The Effect of Idiosyncratic Volatility and the Role of Investors' Sentiment in the Swedish Stock Market

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Abstract

The thesis investigates the presence of arbitrage risk and arbitrage asymmetry, and their relation with investors' sentiment, in the Swedish stock market.

By assuming that stocks' idiosyncratic volatility (IVOL) translates into arbitrage risk, the study analyzes the effects of IVOL on subsequent returns for the OMX Stockholm 30 constituents. Relevant literature suggests that stocks with the highest-IVOL are the most mispriced – either overpriced or underpriced –, and arbitrage risk is stronger for high-IVOL overpriced than for high-IVOL underpriced stocks due to arbitrage asymmetry.

After dividing the sample stocks in two categories of mispricing, the analysis finds that, because of arbitrage risk, the highest-IVOL stocks tend to be contemporaneously the most overpriced, within the group of overpriced stocks, and the most underpriced, within the group of underpriced stocks. This suggests the existence of a negative effect of IVOL on subsequent returns among overpriced stocks and a positive IVOL effect among underpriced stocks.

Furthermore, by introducing a sentiment index, the thesis finds a negative relation between investors' sentiment and IVOL effect: despite low levels of significance, the negative IVOL effect among overpriced stock is stronger in high-sentiment periods, while the positive IVOL effect among underpriced stock is stronger in low-sentiment periods. This also implies that arbitrage asymmetry is more relevant in high-sentiment periods.

Most importantly, even after controlling for macroeconomic variables, the results confirm the role of pure investors' sentiment, implying that behavioral aspects primarily influence the extent of arbitrage limits.

Keywords: Arbitrage risk, arbitrage asymmetry, idiosyncratic volatility effect, Swedish stocks, investors' sentiment

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1 Introduction

1.1 Background

According to the efficient market hypothesis, arbitrageurs assure that market prices are always equal to the rational present value of expected future cash-flows, thus forcing irrational traders out of the market and preventing mispricing. However, the behavioral finance literature questions this hypothesis and proposes alternative models considering psychological aspects of investors' behavior, as well as limits to arbitrage. Indeed, one of the main critiques to the efficient market hypothesis states that arbitrage strategies are risky and costly, even for rational investors. For instance, Delong, Shleifer, Summers and Waldman (1990) and Shleifer and Vishny (1997), argue that arbitrage risk is due to the presence of noise traders, i.e. irrational investors subject to sentiment, who deter rational arbitrageurs with short holding periods from betting against them.

Within this framework, following Stambaugh, Yu and Yuan (2013), the thesis moves from the assumption that, for each stock, arbitrage risk is generated by the stock's idiosyncratic volatility (IVOL), defined as the portion of volatility not explained by systematic risk factors. The higher is the IVOL of a certain stock, the stronger is the arbitrage risk and the lower is the possibility for arbitrageurs to correct prices.

Given the peculiar role of IVOL in determining stocks' mispricing, several empirical works analyze the effect of stocks' IVOL on their subsequent returns – the so-called IVOL effect – both at an individual stock's level and at aggregate level. While the most relevant investigations focus on the U.S. stock market, the purpose of this thesis is to assess whether arbitrage risk is present in the Swedish stock market and what is the role of IVOL in determining future returns for different Swedish stocks, across various phases of investors' sentiment.

1.2 The Study and the Research Questions

This thesis considers the stocks constituting the OMX Stockholm 30 Index – from July 2002 to December 2015 – with the aim to investigate the effect of idiosyncratic volatility on subsequent returns, on a monthly basis. The main reference for the methodology is the work of Stambaugh, Yu and Yuan (2013), who study the same phenomenon in the U.S. stock market.

As a first step, moving from the theoretical background of section 1.1, the study sorts the sample-stocks in two categories of mispricing and, subsequently, in three groups of IVOL within each category, thus forming six portfolios. The objective is to assess whether the following two results hold.

i. Among relatively-overpriced stocks, those with the highest IVOL in a month should be the most overpriced and experience the most negative average benchmark-adjusted returns in the subsequent month. Therefore, a negative monthly IVOL effect should be observed in this group.

ii. Among relatively-underpriced stocks, those with the highest IVOL in each month should be the most underpriced and have the most positive average benchmark-adjusted returns in the subsequent month. Therefore, a positive monthly IVOL effect should be observed in this group.

Subsequently, the analysis shifts to the relation between monthly IVOL and subsequent-month average benchmark-adjusted returns for the entire sample of stocks. For this purpose, the concept of arbitrage asymmetry is introduced. Arbitrage asymmetry is caused by the eventual presence of short-sale constraints, which impose greater arbitrage limits for short-sellers than for purchasers. In this situation, overpriced stocks should experience a greater level of mispricing than underpriced stocks, implying that negative subsequent returns on overpriced stocks should be greater than positive subsequent returns on underpriced stocks. In that case, a negative IVOL effect should be observed in the entire sample. To this extent, while earlier studies on the U.S. market observe either no significant relation – suggesting that the market is efficient – or a positive relation between IVOL and expected returns, recent investigations find instead the existence of an overall negative IVOL effect (Ang et al., 2006; Stambaugh, Yu and Yuan, 2013).

These considerations lead to the first research question of the thesis, which is answered in section 5.

1. *Given the role of IVOL in determining arbitrage risk and thus mispricing, do the overpriced stocks with the highest IVOL in a month experience the most negative subsequent monthly returns among relatively-overpriced stocks? Likewise, do the underpriced stocks with the highest IVOL in a month present the most positive subsequent monthly returns among relatively-underpriced stocks? Overall, is the net IVOL effect negative, consistent with arbitrage asymmetry?*

As it will be largely discussed, the study finds evidence of arbitrage risk. Indeed, the IVOL effect tends to be positive for underpriced stocks and negative for overpriced ones: as expected, the subsequent-month average benchmark-adjusted return for the difference between the highest-IVOL overpriced and underpriced portfolios is the most extreme. However, the data show no evidence of arbitrage asymmetry.

Finally, the last part of this work deepens the analysis by considering changes over time of investors' sentiment, which should influence the direction of mispricing at a market level. Investors' sentiment is defined as a belief about future cash flows and investment risks that is not justified by the actual facts. Two sets of results should be derived from the data.

i. During high-sentiment months, the negative monthly IVOL effect among overpriced stocks should be greater than the positive monthly IVOL effect among underpriced stocks, leading to lower expected aggregate returns in the subsequent month.

ii. Vice versa, during low-sentiment months, the positive monthly IVOL effect among underpriced stocks should be stronger than the negative monthly IVOL effect among overpriced stocks, leading to higher expected aggregate returns in the subsequent month.

Therefore, the thesis lastly analyzes whether the overall relation between IVOL and subsequent returns is more negative in high-sentiment periods as opposed to low-sentiment ones.

These considerations lead to the second research question, which will be answered in section 6.

