	-0.3415		-0.0806	-5.1524	
RANGE [0.50, 0.60]	-0.1857	-5.2616		0.2570	17.2352	.
RANGE [0.60, 0.70]	-0.0935	-2.5868		0.1030	7.3210	
RANGE [0.70, 0.75]	-0.1366	-3.4478		0.1783	12.9570	
RANGE [0.75, 0.80]	0.0231	0.5736		-0.2999	-21.7255	*
RANGE [0.80, 0.85]	-0.0657	-1.5659		0.1194	8.9665	

RANGE [0.85, 0.90]	-0.0595	-1.3351		-0.0872	-6.0786	
RANGE [0.90, 0.95]	-0.0026	-0.0565		0.3877	25.2702	*
RANGE [0.95, 1.00]	-0.2396	-4.9972		-0.2246	-14.9144	
RANGE [1.05, 1.10]	0.1688	3.1491		-0.1264	-7.6046	
RANGE [1.10, 1.15]	-0.3535	-6.3545		0.4140	22.7056	*
RANGE [1.15, 1.20]	-0.0726	-1.2664		-0.2222	-11.5056	
RANGE [1.20, 1.25]	-0.1046	-1.7542		0.1515	7.8140	
RANGE [1.25, 1.30]	-0.3052	-4.8453		0.0625	3.0730	
RANGE [1.30, 1.40]	-0.2597	-4.0501		0.4428	20.6693	*
RANGE [1.40, 1.50]	0.2241	3.0232		0.1070	4.5098	
RANGE [1.50, 1.60]	0.0503	0.6508		-0.1558	-5.9795	
RANGE [1.60, 1.70]	-0.3252	-3.7799		0.0252	0.9042	
RANGE [1.70, 1.80]	0.1452	1.5185		-0.2102	-6.2823	
RANGE [1.80, 1.90]	0.0004	0.0042		-0.6113	-18.1981	.
RANGE [1.90, 2.00]	2.2955	17.2161	*	0.1853	5.2255	
RANGE [2.00[	-0.3096	-3.2353		-0.4665	-12.9960	
R^2	2.50 %			1.9 %		
No. of observations	72600			168916		
No. of variables	58			58		
No. of firms	150			349		

According to Arkes *et al.* (2008), a reference point should also change more after a rise in the stock, rather than a decline. The losers reveal the rising stock in the regression, which results are in Table 15. The first crossings seem to generate larger turnover effects for the losers. Record high and low prices are significant for both groups of losers. The average overpriced losers possess significant results: crossing the level 0.95 decreases turnover and the level 1.00 increases turnover. In line with disposition effect, this would imply the reference price being the offer price. On the other hand, the largely overpriced losers do not give any statistically significant results, although their coefficients are of the positive sign. This result could also be interpreted such, that as the effect of the largest losses is taken away from the sample, the investors seem to act according to the disposition effect.

Figure 16 in Appendix B represents the crossings of the winners and Figure 17 in Appendix C the same for the losers. The losers graphs seem consistent, but the large initial returns winners crossings seem to be more volatile than the average initial returns group. This would be in line with the hypothesis, although the results are not statistically significant.

Therefore, no other clear results can be derived out of the results, because of the lack of significant coefficients on each group. Yet, the average initial returns may incorporate smaller firms that possess more disposition effect and therefore show more statistical significance. On the other hand, the number of these firms is also twice as large, which probably has an effect on the results as well.

The overall effects from these groupings based on the magnitude of the under/overpricing do not seem to provide more beneficial information on the reference price formation. In other words, the results do not show significant implications on investors consciously paying attention to the size of the under/overpricing.

6.5 Analysis on weekly data

Following the study of Kaustia (2004), I have analyzed the winners and losers on a weekly basis. The results can be seen in Table 16. Each level represents a first crossing. For example, if the level 0.95 is crossed, the five days during that week receive the dummy value of one. For the following weeks the days act as dummy variables in the same manner. This analysis is done to model the turnover effects in time.

As it can be seen, the new maximum price gains statistically significant results throughout the weeks. The first week the maximum high price is discovered, it seems to immediately affect the turnover. The first two weeks give significant indications and the last two weeks highly significant results. This could serve as a sign of investors reacting slower to the new maximum. This is however only a speculation.

Other highly significant results are gained two weeks after crossing the 1.05, 1.00 and 0.95 levels from above for the first time. This crossing of these levels seems to give a lagged response only on the second week after the price drop. Falling below 0.95 continues to have a significant effect still after four weeks, increasing trade. The results imply that if the winner falls only somewhat below the offer price, it has a lagged trade increasing effect, but as it further declines below 0.85 the effect turns into an incentive to sell after two weeks.

Table 16: **The Impact of New Maximum Price and Crossing Price Levels during the Following Weeks**

The effect of achieving new price maximum along with the effect of crossing new price levels for the first time are assessed during four weeks following the initial public offering. The sample period runs from 1 January 1996 to 31 December 2011.

Winners	Week 1			Week 2			Week 3			Week 4		
	Coefficient	*t-value*		*Coefficient*	*t-value*		*Coefficient*	*t-value*		*Coefficient*	*t-value*	
New maximum	2.3064	33.7300	*	0.5863	53.4900	*	1.1229	91.4300	**	1.2927	101.4000	**
0.85	-0.1586	-2.3200		0.5952	54.3000	*	0.0174	1.4200		0.3548	27.8300	.
0.9	0.0911	1.3300		0.3948	36.0300	.	0.9019	73.4400	**	0.2092	16.4100	
0.95	0.3494	5.1100		0.8313	75.8500	**	0.5935	48.3300	*	0.0513	4.0200	*
1	0.0502	0.7300		1.1975	109.2600	***	0.0437	3.5600		0.6053	47.4800	
1.05	-0.0019	0.0300		0.7767	70.8700	**	0.0144	1.1700		0.1624	12.7400	
1.1	-1.0521	15.3800		0.0619	5.6500		0.2561	20.8500		0.2214	17.3600	
1.15	0.1436	2.1000		0.0356	3.2500		0.4533	36.9100	.’	0.4160	32.6300	.
1.2	0.4045	5.9100		0.0000	0.0000		0.0366	2.9800		0.7360	57.7300	*
New maximum	0.2200	14.6	***									
New minimum	0.0500	3.1	.									
Cum. abnormal vol	105.6500	7149.7	***									

Losers	Week 1			Week 2			Week 3			Week 4		
	Coefficient	*t-value*		*Coefficient*	*t-value*		*Coefficient*	*t-value*		*Coefficient*	*t-value*	
New maximum	19.7300	2.1900		27.170	11.062	***	103.14	14.423	***	199.59	19.4280	***
0.85	0.6200	0.0700		2.0800	0.8500		0.3000	0.0400		7.0000	0.6800	
0.9	-0.1000	0.0100		0.2300	0.0900		0.0000	0.0000		4.3000	0.4100	
0.95	0.0200	0.0000		0.1100	0.0500		1.4000	0.2000		0.6000	0.0600	
1	0.1900	0.0200		1.4200	0.5800		0.8000	0.1100		0.0000	0.0000	
1.05	0.0000	0.0000		-0.0900	0.0400		3.0000	0.0100		0.1000	0.0000	
1.1	-0.1100	0.0100		0.2600	0.0300		1.6000	0.0100		0.0000	0.0000	
1.15	-0.1100	0.0100		0.0000	0.0000		0.7000	0.0000		0.1000	0.0000	
1.2	-0.1100	0.0100		0.0000	0.0000		0.0000	0.0000		0.3000	0.0000	
New maximum	165	56.272	***									
New minimum	0	0.009										
Cum. abnormal vol	42873	14646.907	***									

The losers' results continue with almost the same pattern as the winners. The all-time high price results in statistically significant turnover increasing effects after two, three and four weeks the new high has been met. However, the first week's variable is not significant, which could imply the effect in turnover comes with a delay. On the other hand, as the disposition effect implies, losers are kept and not sold. Even more, it is not established what other factors affect the turnover during the next weeks, such as how many crossings happen during that time that can have an effect on the results. Therefore, insinuating anything else than, that the new maximum price plays a significant role in the turnover fluctuation, would be highly speculative.

6.6 Robustness checks

In order to guarantee the robustness of the results, I have run several other regressions by different variable combinations. For example, the preliminary regression variables were tested to be included in the first-stage regression in determining the normal turnover effects. The effect on the residuals was not as significant that it would have affected the second-stage regression results.

The initial data for the whole analysis was retrieved and sampled twice in order to be sure that the segmentation would result in the same tickers and corresponding determinant values.

Additional robustness checks include testing different panel data regression estimators. As the regressions are run with different estimators, the coefficients vary somewhat, but no real separating statistical implications arise from these measures, which reinforces the validity of the results. The pooled method was tested also with the fixed and random methods. Actually, as the analysis was done in the "R" environment, the analysis method itself had an incorporated feature to detect the right estimator based on the quality of the data. Nevertheless, to be sure to exclude for example the random estimator from the second-stage regressions, I run a Hausman test by comparing the fixed and random effects, which preferred the first one. Nevertheless, this is only a rhetoric procedure, as the model determinants were justified already in the panel data description.