2. *Since investor sentiment changes over time, during high-sentiment months, as opposed to low-sentiment ones, is the negative monthly IVOL effect among overpriced stocks more pronounced than the positive monthly IVOL effect among underpriced stocks? Overall, is the IVOL effect more negative in high-sentiment periods?*

The study finds that investors' sentiment is negatively related with the observed IVOL effects: despite low levels of significance, the negative IVOL effect among overpriced stock is stronger in high-sentiment periods, while the positive IVOL effect among underpriced-stock is stronger in low-sentiment periods. This also implies that arbitrage asymmetry is more relevant in high-sentiment periods. Most importantly, even after controlling for macroeconomic variables, the results confirm the role of pure investors' sentiment, suggesting that behavioral aspects primarily influence the extent of arbitrage limits.

1.3 Structure

Section 2 presents a review of the most relevant literature on arbitrage risk, arbitrage asymmetry and the role of stocks' IVOL in determining their future returns. Section 3 describes the data used. Section 4 outlines the methodologies followed to sort stocks in portfolios double-ordered on mispricing and IVOL. Section 5 addresses the first research question. Section 6 aims at answering the second research question. Section 7 illustrates the conclusions. Section 8 contains the reference list. The Appendix contains some more-detailed assumptions regarding the methodology.

2 Literature Review

2.1 Introduction

Sections 2.2-2.4 introduce the most relevant literature on arbitrage limits and their sources, which represent the theoretical framework underlying the whole empirical analysis in the thesis. Indeed, by using stocks' IVOL as an indicator of arbitrage risk, the work ultimately aims at testing whether inefficiencies related to arbitrage risk and asymmetry are in place in the Swedish stock market, and whether their size and direction depends on investors' irrational behavior.

Section 2.5 discusses the most relevant papers on the role of stocks' idiosyncratic volatility in predicting their future returns, which is at the core of the thesis' first research question. The focus is on the work of Stambaugh, Yu and Yuan (2013).

Section 2.6 presents the most relevant empirical works on the change in IVOL effect over different sentiment phases, which is the subject of the thesis' second research question. Once more, the discussion of the relevant results is centered on Stambaugh, Yu and Yuan (2013), while the definition of investors' sentiment is derived from Baker and Wurgler (2006).

2.2 Main Limits to Arbitrage: Arbitrage Risk and Arbitrage Costs

The efficient market hypothesis argues that, although some market participants may not be fully rational, arbitrageurs are always able to assure that prices mirror fundamental values, thus forcing irrational traders out of the market. Sharpe and Alexander (1990) define arbitrage as "the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices". This academic characterization relies on three assumptions. Firstly, arbitrage does not entail any costs in terms of either cash outlays or capital requirements. Secondly, a positive profit can be achieved with certainty within the expected time horizon. Thirdly, arbitrageurs do not face any risks, in terms of future obligations, before the actual profit appears.

Criticizing these three features of arbitrage, behavioral finance literature questions the effectiveness of arbitrage in enforcing market efficiency, since several arbitrage limits make arbitrage strategies risky and costly. As observed above, the sources of these risks and costs are of outmost importance for the theoretical foundation of this thesis. For this reason, the following section discusses two major sources of arbitrage risk – noise traders and fundamental news. Specifically, the noise-trader model may help explain why the highest-IVOL stocks tend to be the most mispriced.

2.3 Arbitrage Risk: Noise-Trader Risk and Fundamental Risk

The first relevant source of arbitrage risk is the presence of noise traders in the market, which affect arbitrageurs with a short holding-period by causing securities' mispricing to worsen in the short-run, even in case perfect substitutes for mispriced securities exist.

Delong, Shleifer, Summers and Waldman (1990) develop a model for noise-trader risk, distinguishing two types of market participants: Noise traders and sophisticated investors. On the one hand, noise traders are irrational investors who pick the securities in their portfolio following the false belief that they possess correct information about future price movements. On the other hand, sophisticated investors are rational market participants, who should purchase securities whenever noise traders irrationally push prices down, and sell them short in the opposite case.

The model assumes that fundamental risk is absent, that both noise traders and sophisticated investors are risk averse, and that noise-trader risk is systematic. Most importantly, while there is an infinite number of trading dates, each market participant has an investment horizon of one period. This final assumption is based on an overlapping-generations model, in which young investors in each period get old in the subsequent period, when they are replaced by new young traders. Therefore, a new generation of noise traders allocate the assets in their portfolio based on their false beliefs, eventually making prices diverge even more from fundamental values.

Combined with the short investment horizon, the possibility of further mispricing in the future prevents smart investors from leaning against noise traders. In the setting of the thesis, the highest-IVOL stocks should be the most mispriced because they are the most affected by unpredictable noise trading, which deters arbitrageurs the most from exploiting mispricing.

Although the assumption of a single holding period may seem simplistic, it is a valuable approach for modelling some real-world situations involving smart investors. Indeed, adverse price movements may determine additional capital requirements when short-sales or leverage are employed, thus forcing sophisticated investors to close positions that would have proved correct in the long-run. Moreover, as pointed out by Shleifer and Vishny (1997), when arbitrageurs (e.g. fund managers) manage money of outside investors, their performance may be evaluated before the mispricing correction takes place, thus encouraging them to pay more attention to short-term rather than to long-term performances. For this reason, despite the attractive long-run returns offered by certain strategies, arbitrageurs try to avoid the highest-IVOL stocks, which may also explain why the most extreme benchmark-adjusted returns are observed for the highest-IVOL securities (section 5).

As Delong, Shleifer, Summers and Waldman (1990) suggest themselves, if arbitrageurs had longer time-horizon than the duration of noise traders' misperception, they could implement their arbitrage strategies profitably in absence of fundamental risk. However, the actual existence of a second source of arbitrage risk – undesired fundamental news about a stock – further undermines arbitrageurs' ability to exploit overpricing and underpricing. Indeed, as pointed out by Wurgler and Zhuravskaya (2002), without perfect substitutes for mispriced stocks, arbitrageurs could correctly sell short an actual overpriced stock based on currently available information, but they may suffer future losses after the release of positive news about the stock's fundamental value. Since in real world it is often difficult to find perfect substitutes for mispriced securities, arbitrageurs are rarely able to modify their position by replacing the previous stock with another equivalent security, thus reporting a loss.

In conclusion, whatever the source of arbitrage risk – noise traders, uncertain fundamental news, or both – risk-averse arbitrageurs find actual impediments in efficiently exploiting arbitrage strategies. Therefore, arbitrage risk plays a primary role in generating securities' mispricing,

2.4 Arbitrage Costs and Arbitrage Asymmetry

Now the discussion shifts to the second key concept, arbitrage asymmetry, i.e. the situation in which higher short-selling costs cause greater arbitrage limits for short-sellers than for purchasers.

While some execution costs – such as brokerage commissions, bid-ask spreads and price impact in presence of low levels of liquidity (Perold, 1988) – are common to purchasers and short sellers, short-sale constraints impose greater arbitrage impediments to short-sellers than to purchasers. Financial literature contains several examples of these costs. For instance, since stocks must be borrowed to be sold short, short sellers face the additional risk that stock lenders may recall the stock loan. If they are unable to find new lenders, the short sellers are obliged to close the position, thus missing a potential profit (Lamont, 2005). Moreover, while it is typically cheap to borrow large cap stocks, smaller illiquid stocks may be expensive to short. The same applies to stocks that present high demand for borrowing, which is usually associated with high borrowing rates. As discussed by Lamont (2005), there are also several regulations and procedures in various markets, including the U.S., that can forbid short selling in certain conditions, as well as other legal and institutional constraints discouraging short-selling.