Furthermore, the sample could have been divided into different time periods based on *e.g.* crisis times, but essentially the now employed method should lead to the same result because the firms are divided by their tickers on the basis of the market trend at hand at the time of the offering.

As I believe the general preliminaries of the methods to have been well justified, there would be no need for additional robustness checks, that would significantly alter the results.

7 Summary and conclusions

I have studied the determinants of reference prices under different market conditions. The results characterize the investor market behavior, as the data sample bases on aggregate market-wide information, comprising not only individual observations but a representing sample of the whole market. In this paper, disposition effect is the key preconditioning theory in studying the reference price formation, as it can be modeled through the post-IPO trading volume changes.

In the preliminary analysis, I have assessed the determinants potentially affecting the turnover of individual firms, by incorporating additional variables to the model of Kaustia (2004). However, not the firm size, nor being subject to a lock-up agreement or a risky hightech firm, had a significant effect on the turnover. Market conditions at the time of the issue, on the other hand, were found to significantly affect the turnover, which justified the use of this variable as a basis for the segmentation of the regression groups. Furthermore, firms were analysed based on the size of their initial returns, which was hypothesized to generate stronger results for firms with larger initial returns, yet did not yield significant results. Finally, the firms were regressed separately through the weeks following the initial public offering, partly serving as a robusting last analysis, that reinforced the reference point observations of the previous regressions.

I will next briefly assess the outcomes for each hypothesis.

H1*: Post-IPO trading volume is higher in the price levels above the offer price*

H0 is accepted for the winners and rejected for losers. Especially the results from the pooled regression for winners are significant, when the price trades at a range above the initial offer price. The losers however seem to suffer from a "loser stigma" as the trading does not increase when the stock is trading above the offer price.

H2*: Trading volume for negative initial return IPOs increases when the offer price is surpassed for the first time*

H0 is rejected. Unlike the study of Kaustia (2004), my results seem to decrease the turnover as this record high price is reached. It seems that investors are reluctant to realize the losers as they reach new record high prices. This may be a sign of a loser stigma. Furthermore, when the IPO market price with a negative initial return exceeds the offer price for the first time, there should be an immediate effect in terms of trading volume, and not a lagged one. Accordingly, the disposition effect would not seem significant enough to affect the asset pricing of the losers.

Reasons behind the difference in results of this study compared to the study of Kaustia (2004) can be sought from the data samples. The correlations of the first-stage regression variables are placed in Appendix D. The losers variables seem to be much more correlated with each other than the winners' variables. In fact, as the market return increases, it seems the turnover of the losers almost perfectly linearly decreases. This could provide an explanation on the differing results on the losers' regression, where crossing the offer price should lead to an increase in turnover whereas this does not seem to hold. If the normal turnover of the losers moves to the opposite direction than the market, this alone could reverse the effect of the level crossings. It would require further research into what drives the turnover into react differently in my study than in the results of Kaustia (2004). As I do not have the base data for his research, I can only speculate on the underlying reasons. Nevertheless, this paper does not find significant results in support of this hypothesis.

H3: *Trading volume for positive initial return IPOs increases when the offer price is surpassed for the first time*

H0 is accepted. Falling below 0.95 level causes the highest increase in turnover, which could be due to price support, as the offer price is surpassed for the first time. Still the results are somewhat controversy, as trading at ranges just below the offer price seems to lead to a decrease in the total turnover. Falling below the offer price still corresponds to a new record low price, which is significant when the fall is more than 5%. About half of this turnover increase can be explained by the new record high price, one third by the price range change and about 5% from crossing the reference level for the first time.

H4: *When new price maximums (minimums) are reached, trading volume increases*

H0 is accepted. Highly significant results are gained from both pooled regressions for winners and losers, as well as from market regressions for both, and are also reinforced by the weekly analysis data. This is a strong indication into the result that the new price maximums and minimums alter the investor's mental account and the reference price is adjusted accordingly. These results are in line with the study of Gneezy (2005) who examines the effects of prior losses and gains on the formation of reference prices, and finds that historical peaks tend to be the most descriptive reference prices that investors base their decisions on.

H5*: Market conditions (bullish/bearish trends) affect the reference price formation*

H0 is accepted. For the case of the winners under bull markets, the investors seem to be more optimistic with the reference price formation. As explained, the highest turnover peak for the bull period occurs at crossing the level of 0.90, whereas the highest peak for the bear period (as well as for the overall period in pooled regression for winners) occurs at the level of 0.95. These peaks represent the new record low points for the winners. Moreover, because the level of 0.90 is significant, it would seem that during bull markets investors are more optimistic and therefore the reference price allows for a lower break-even point, than during bear markets. The total effect on the turnover did not however vary significantly between different market conditions. This could further suggest, that there lies no difference between the market conditions' total effect on the turnover, but it is indeed incorporated within the prices. The most significant finding is however, that the reference price seems to vary according to the prevailing market trend, at least for the winners. Also the losers' reference prices seem to shift during the bull market to a more optimistic level.

H6*: Reference price updating is more frequent under bull markets*

H0 is accepted. When examining the first and second crossings, it can be noticed that the adaptation to the new levels, represented by the second crossings line, is steadier under bear markets and there are no sudden turnover movements, when compared to the bull market lines. Moreover, the effects of the individual variables are less observable under bear markets, as there are no statistically significant impacts. The second crossings of the bull period for winners seem to adjust to the prices more quickly, as the turnover peaks are obtained at earlier crossing levels than the during the first crossings. These results further implicate that the markets are followed more actively during bull conditions, as the reactions are quicker. Additional market trend effects include the finding that volatility seems to decrease the trading during bear markets, and increase during bull markets.

Moreover, these results comply with the study of Arkes *et al.* (2008), who finds that reference point adaption is found to be occurring more with rising stocks than the falling ones, which makes it asymmetric. This also suggests that, as the investors on average have more winning stocks than losing ones during rising markets, their reference point adaption is also faster. This could explain the results of different reference points varying by market conditions.

H7*: Large initial returns cause more reference point adaptation*

H0 is rejected. The overall effects from these groupings based on the magnitude of the under/overpricing do not seem to provide more beneficial information on the reference price formation. In other words, the results do not show significant implications on investors consciously paying attention to the size of the under/overpricing.

Furthermore, the analysis on the weekly data effects implies that if the winner falls only somewhat below the offer price, it has a lagged trade increasing effect, but as it further declines below 0.85 the effect turns into an incentive to sell after two weeks. For the losers, the all-time high price results in statistically significant turnover increasing effects after two, three and four weeks the new high has been met. The first week's variable is not however statistically significant, which could mean that the turnover effect lags. Moreover, it is not established what other factors affect the turnover during the next weeks. In other words, more crossings probably happen during that time that can have an unknown effect on the results.

Finally, the driving forces behind investor behavior seem to be overconfidence and selective attention during bull markets, as the reference prices adapt more quickly. As Kliger and Kudryavtsev (2008) found, investors update the reference levels when they are exposed to new information, which could apply here as well in the form of new record high and low stock prices, which are quite significant reference prices according to the results. Also mental accounting can be characterized as an important factor when it comes to the new maximum and minimum prices, as they shift the reference price notions within the mental accounts.

The most important finding of this study however is the fact that the reference prices seem to be formed differently based on the prevailing market conditions. Even though it would seem that the total turnover is not changed due to reverse market conditions, the reference prices, on the other hand, are. Implications for further study would therefore include *e.g.* tracking the specific reference price levels and measuring whether they are industry-connected or firm-size-connected during different market conditions, or whether a specific market event, such as earnings or dividend announcements, have a different effect during reverse market conditions. These could shed supplementary light on the underlying reference price determinants driving the investor behavior.

References

Aggarwal, R. (2000). Stabilization activities by underwriters after initial public offerings. *The Journal of Finance*, **LV**(3).

Allen, F. and Faulhaber, G. (1989). Signaling by Underpricing in the IPO market. *Journal of Financial Economics*, **23**.

Arkes, H. R., Hirshleifer, D., Jiang, D., and Lim, S. (2008). Reference point adaptation: Tests in the domain of security trading. *Organizational Behavior and Human Decision Processes*, **105**(1), 67–81.

Arkes, H. R., Hirshleifer, D., Jiang, D., and Lim, S. S. (2010). A cross-cultural study of reference point adaptation: Evidence from China, Korea, and the US. *Organizational Behavior and Human Decision Processes*, **112**(2), 99–111.

Baker, M. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, **21**(2), 129–151.

Barber, B. M. and Odean, T. (2007). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies*, **21**(2), 785–818.

Barberis, N., Shleifer, A., Vishny, R., Laibson, D., Lamont, O., Prelec, D., and Ritter, J. (1998). A Model of Investor Sentiment. *Journal of Financial Economics*, (49), 307–343.

Baron, D. (1982). A model of the demand for investment banking advising and distribution services for new issues. *The Journal of Finance*.

Baucells, M. and Weber, M. (2011). Reference-point formation and updating. *Management Science*, pages 1–33.

Bloomfield, R. (2002). Predicting the next step of a random walk: Experimental evidence of regime-shifting beliefs. *Journal of Financial Economics*, **65**, 397–414.

Boehmer, E. (2002). Price Support by Underwriters in Initial and Seasoned Public Offerings. *EFA 2002 Berlin Meetings Presented Paper.*, (Unpublished working paper).