In addition, Stambaugh, Yu and Yuan (2013) outline that short-selling requires a margin deposit to be kept at some percentage of the position size, thus generating higher risk of margin calls for short-sellers compared to purchasers. This is true regardless the fact that purchasers use leverage or not. While the latter case is straightforward, the former is more interesting. Indeed, both leveraged purchasers and short-sellers are usually required to maintain a margin above a certain specified level, determined as the ratio between equity and position size. Assuming that a leveraged purchaser and a short-seller have both the same initial position and the same equity, an adverse rate of return for the short-seller implies greater exposure to a margin call than an equivalent rate of return for a purchaser. While an equal adverse movement causes the two investors the same loss in terms of equity, its impact on the position size is different. As the position size surges for short positions, but declines for long positions, the maintenance margin decreases by a higher extent for short positions. Following this observation, Stambaugh, Yu and Yuan (2013) prove that the sensitivity to stocks' idiosyncratic volatility of the probability of facing a margin call, is usually higher for short positions than for long positions, implying arbitrage asymmetry.

In conclusion, the literature offers various examples of arbitrage asymmetry that may occur in the stock market, leading to an overall tendency for overpricing. It is worth stressing that these costs are usually higher for smaller, less liquid stocks than the ones considered in the thesis' sample.

2.5 The Effect of IVOL on Future Returns

With reference to theoretical framework of sections 2.2-2.4, Stambaugh, Yu and Yuan (2013) employ the concepts of arbitrage risk and arbitrage asymmetry to study the role of stocks' idiosyncratic volatility (IVOL) in predicting future returns. As discussed, their work is extremely important, since this thesis aims at reproducing and applying their methodology to the Swedish market.

The three Authors move from the assumption that a stock's idiosyncratic volatility generates arbitrage risk. Indeed, being the portion of a stock's volatility not explained by systematic risk factors, idiosyncratic volatility is a better proxy for arbitrage risk than total volatility. In fact, arbitrageurs could diversify their portfolios and become neutral to market risk. Thus, idiosyncratic volatility can be considered as a signal of either noise trading on single stocks or uncertainty about companies' fundamental news. Combined with short-time horizons, high levels of undiversifiable risk discourage purchasers to correct underpricing and short-sellers to correct overpricing.

To empirically test their assumptions, they implement a double-sorting procedure to generate twenty-five monthly portfolios of the U.S. stocks traded on NYSE – over the sample period August 1965—

January 2011. Firstly, they divide stocks into five categories of mispricing by employing accounting variables. Subsequently, within each mispricing group, they further classify stocks based on their previous-month idiosyncratic volatility, forming five portfolios per group.

The mispricing ranking is computed through eleven relevant anomalies that are not captured by the Fama-French three-factor model (1993): The failure probability, the Ohlson's (1980) O-score, the net stock issues and the composite equity issues of each firm, the total accruals, the growth in net operating asset, the stocks' momentum, the gross profitability premium, the asset growth, the return on assets, and the share of investments in total assets.

The idiosyncratic volatility is calculated as in Ang et al. (2006). For each stock, IVOL is defined as the standard deviation of the residuals in the regression of last-month daily returns on the Fama-French daily three factors. Thanks to this definition, for each month, Stambaugh, Yu and Yuan (2013) capture arbitrage risk in the previous month and prove that the idiosyncratic volatility at a portfolio level follows the same ordering as the one at an individual stock's level. Indeed, arbitrage risk cannot be eliminated completely through diversification.

After completing this sorting, Stambaugh, Yu and Yuan (2013) move to the actual empirical investigation. They regress monthly portfolios returns on the monthly Fama-French factors, with the aim to analyze the intercept for each portfolio's regression, i.e. the average benchmark-adjusted return.

As expected, their findings suggest evidence of arbitrage risk. Indeed, among each mispricing category, the highest-IVOL portfolio shows the most extreme subsequent monthly benchmark-adjusted return: The size of the benchmark-adjusted returns decreases with the level of IVOL, signaling the declining arbitrage risk. Furthermore, this return is on average negative and statistically significant for the highest-IVOL overpriced portfolio, while it is on average positive and statistically significant for the highest-IVOL underpriced portfolio: the highest-IVOL overpriced portfolio experiences the most negative IVOL effect, while the highest-IVOL underpriced portfolio presents the most positive IVOL effect.

Moreover, the study indicates also the presence of arbitrage asymmetry, since the negative IVOL effect for overpriced stocks is higher than the positive IVOL effect for underpriced stocks.

In summary, assuming that stocks' idiosyncratic volatility is a good measure for mispricing, Stambaugh, Yu and Yuan (2013) find empirical evidence of arbitrage risk and arbitrage asymmetry in the U.S. stock market. As a matter of fact, they observe a negative monthly IVOL effect among overpriced stocks and a positive monthly IVOL effect among underpriced stocks, with the former being overall stronger than the latter.

2.6 Investors' Sentiment and IVOL Effect

Since investors' sentiment influences the overall tendency for overpricing or underpricing in the stock market, Stambaugh, Yu and Yuan (2013) investigate whether variations in investors' sentiment cause changes in IVOL effect over time.

In order to measure investors' sentiment, the Authors employ the index built by Baker and Wurgler (2006), which is based on the Principal Component Analysis of six proxies for sentiment: NYSE turnover, the average closed-end fund discount, the dividend premium, the equity share of total new issues, and the number and the first-day returns of IPOs. The linear combination of these variables, each entering with a coefficient equal to its loading in the first principal component, produces an index where each variable gives the expected contribution in defining investors' sentiment.

By exploiting the index, Stambaugh, Yu and Yuan (2013) find that the IVOL effect changes over time in the predicted direction. Indeed, in high-sentiment periods, the monthly IVOL effect among overpriced stocks is more negative than it is in low-sentiment periods. Likewise, in low-sentiment periods, the monthly IVOL effect among underpriced stocks is more positive than it is in high-sentiment periods. Moreover, the net IVOL effect is more negative in high-sentiment periods, signaling the presence of greater short-sale constraints when the tendency for general overpricing is higher.

Thus, they find a statistically-significant negative relation between IVOL and the level of investor sentiment, among both overpriced and underpriced stocks. By adding the lagged-sentiment index to the Fama-French factors, it is possible to improve the estimate of the subsequent-month return for the highest-IVOL portfolio, within both the most overpriced and most underpriced groups. As predicted by the theory on arbitrage asymmetry, this evidence is stronger among overpriced stocks.

Finally, Stambaugh, Yu and Yuan (2013) deepen the analysis by implementing two types of controls.