Brav, a. and Gompers, P. (2003). The role of lockups in initial public offerings. *Review of Financial Studies*, **16**(1), 1–29.

Bremer, M. (1996). Trading Volume for Winners and Losers on the Tokyo Stock Exchange. *Journal of Financial and Quantitative*, **31**(1), 127–142.

Brown, G. W. and Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, **11**(1), 1–27.

Campbell, J. Y., Lo, A. W., MacKinlay, a. C., and Whitelaw, R. F. (1998). the Econometrics of Financial Markets. *Macroeconomic Dynamics*, **2**(04).

Chong, T. T.-L. and Ng, W.-K. (2008). Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30. *Applied Economics Letters*, **15**(14), 1111–1114.

Daniel, K. and Hirshleifer, D. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance*, **53**(6), 1839–1885.

Derrien, F. (2005). IPO Pricing in "Hot" Market Conditions : Who Leaves Money on the Table? *The Journal of Finance*, **LX**(1).

Ellis, K., Michaely, R., and O'hara, M. (2000). When the underwriter is the market maker: An examination of trading in the IPO aftermarket. *The Journal of Finance*, **LV**(3).

Ellis, K., Michaely, R., and O'hara, M. (2002). When the underwriter is the market maker: An examination of trading in the IPO aftermarket. *The Journal of Finance*.

Fama, E. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics*, **49**, 283–306.

Ferris, S. and Haugen, R. (1988). Predicting contemporary volume with historic volume at differential price levels: Evidence supporting the disposition effect. *The Journal of Finance*.

Frazzini, A. (2006). The disposition effect and underreaction to news. *The Journal of Finance*, **61**(4), 2017–2046.

Gneezy, U. (2005). Updating the Reference Level: Experimental Evidence. *Experimental business research*, **XX**(1986), 404–425.

Grinblatt, M. (1989). Signalling and the pricing of new issues. *The Journal of Finance*, **44**(2), 393–420.

Grinblatt, M. (2002). The Disposition Effect and Momentum. *National Bureau of Economic Research*, (Unpublished working Paper No. 8734).

Grinblatt, M. and Keloharju, M. (2001). What makes investors trade? *The Journal of Finance*, **LVI**(2).

Hanley, K., Kumar, A., and Seguin, P. (1993). Price stabilization in the market for new issues. *Journal of Financial economics*, **34**, 177–197.

Ibbotson, R. and Jaffe, J. F. (1975). "Hot Issue" Markets. *The Journal of Finance*, **30**(4), 1027–1042.

Kahneman, D. and Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. *Econometrica: Journal of the Econometric*, **47**(2), 263–292.

Karlsson, N., Loewenstein, G., and Seppi, D. (2009). The ostrich effect: Selective attention to information. *Journal of Risk and Uncertainty*, **38**(2), 95–115.

Kaustia, M. (2004). Market-wide impact of the disposition effect: evidence from IPO trading volume. *Journal of Financial Markets*, **7**(2), 207–235.

Kliger, D. and Kudryavtsev, A. (2008). Reference point formation by market investors. *Journal of Banking & Finance*, **32**(9), 1782–1794.

Lakonishok, J. (1986). Volume for winners and losers: Taxation and other motives for stock trading. *The Journal of Finance*, **41**(4), 951–974.

Lee, C., Shleifer, A., and Thaler, R. (1991). Investor sentiment and the closed-end fund puzzle. *The Journal of Finance*, **XLVI**(1).

Lee, W. and Jiang, C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking & Finance*, **26**(12), 2277–2299.

Levis, M. (1990). The Winner's Curse Problem, Interest Costs and the Underpricing of Initial Public Offerings. *The Economic Journal*, **100**(399), 76–89.

Ljungqvist, A. (2003). IPO Pricing in the Dot-com Bubble. *The Journal of Finance*, **58**(2), 723–752.

Ljungqvist, A., Nanda, V., and Singh, R. (2006). Hot Markets, Investor Sentiment, and IPO Pricing*. *The Journal of Business*, (1986).

Long, J. B. D., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy*, **98**(4), 703–738.

Loughran, T. (2002). Why don't issuers get upset about leaving money on the table in IPOs? *Review of Financial Studies*, **15**(2), 413–443.

Lowry, M. and Officer, M. (2010). The Variability of IPO Initial Returns. *The Journal of Finance*.

Matyas, L. and Sevestre, P. (2008). *The Econometrics of Panel Data*, volume 46.

Mongin, P. (1997). Expected utility theory. *Handbook of Economic Methodology. London: Edward*, pages 342–350.

Neal, R. and Wheatley, S. (1998). Do measures of investor sentiment predict returns. *Journal of Financial and Quantitative Analysis*.