Firstly, they control for the macroeconomic components that may affect the previous base index. To this extent, they use the adjusted index of Baker and Wurgler (2006), constructed by regressing each of the sentiment proxies on six macroeconomic variables: the growth in industrial production, the growth in durable, non-durable, and services consumption, the growth in employment, and a flag for NBER recession. Even after this control, the previous evidences are confirmed, meaning that the role of actual investors' sentiment is prominent.

Secondly, the Authors introduce a control for firms' size, since the sensitivity of the empirical findings may depend on the size of the firms in the sample. Indeed, they notice that IVOL is usually greater for smaller firms and firms' size tends to decrease at the increase of the mispricing measure. Therefore, they remove from the sample, in sequence, the smallest 20 percent, 40 percent, 60 percent, and 80 percent. Indeed, by excluding the bottom quintiles, they find a weakening of the IVOL effect, although the overall results maintain statistical significance.

2.7 Relevant Conclusions

In the U.S. stock market, the empirical analyses confirm that the effect of stocks' idiosyncratic volatility on subsequent returns differs across various levels of mispricing. Indeed, among overpriced stocks, a higher idiosyncratic volatility in one month generates more negative benchmark-adjusted returns in the subsequent month. Likewise, among underpriced stocks, a higher idiosyncratic volatility in one month generates more positive benchmark-adjusted returns in the subsequent month. Moreover, the IVOL effect is influenced by arbitrage asymmetry, which makes the net IVOL effect negative. Finally, the IVOL effect varies over time, following the level of actual investors' sentiment, and the related tendency for general overpricing or underpricing in the market. Most importantly, this finding is robust even after controlling for macroeconomic variables, suggesting that investors' sentiment plays a major role in determining the size and direction of the IVOL effect.

The overall results from the relevant literature seem to have a key implication. Inconsistent with the efficient market hypothesis, the irrationality of some market participants, combined with the presence of arbitrage risk and costs, implies that the observed returns' anomalies can be fully explained only when controlling for time-changes in investors' behavior.

3 Data

3.1 Universe of Stocks and Sample Period

The sample of stocks is represented by the constituents of the OMX Stockholm 30 Index (OMXS30), which encompasses the thirty most-frequently-traded stocks on the Stockholm Stock Exchange. The time-period covered in the study starts in July 2002 and ends in December 2015, spanning over 162 months (13 years and 6 months).

Since the thesis analyzes monthly returns of portfolios of OMXS30 stocks, the universe of stocks taken into consideration to form such portfolios includes the actual constituents of the index in each month. The index re-considers its constituents semi-annual, with eventual variations in the index composition being effective since the first trading days of January and July. Consequently, the study considers all the changes in the index' constituents from January 2003 to July 2015[1].

Therefore, this thesis differentiates from Stambaugh, Yu and Yuan (2013) because it analyzes only large capitalization stocks, rather than the entire universe of stocks traded on the stock exchange, as they do while dealing with U.S. stocks in their work (section 2.5). This choice is due to two reasons.

Firstly, as explained in section 2.6, since the sensitivity of the empirical findings may depend on the size of the firms in the sample, at the end of their paper the same Authors control for firms' size by excluding from the sample, in sequence, the smallest 20 percent, 40 percent, 60 percent, and 80 percent. Indeed, by excluding the bottom quintiles, they find a weakening IVOL effect, although the overall results remain statistically significant.

Secondly, the choice of the OMX Stockholm 30 Index ensures that the stocks in the sample are characterized by comparable accessibility and liquidity for both domestic and international investors. Moreover, the systematic methodology in determining the index composition runs out any personal arbitrary choice on the definition of large-cap stocks, thus making the stocks homogeneous and better comparable.

3.2 Data Collections and Sources

The stock prices employed to compute daily and monthly stocks' returns, and the market capitalization of each stock, are collected from the Swedish House of Finance FinBas Database, over the sample period

[1] The complete list of the changes in the index composition throughout the sample period is presented in the Appendix – Section 9.1, page 44.

outlined above. The procedure adopted for the calculation of returns is described in section 4.2. All stock prices are expressed in Swedish Krona (SEK).

The accounting data used to compute the measures of mispricing presented in section 4.3, are derived from Thomson Reuters Datastream database.

The Fama-French three factors (market returns minus risk-free rate, small-minus-big factor, and high-minus-low factor) are the European factors, expressed in U.S. Dollars (USD) and collected through Professor French's website database. Since the SMB and HML Swedish factors are not available from the database, it is used also the time-series of European excess market returns provided by Professor French to avoid inconsistency with the other two factors, although the same time-series may be derived for the OMX Stockholm 30 Index. This choice is supported by two empirical observations. Firstly, as described in Professor French's website, the European factors are built from the most relevant European stock markets, including the Swedish one, implying that they can be used to explain returns for each stock in the OMXS 30 index. Secondly, in every regression of the thesis, the market-beta is always significant, meaning that the European excess market returns adequately captures systematic risk for the Swedish stocks. Indeed, by regressing the European excess market returns on the OMXS30 returns, the intercept of the regression is very close to 0 in absolute value and not statistically different from zero.

The USD/SEK and EUR/SEK exchange rates employed to make the results currency-consistent, are derived from Thomson Reuters Datastream database.

Regarding the construction of the sentiment index, the book-value used to calculate the dividend premium, as well as the OMXS30 turnover, are derived from Thomson Reuters Datastream database. The Swedish industrial production and composite leading indicator are taken from the OECD database.

4 Sorting Methodologies

4.1 Preliminary Considerations

This section illustrates the methodology followed to sort the stocks of the OMX Stockholm 30 Index into six portfolios in each month. The portfolios are ordered with respect to a mispricing measure – two portfolios – and, subsequently, with respect to the stocks' idiosyncratic volatility – three sub-portfolios for each level of mispricing. While Stambaugh, Yu and Yuan (2013) create twenty-five portfolios, this thesis constructs six portfolios of five stocks, given the lower number of securities in the sample.

A preliminary definition of mispricing and IVOL, and a description of the double-sorting methodology, are necessary to answer the two fundamental research questions. By sorting stocks firstly on the level of mispricing and subsequently on the level of volatility, it is possible to empirically assess whether:

i. The stocks with the highest IVOL among the high-mispricing category in a month have the most negative average subsequent monthly returns; likewise, the stocks with the highest IVOL among the low-mispricing category in a month have the most positive average subsequent monthly returns.

ii. During high-sentiment months, the negative IVOL effect is more pronounced for overpriced stocks than the positive IVOL effect for underpriced stocks, as opposed to low-sentiment months.

4.2 Computation of Stocks' Returns

For each stock of the OMX Stockholm 30 Index, and for each month from July 2002 to December 2015, the monthly stocks' returns are computed from the last traded prices of the stocks at the end of the last trading days in subsequent months. The stock prices – collected through the Swedish House of Finance FinBas Database (section 3.2) – are adjusted for corporate actions, as to make the prices in a time series comparable over time. Since all prices are express in SEK, the returns are computed in the same currency.