Neumann, J. V., Morgenstern, O., and Rubinstein, A. (1944). Theory of games and economic behavior. In *Princeton University Press*, volume 157.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance*, **LIII**(5), 1775–1799.

Ofek, E. and Richardson, M. (2000). The IPO Lock-Up Period : Implications for Market E ciency And Downward Sloping Demand Curves. *Stern School Of Business, New York University*, (Unpublished working paper, January 2000).

Pástor, A. and Veronesi, P. (2005). Rational IPO Waves. *The Journal of Finance*.

Ranguelova, E. (2001). Disposition Effect and Firm Size : New Evidence on Individual Investor Trading Activity. *Goldman Sachs Group, Equity Derivatives Research*, (Unpublished working paper).

Ritter, J. R. (1984). The " Hot Issue " Market of 1980. *Journal of Business*, **57**(2), 215–240.

Rock, K. (1986). Why new issues are underpriced. *Journal of financial economics*, **15**, 187–212.

Samuelson, W. (1988). Status quo bias in decision making. *Journal of risk and uncertainty*, **59**, 7–59.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, **XL**(3), 777–790.

Shleifer, A. and Vishny, R. W. (1995). The limits of arbitrage. *The Journal of Finance*, **52**(1), 35–55.

Statman, M., Thorley, S., and Vorkink, K. (2006). Investor overconfidence and trading volume. *Review of Financial Studies*, **19**(4).

Thaler, R. (1985). Mental accounting and consumer choice. *Marketing science*, **4**(3), 199–214.

Tinic, S. (1988). Anatomy of Initial Public Offerings of Common Stock. *The Journal of Finance*, **43**(4), 789–822.

Tkac, P. (1999). A Trading Volume Benchmark : Theory and Evidence. *Journal of Financial and Quantitative Analysis*, **34**(1), 89–114.

Tversky, A. and Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and uncertainty*.

Weber, M. and Camererb, C. F. (1998). The disposition effect in securities trading : an experimental analysis. *Journal of Economic Behavior & Organization*, **33**, 167–184.

Welch, I. (1992). Sequential sales, learning, and cascades. *The Journal of Finance*, **47**(2), 695–732.

Whaley, R. (2008). Understanding VIX. *Vanderbilt University - Owen Graduate School of Management*, (Unpublished working paper, 615).

A Appendix

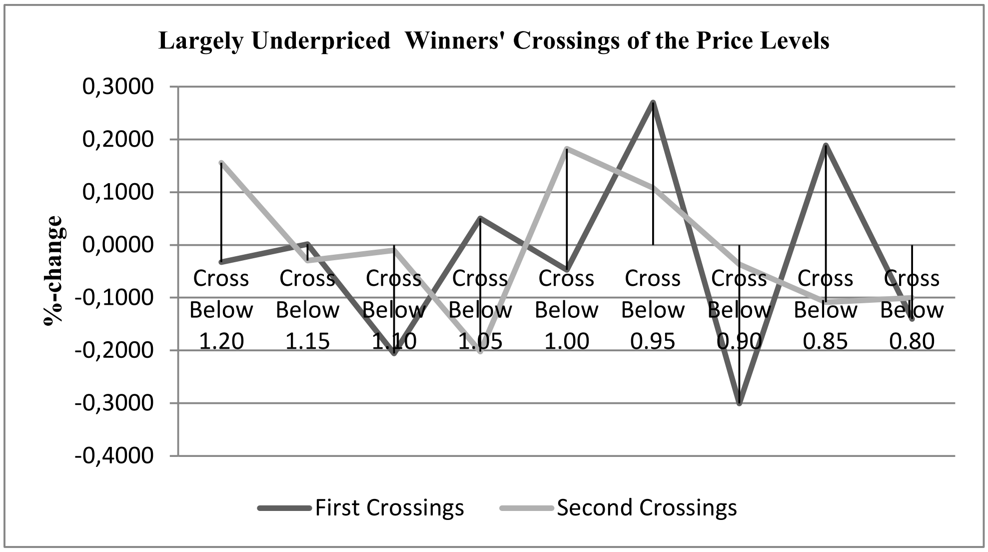
Table 17: **Statistics of the Subsample Divided by Different Market Conditions**

The yearly number of winners and losers divided by the prevailing market conditions at the time of the offering. Sample period runs from 1 January 1996 to 31 December 2011.