4.3 Sorting Methodology: Mispricing Measure

Mispricing is defined as the difference between the observed price and the price that would prevail in absence of arbitrage risk and other arbitrage impediments (Stambaugh, Yu and Yuan, 2013). This theoretical price is assumed to be the price predicted by using the Fama-French three-factor model.

Following Stambaugh, Yu and Yuan (2013), other anomalies than those captured by the Fama-French three factors (1993) should be used as a relative measure of mispricing across stocks. Thus, referring to relevant literature, a ranking of the thirty stocks is created based on three anomalies, namely growth in total asset, growth in outstanding shares and profitability, which are available for all the stocks across the sample period. Although each anomaly constitutes itself a mispricing measure, the combination of the three anomalies aims at producing a single, univariate measure that should reduce the residual noise in every single anomaly. Thanks to this procedure, it is possible to increase the overall significance of the mispricing measures and of the entire empirical findings.

Now a more detailed description of the three variables is presented.

i. Consistent with Cooper, Gulen, and Schill (2008), growth in total assets is defined as the growth rate of total asset in the previous fiscal year.

   By analyzing U.S. stocks, the Authors find that growth in total assets strongly predicts future abnormal returns: A higher growth in total assets implies lower subsequent returns. The reason for this empirical finding lies in investors' overreaction to the better outlook for the firms' business determined by expansions in total assets, including investments, acquisitions, bank loans initiations, and public equity and debt offerings. They find that the anomaly persists also in large-cap stocks.

ii. Consistent with the methodology in Stambaugh, Yu and Yuan (2013), growth in outstanding shares is defined as the growth rate of split-adjusted outstanding shares in the previous year.

   While Ritter (1991) finds evidence of relative underperformance of stocks after their IPOs (initial public offerings), Loughran and Ritter (1995) extend these studies to measure the relative underperformance of stocks after SEOs (seasonal equity offerings). They conclude that equity issuers underperform non-issuers. The underperformance cannot be explained by either Fama-French three factors or long-term return reversals, and it remains robust even after controlling for book-to-market effects. Except for the case of Alfa Laval AB, which went public in 2002, the current analysis focuses only on SEOs, captured by the growth in outstanding shares in year *t-1*.

iii. Starting from Fama and French (2015), profitability is defined as the ratio between operating income of the previous fiscal year – net of operating interest expenses – and book value of equity at the end of the previous fiscal year.

   This third measure shows the robustness or weakness of the companies' operating profitability, moving from the empirical observation that more profitable firms tend to deliver higher future returns than less profitable ones (Fama and French, 2006). Further relevant literature (Chen et al., 2010, and Novy-Marx, 2012) uses other measures of profitability, which employ total assets at the denominator of the ratio. However, the presence of financial firms in the sample makes those definitions less robust, given the much higher leverage of financial institutions.

Consistent with the methodology adopted by Fama and French (1992) for the calculation of small-minus-big (SMB) and high-minus-low (HML) factors, the three accounting variables for each company are computed on December 31st of the year *t-1*. The stocks are then ranked based on the resulted mispricing measures from July of year *t* to June of year *t+1*. As previously outlined (section 4.1), two portfolios of fifteen stocks are formed in this way.

From an operational point of view, the rank is computed as follows[2].

As a first step, the stocks are ordered – from 1 to 30 – according to each one of the three variables. Lower rankings imply higher levels of mispricing.

i. Since higher asset growth should be associated with lower future returns, the lowest ranking is given to the stocks with the highest asset growth in year *t-1*.
ii. Since higher growth in outstanding shares should be associated with lower future returns, the lowest ranking is given to the stocks with the highest growth in outstanding shares in year *t-1*.
iii. Since lower profitability should be associated with lower future returns, the lowest ranking is given to the stocks with the lowest profitability in year *t-1*.

After this procedure, the average of the three rankings for each stock is computed, and the stocks are sorted into a highly-mispriced portfolio and a lowly-mispriced portfolio, based on the resulting average ranking. Consequently, the mispricing measure is purely cross-sectional.

4.4 Sorting Methodology: Idiosyncratic Volatility

After sorting the stocks in two portfolios with respect to mispricing, a further sort is made with the aim of creating three sub-portfolios ordered by idiosyncratic volatility within each level of mispricing.

As in Ang et al. (2006) and Stambaugh, Yu and Yuan (2013), the idiosyncratic volatility is computed at an individual stock's level. In each month over the sample period, the stocks are sorted based on their preceding-month IVOL. Indeed, for any given month in which monthly returns are computed, IVOL is defined as the standard deviation of the residuals of the regression of each stock's daily returns in the preceding month on the corresponding Fama-French daily three factors. By using the daily returns of the

[2] Additional details regarding the sorting procedure are presented in the Appendix – section 9.2, page 44.

preceding month, it is possible to introduce a relationship between past arbitrage risk and current return. Indeed, for each month, we expect the monthly returns to be influenced by the level of arbitrage risk (IVOL) in the previous period. In formula,

$$R_{i,t} = \alpha_i + \beta_i MKT_t + \gamma_i SMB_t + \theta_i HML_t + \varepsilon_{i,t} \qquad (1)$$

$$Idiosyncratic\ Volatility = \sigma_\varepsilon \qquad (2)$$

where $R_{i,t}$ are the excess daily returns of each stock in the previous month, adjusted for the USD/SEK exchange rate and in excess with respect to 1-month T-Bill, consistent with Fama-French factors; likewise, consistent with Fama-French methodology, the returns include dividends and capital gains and are not continuously compounded; MKT_t, SMB_t, HML_t are the daily Fama-French European factors for the previous month, expressed in USD, as derived from French's website; $\varepsilon_{i,t}$ are the residuals of the regression, whose standard deviation is used as a measure of idiosyncratic volatility[3].

From the definition of IVOL given above, the daily returns used refer to the period from June 3rd, 2002, to November 30th, 2015. The total number of daily observations is 3392.

Once the IVOLs are derived for each stock, the stocks are sorted each month based on their idiosyncratic volatility, thus forming three portfolios within each of the previous two mispricing levels. The final objective is to obtain – for each month – six portfolios: High Mispricing & High IVOL, High Mispricing & Medium IVOL, High Mispricing & Low IVOL; Low Mispricing & High IVOL, Low Mispricing & Medium IVOL, Low Mispricing & Low IVOL.

Thus, since in the setting of this thesis IVOL – and consequently arbitrage risk – should be analyzed at a portfolio level rather than at an individual stock's level, it is crucial to ensure that differences among individual stocks' IVOLs are automatically reflected into differences in portfolios IVOLs.

Table 1 reports the weighted-average monthly IVOLs of the six portfolios defined above, over the sample period.

The IVOL of the portfolio is calculated as the average of the IVOLs of its components, weighted by the market capitalization of each stock at the end of the previous month. It is expressed in percentage points.

[3] Further details regarding IVOL calculation are presented in the Appendix – section 9.3, page 45.

Table 1. Idiosyncratic Volatility of each Portfolio

	Highest IVOL	Medium IVOL	Lowest IVOL
Overpriced Stocks	1.93	1.26	0.93
Underpriced Stocks	1.81	1.27	0.94

The data show that portfolios' IVOLs follow the same ordering as the individual stocks constituting each portfolio, within each category of mispricing. For instance, in the category of overpriced stocks, the IVOL declines from 1.93 percent in the highest-IVOL group to 1.26 percent in the medium-IVOL group to 0.93 percent in the lowest-IVOL group. Likewise, in the category of underpriced stocks, the IVOL declines from 1.81 percent in the highest-IVOL group to 1.27 percent in the medium-IVOL group to 0.94 percent in the lowest-IVOL group.

Consistent with Stambaugh, Yu and Yuan (2013), the first important finding from Table 1 is that the differences in idiosyncratic risk across different stocks persist at a portfolio level. This means that arbitrage risk is still present at a portfolio level.

A further result from Table 1 is that in general the difference in IVOL between overpriced and underpriced portfolios is small and not likely to suggest a strong evidence of arbitrage asymmetry. Despite being different from the findings by Stambaugh, Yu and Yuan (2013) for the U.S. stocks, this result is indeed consistent with what discussed in sections 2.4-2.6: as the sample is formed by large-capitalization and frequently-traded stocks, short-sale constraints are likely to be weaker than they are for smaller and less-liquid stocks.

In summary, the double sorting procedure implemented suggests the presence of arbitrage risk across the six portfolios, exactly as predicted by the theory, but it seems to show little evidence of arbitrage asymmetry.

These observations are further empirically investigated and discussed in the next section.

5 The IVOL Effect across Different Levels of Mispricing

5.1 Introduction

The purpose of this section is to answer the first research question, thus determining the effect of idiosyncratic volatility on subsequent monthly portfolios' returns, among different levels of mispricing, and the net effect of idiosyncratic volatility across the overall sample of stocks.

As discussed in Stambaugh, Yu and Yuan (2013), arbitrage risk implies that the highest-IVOL stocks should be the most difficult to arbitrage among the relatively-overpriced stocks. Therefore, they should present the highest level of mispricing, and the lowest subsequent returns. Likewise, among the relatively-underpriced stocks, the highest-IVOL stocks should experience the highest level of mispricing, and the highest subsequent returns.

Moreover, in the eventual presence of arbitrage asymmetry, the net IVOL effect should be negative. Indeed, if short-sellers are faced with more constraints than purchasers, it should be more difficult for them to correct mispricing through arbitrage.

5.2 Methodology for the Computation of Benchmark-adjusted Monthly Returns

As a first step, the average benchmark-adjusted returns are computed for each of the six portfolios derived above. The average benchmark-adjusted returns are defined as the average monthly excess returns of the six portfolios over the corresponding returns predicted by the Fama-French three-factor regression

$$R_{i,t} = \alpha_i + \beta_i MKT_t + \gamma_i SMB_t + \theta_i HML_t + \varepsilon_{i,t} \qquad (3)$$

where $R_{i,t}$ is the excess value-weighted monthly return over the risk-free rate at month *t* for each portfolio *i* (High Mispricing & High IVOL, High Mispricing & Medium IVOL, High Mispricing & Low IVOL; Low Mispricing & High IVOL, Low Mispricing & Medium IVOL, Low Mispricing & Low IVOL). This is obtained by weighting the monthly returns of each stock within a given portfolio by its market capitalization at the close of the last trading day of the previous month. The returns are expressed in USD and in excess with respect to 1-month T-Bill, to be consistent with the Fama-French factors; likewise, consistent with the Fama-French methodology, the returns include dividends and capital gains and are not continuously compounded; MKT_t, SMB_t, HML_t are the contemporaneous monthly Fama-French European factors; α_i is the average benchmark-adjusted return for each portfolio *i*; $\varepsilon_{i,t}$ are the residuals of the regression.

Some further considerations about the methodology are outlined in the following paragraph.

The monthly value-weighted returns are originally expressed in SEK and then converted into USD, to be consistent with the Fama-French three factors, through the standard formula:

$$Monthly\ Return\ in\ USD = \frac{1 + Monthly\ Return\ in\ SEK}{1 + Monthly\ Percentage\ change\ in\ USD/SEK} - 1 \qquad (4)$$

where the monthly return in SEK is defined as above; the monthly percentage change in USD/SEK exchange rate is computed using as references the last traded prices of the exchange rate at the end of the previous month and at the end of the current month. Then, the monthly excess returns in USD are computed from the monthly returns in USD by subtracting the 1-month T-Bill rate.

5.3 Expected Results from the Theory

Now, before moving to the discussion of the empirical findings, it is useful to recap which results should be observed, given the described methodology and the findings of Stambaugh, Yu and Yuan (2013).

Firstly, the theory on arbitrage risk would suggest that, among underpriced stocks, the IVOL effect is expected to be positive, meaning that the average benchmark-adjusted return should be declining in value from the highest IVOL portfolio to the lowest IVOL portfolio. That would mean that the highest-IVOL stocks are also the most mispriced, since the highest undiversifiable volatility deters smart investors from exploiting underpricing (Shleifer and Vishny, 1997). On the contrary, among overpriced stocks, the IVOL effect is expected to be negative, meaning that the average benchmark-adjusted return should increase as IVOL decreases.

Secondly, in the eventual presence of arbitrage asymmetry, the net IVOL effect should be negative, implying that the benchmark-adjusted return of the overall high-IVOL-minus-low-IVOL portfolio should be negative. Indeed, that would signal that short-sales constraints make arbitrage more difficult for short-sellers than for purchasers.

5.4 Actual Results and Discussions on Arbitrage Risk and Arbitrage Asymmetry

Table 2 shows the benchmark-adjusted returns for each of the six portfolios created by sorting stocks on their relative level of mispricing and, subsequently, on the idiosyncratic volatility of their returns. Moreover, it reports the average benchmark-adjusted returns for the two portfolios formed by simply sorting on mispricing across the stock universe, and the average benchmark-adjusted returns for the three portfolios formed by simply sorting on idiosyncratic volatility across the stock universe, as well as the differences of the returns of the overpriced and underpriced portfolios for each level of IVOL and the differences of the returns of the highest and lowest IVOL portfolios for each level of mispricing. The relative level of mispricing is derived as in section 4.2. The IVOL is defined as in section 4.3.

Benchmark-adjusted returns are defined as in section 5.2.

All the portfolios' returns used in the regressions are value-weighted.

The t-statistics are reported in the parentheses below the coefficients. For each regression, the Breusch-Pagan test for heteroscedasticity of the residuals is conducted. Thus, in the eventual presence of heteroskedasticity, the heteroskedasticity-consistent standard errors of White (1980) are used to derive the t-statistics for the estimators of the monthly benchmark-adjusted returns. The stars show the level of statistical significance (one star for 90 percent confidence level, two stars for 95 percent, and three stars for 99 percent).