Year	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**
Winners	95	86	41	118	78	35	15	29
Bull	79	86	35	60	0	0	0	28
Bear	16	0	6	58	78	35	15	1
Losers	76	61	54	51	38	23	25	13
Bull	61	61	47	29	0	0	0	12
Bear	15	0	7	22	38	23	25	1
All	171	147	95	169	116	58	40	42

Year	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**Total**	**%**
Winners	62	68	73	94	17	39	83	95	1028	100 %
Bull	62	49	53	75	0	21	83	81	712	69 %
Bear	0	19	20	19	17	18	0	14	316	31 %
Losers	22	17	18	28	9	15	21	28	499	100 %
Bull	22	13	13	22	0	12	21	19	332	67 %
Bear	0	4	5	6	9	3	0	9	167	33 %
All	84	85	91	122	26	54	104	123	1527	100 %

B Appendix



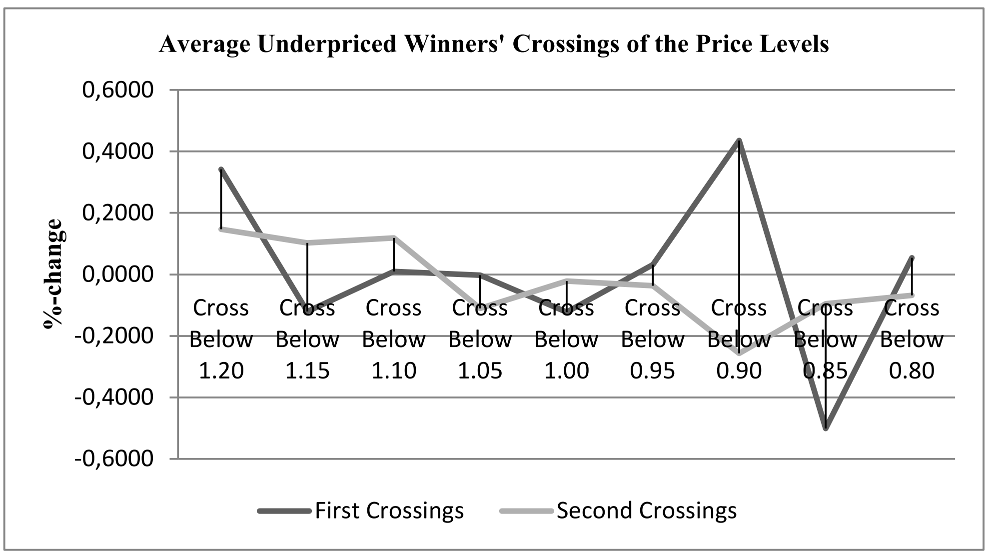
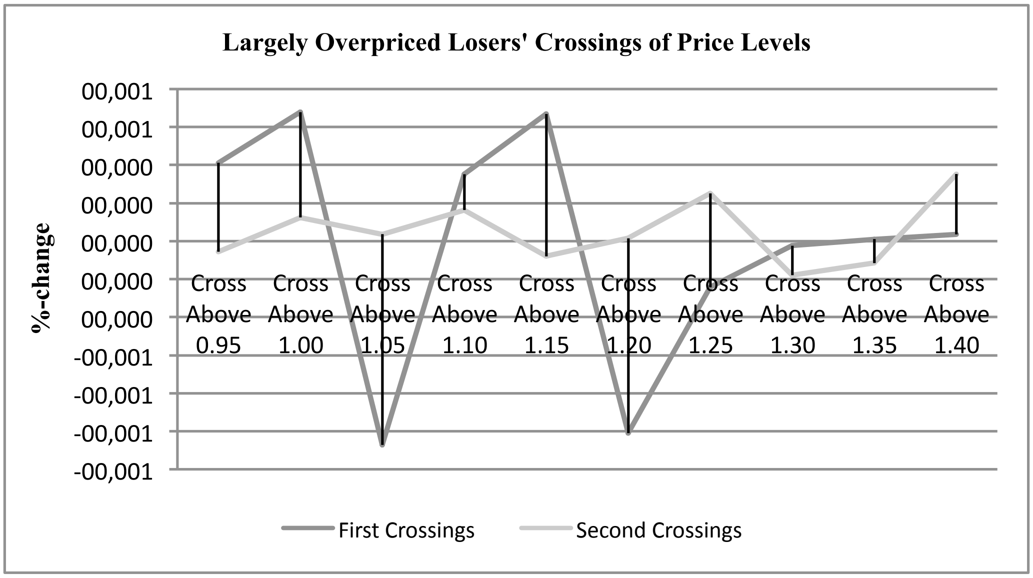


Figure 16: **Initial Return- Based Underpriced Winners' Price Level Crossings**
First and second crossings represent the coefficients of the winners' regression. *E.g.* An all-time low turnover decrease at the level of Cross Below 0.90 for the largely underpriced winners corresponds to the level of 0.85 for the average underpriced winners.