Table 2. Idiosyncratic Volatility Effects in Overpriced and Underpriced Stocks

	Highest IVOL	Medium IVOL	Lowest IVOL	Highest minus Lowest IVOL	All Stocks
Underpriced Stocks	0.74* (1.70)	0.66* (1.84)	0.31 (1.15)	0.33 (0.67)	0.39* (1.80)
Overpriced stocks	0.07 (0.15)	0.03 (0.06)	0.20 (0.67)	-0.23 (-0.47)	0.14 (0.55)
Overpriced minus Underpriced	-0.78* (-1.64)	-0.74* (-1.64)	-0.22 (-0.60)	-0.67 (-1.11)	-0.36 (-1.26)
All Stocks	0.45 (1.21)	0.03 (0.08)	0.34 (1.56)	0.01 (0.01)	

The Table shows some interesting results regarding arbitrage risk.

Starting from the group of underpriced stocks, as predicted by the theory, the effect of idiosyncratic volatility on subsequent returns is clearly positive, since the average monthly benchmark-adjusted return of the three underpriced portfolios declines as IVOL decreases. Indeed, while the estimate for average monthly benchmark-adjusted return is equal to 0.74 and statistically significant at 90 percent confidence level for the highest-IVOL portfolio, it declines to 0.66 (still significant at 90 percent confidence level) for the medium-IVOL portfolio, and to a not-statistically-significant value of 0.31 for the lowest-IVOL portfolio. As a further evidence, a value-weighted long-short trading strategy buying the highest-IVOL portfolio and selling the lowest-IVOL portfolio would yield a benchmark-adjusted return of 0.33, despite low level of significance.

Consistent with Stambaugh, Yu and Yuan (2013), the results from the group of underpriced stocks imply that IVOL plays an important role in causing arbitrage risk. Indeed, the positive monthly average benchmark-adjusted returns for high- and medium-IVOL portfolios suggest that a higher stocks' IVOL in one month makes arbitrage more difficult during that month, and generates statistically significant abnormal returns in the subsequent month, when arbitrage can finally be corrected. On the other hand, low-IVOL stocks do not experience 1-month-ahead abnormal returns because their lower idiosyncratic volatility represents a weak source of arbitrage risk, thus allowing arbitrageurs to immediately correct mispricing: low-IVOL stocks tend to be less underpriced, as opposed to medium- and high-IVOL stocks. To this extent, when most of the risk is diversifiable (as in low IVOL stocks), the Fama-French three-factor model tend to correctly predict securities' returns, implying that the market is more efficient. Therefore, the empirical findings on the OMX Stockholm 30 Index confirm that arbitrage risk is a source of market inefficiency, as discussed in behavioral finance literature (sections 2.2-2.5).

Moving to the overpriced category, the value of benchmark-adjusted returns increases as IVOL decreases, implying that the effect of idiosyncratic volatility on subsequent returns is negative, with the highest-IVOL-portfolio alpha coefficient (0.07) being lower than the lowest-IVOL-portfolio alpha coefficient (0.20). However, as it can be inferred also from the values of the estimates, the average monthly benchmark-adjusted returns are not statistically different from zero (with t-statistics respectively equal to 0.15 and 0.67). Therefore, despite being negative, the IVOL effect in the overpriced portfolio seems weaker than the positive IVOL effect in the underpriced portfolio. The same value-weighted long-short strategy buying highest-IVOL stocks and selling lowest-IVOL stocks would yield a benchmark-adjusted return of -0.23, with low statistical significance.

These results seem to hint that the net IVOL effect in the overall sample is not strongly negative, as it is instead found by Stambaugh, Yu and Yuan (2013). As a matter of fact, as reported in Table 2, a value-weighted long-short strategy that buys all the highest-IVOL stocks and sells all the lowest-IVOL stocks across the entire sample, would yield an average monthly benchmark-adjusted return of virtually zero (0.01). However, this finding is not surprising, since arbitrage asymmetry is *per se* weaker in samples of large stocks such as the one of the thesis. As predicted by the theory, because of the much higher liquidity, arbitrage constraints are generally looser than in small stocks.

In summary, consistent with the underlying theory, the data show some evidence of arbitrage risk, especially for underpriced stocks. Indeed, the IVOL effect among underpriced stocks is positive and generates statistically-significant abnormal returns for highest-IVOL stocks, while the IVOL effect among overpriced stocks is negative, despite not generating statistically significant returns. However, overall the net IVOL effect is estimated to be virtually zero. Despite being inconsistent with Stambaugh, Yu and Yuan (2013), the absence of arbitrage asymmetry is actually in line with the features of the sample used, composed by large-cap stocks only.

5.5 Exploiting Arbitrage Risk

The above-mentioned absence of arbitrage asymmetry does not undermine the role of IVOL in causing arbitrage risk – and market inefficiencies – across different levels of mispricing.

Indeed, the role of arbitrage risk is very clear from the analysis of other relevant results from Table 2.

In particular, a further confirmation of arbitrage risk is offered by the overpriced-minus-underpriced portfolios for each level of IVOL. While the average monthly benchmark-adjusted return is negative (-0.78) and significant at 90 percent confidence level for the highest-IVOL group, its size declines for the medium-IVOL category (-0.74, still significant at 90 percent confidence level), and especially for low-IVOL portfolios (-0.22, not statistically significant).

Once more, these empirical findings clearly show that, because of arbitrage risk, the highest-IVOL stocks are contemporaneously the most overpriced, within the group of overpriced stocks, and the most underpriced, within the group of underpriced stocks. This means that there is a positive IVOL effect among underpriced stocks and a negative IVOL effect among overpriced stocks.

As a consequence, the results may also suggest a possible trading strategy exploiting arbitrage risk. Over the sample period, a value-weighted long-short trading strategy that buys the Low Mispricing & High IVOL portfolio and sells High Mispricing & High IVOL portfolios, would lead to a positive average monthly benchmark-adjust return of 0.78, significant at 90 percent confidence level. As reported in the Table, this extra return – the alpha – is 42 basis points higher than the alpha obtained by buying the entire portfolio of underpriced stocks and selling the entire portfolio of overpriced stocks. It is worth mentioning that this represents a gross return, which does not include transaction costs. Indeed, as it follows from portfolios' construction, transaction costs should be higher for the former strategy than for the latter, since monthly – rather than yearly – rebalances are required. This may lead to divergences between theoretical and actual performances, the so-called implementation shortfall (Perold, 1988).

Finally, consistent with arbitrage risk, it is important to stress once more that the same long-short trading strategy would yield lower returns for value-weighted medium-IVOL portfolios, and no statistically-significant returns for low-IVOL portfolios.

5.6 Robustness Check on Currency Translation

Since the stocks' returns are originally expressed in SEK while the Fama-French factors in USD, this last section discusses a potential problem that may emerge due to the direction of currency translation. Indeed, it may be the case that the choice to convert the portfolios' excess returns from SEK to USD, rather than the Fama-French factors from USD to SEK, generates either higher or lower benchmark-adjusted returns due to the currency component.

To overcome this problem, the following robustness check has been conducted. The exact same procedure of the previous sections has been repeated by using the portfolios' excess returns expressed in SEK and computed over the Swedish 1-month risk free rate, and the Fama-French three factors converted in SEK.