C Appendix



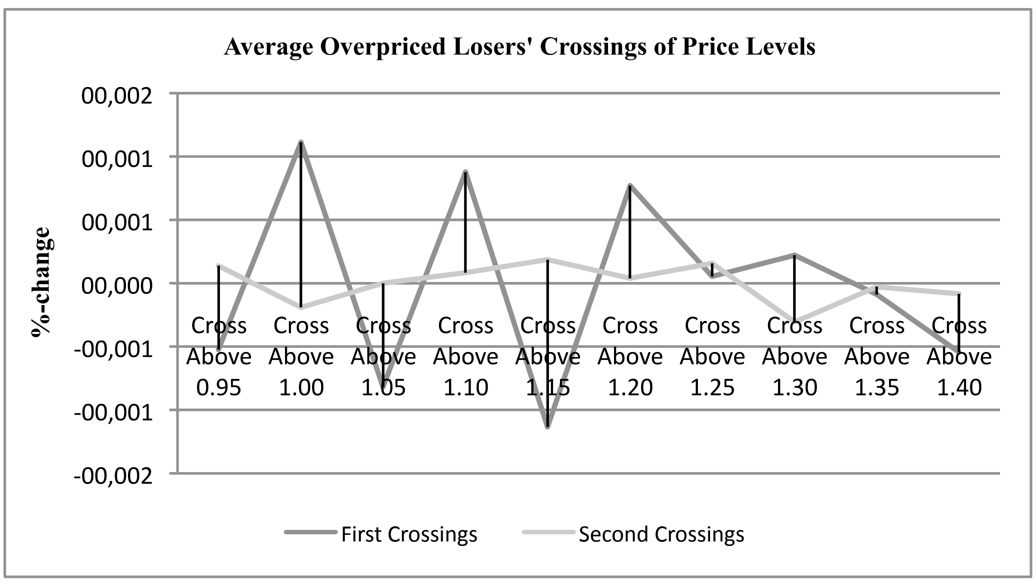


Figure 17: **Initial Return- Based Overpriced Losers' Price Level Crossings**
First and second crossings represent the coefficients of the losers' regression. The coefficients of crossing the price levels represent the changing effect on the turnover of the losers.

D Appendix

Winners Correlation

	Constant	Market turnover	Turnover -1 day	Turnover -2 days	Time	Time ^{2}	Max return	Min return	Volatility	Returns -1 day	Returns -2 days
Constant	1										
Market turnover	0.052	1									
Turnover -1 day	0.029	0.023	1								
Turnover -2 days	-0.011	0.029	-0.250	1							
Time since offer	-0.881	-0.285	-0.027	0.006	1						
Time sqrt	0.694	0.356	0.018	-0.008	-0.947	1					
Maximum return	-0.195	-0.003	-0.056	0.070	0.304	-0.349	1				
Minimum return	-0.336	-0.029	-0.007	0.053	0.396	-0.400	0.913	1			
Volatility	0.030	-0.042	0.033	-0.138	-0.069	0.094	-0.794	-0.685	1		
Returns -1 day	-0.264	0.057	0.121	0.073	0.280	-0.246	-0.204	-0.247	0.117	1	
Returns -2 days	0.354	0.104	-0.117	-0.025	-0.432	0.426	0.198	0.119	-0.189	-0.725	1

Losers Correlation

	Constant	Market turnover	Turnover -1 day	Turnover -2 days	Time	Time ^{2}	Max return	Min return	Volatility	Returns -1 day	Returns -2 days
Constant	1										
Market turnover	-0.997	1									
Turnover -1 day	-0.108	0.112	1								
Turnover -2 days	0.074	-0.075	0.040	1							
Time since offer	-1.000	0.997	0.109	-0.075	1						
Time sqrt	1.000	-0.997	-0.110	0.075	-1.000	1					
Maximum return	0.997	-0.996	-0.109	0.075	-0.998	0.998	1				
Minimum return	0.978	-0.980	-0.123	0.075	-0.979	0.979	0.986	1			
Volatility	-0.985	0.985	0.115	-0.079	0.986	-0.986	-0.992	-0.986	1		
Returns -1 day	-0.992	0.993	0.102	-0.076	0.992	-0.992	-0.994	-0.982	0.985	1	
Returns -2 days	-0.975	0.969	0.097	-0.071	0.976	-0.976	-0.972	-0.931	0.950	0.952	1

Figure 18: **Correlation Matrix of the First-Stage Regression Variables**
The first-stage regression variables are correlated against each other separately for the winner and loser subsamples. Variables are used to determine the daily normal turnover volume for each firm. Values close to 1.00 imply a large positive linear correlation between the variables, whereas values close to -1.00 indicate a negative linear relationship between the variables. Sample period runs from 1 January 1996 to 31 December 2011.