This empirical check provides very similar results to the ones presented in section 5, both in terms of size and significance, leading to the conclusion that currency translation does not affect by any means the relevant findings on arbitrage risk and arbitrage asymmetry.

6 Sentiment and IVOL Effect

6.1 Introduction

The previous section clearly shows that IVOL plays a crucial role in causing mispricing, since it deters arbitrageurs from exploiting market inefficiencies.

Now, the aim of the current section is to answer the second research question, i.e. assessing whether investors' sentiment influences the direction and size of IVOL effect. For this purpose, two steps will be taken.

Firstly, it is crucial to define investors' sentiment and measure it, by discriminating between low-sentiment periods – with an overall tendency for underpricing – and high-sentiment periods – with an overall tendency for overpricing in the market.
Regarding the definition, as already pointed out, investors' sentiment is the investors' belief about future cash flows and investment risks that is not justified by the facts at hand.
Regarding the measurement, a monthly proxy for sentiment – the so-called sentiment index – is introduced in sections 6.2, 6.3.1 and 6.4.1, based on the one built by Baker and Wurgler (2006). The sentiment index indicates whether in a certain month investors' sentiment is high or low, i.e. whether a certain month belongs to either a high-sentiment period or a low-sentiment one.

Secondly, the sentiment index is used as an additional factor to predict subsequent returns for the six portfolios previously defined across different levels of mispricing and IVOL. As discussed in sections 6.3-6.4, this allows to explain the actual role of sentiment in influencing the size and direction of arbitrage risk, and thus of the IVOL effect for different categories of stocks.

Consistent with the underlying theory (Stambaugh, Yu and Yuan, 2013), the following results should hold.

During high-sentiment months, it should be observed a more pronounced negative IVOL effect among overpriced stocks and a weaker positive IVOL effect among underpriced stocks, leading to lower global returns in the subsequent month. Vice versa, during low-sentiment months, the data should indicate a stronger positive IVOL effect among underpriced stocks and a less pronounced negative IVOL effect among overpriced stocks, leading to higher global returns in the following month.

At an aggregate level, arbitrage asymmetry should be more significant in high-sentiment periods as opposed to low-sentiment ones.

6.2 Methodology: Sentiment Proxies' Computation

This section discusses how the U.S.-related sentiment index constructed by Baker and Wurgler (2006) is adapted to the Swedish sample of this study.

The first major difference with respect to Baker and Wurgler (2006) is that, while they compute the index with an annual frequency, this thesis employs a monthly frequency. This choice is due to the different length in the sample period. In fact, Baker and Wurgler (2006) analyze changes in the sentiment index over forty years, from 1962 to 2001. Moreover, by considering monthly changes in the index, the analysis below is time-consistent with the one conducted in section 5, where the six portfolios are rebalanced monthly.

The second main difference concerns the number of underlying proxies for sentiment. This thesis considers the common variation of two proxies for sentiment: the turnover of the OMX Stockholm 30 Index and the dividend premium. As described in section 2.6, Baker and Wurgler (2006) use a wider range of proxies: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The choice of using only two variables is due to data availability.

The following paragraphs present a detailed description of the two proxies for sentiment, computed monthly from June 2002 to December 2015.

i. The study computes a monthly turnover index (TURN) by assessing the monthly pattern of the OMXS30 turnover and controlling for its seasonality. For this purpose, the monthly TURN is defined as the natural logarithm of the turnover in that month divided by the average monthly turnovers of the same month in the last two years. The indicator is standardized to have zero mean and unit variance.
Indeed, Baker and Stein (2004) find that market liquidity, expressed in terms of share turnover, can be employed as an indicator of sentiment and predict lower future returns both at a firm level and at an aggregate level. In presence of short-sales constraints, the small over-confident investors tend to trade more during periods of optimism, thus increasing liquidity and share turnover. Consequently, a relatively high share turnover signals high sentiment in the market.

ii. As shown by Baker and Wurgler (2004), the dividend premium (DIVPREM) represents a valuable proxy for investors' demand for dividend-paying rather than non-paying stocks. Since Fama and French (2001) find that the latter category of companies is usually smaller, less profitable and with stronger growth opportunities, a relatively higher demand for them can be interpreted as an indicator of a higher level of sentiment from market participants.

From a practical point of view, it is essential that the proxy captures the monthly pattern of the dividend premium, while controlling for its past behavior. To ensure that the index mirrors such requisites, the following steps are implemented.

Firstly, for each year from 2001 to 2015, the thirty stocks in the sample are evenly split in two groups (high-dividend payers and low-dividend payers), based on their dividend pay-out ratios. The dividend pay-out ratio is computed as the ratio of the dividends paid by each stock in a given year, and the bid price not adjusted for later corporate actions on the day of the dividends payment.

Secondly, in each month of the year, the price-to-book-value ratio is computed for each stock. The price of a stock is defined as the market cap of the stock at the end of the month. The book value of a stock is defined as its book value of equity at the end of the latest quarter, which is considered the most indicative and time-consistent measure for the book value of equity.

Thirdly, the weighted-average of the price-to-book-value ratios is derived for high- and low-dividend-paying stock, using stocks' market capitalizations as weights[4].

Finally, DIVPREM is defined as the difference between a transformation of the price-to-book-value ratio of high-dividend-paying and low-dividend-paying stocks. The transformation is obtained by dividing the weighted-average of the price-to-book-value ratio of a stock in each month by the average of the price-to-book-value ratios of the same stocks in the past twelve months. This procedure allows to smooth possible exogenous changes in the value of the indicator, due to variation in the composition of the index. As for TURN, the indicator is standardized to have zero mean and unit variance.

Once the two proxies for sentiment are derived, they are employed to construct the sentiment index, following the same procedure as in Baker and Wurgler (2006).

[4] In this process, it is chosen not to consider the ratio for Swedish Match AB stocks, when it is negative because of the stock's negative book-value (Appendix – Section 9.2), or when it is above twenty times due to the stock's extremely low book value. This last assumption concerns the period from July 2007 to February 2009.

6.3 Base Sentiment Index: Methodology, Results and Discussion

6.3.1 Methodology: Base Sentiment Index

This section introduces the sentiment index, constructed for the Swedish stock market following the methodology described by Baker and Wurgler (2006). The sentiment index is called *base* because it does not control for macroeconomic variables, differently from the adjusted sentiment index presented in the next section.

As observed by Baker and Wurgler (2006), three important factors should be considered in the derivation of the Swedish base sentiment index.

Firstly, each of the two sentiment indicators is likely to be composed by an actual sentiment portion and an idiosyncratic non-sentiment-related one. To overcome this problem, as in Baker and Wurgler (2006), this study employs Principal Component Analysis, and extracts the common, sentiment-connected portion from the two indicators.

Secondly, one of the two variables may mirror variations in sentiment earlier than the other. To deal with this issue, it is useful to implement the same procedure as in Baker and Wurgler (2006), thus assessing whether the contemporaneous value or the first lag of each component is more significant in predicting the sentiment level.

Thirdly, since stocks' returns and Fama-French European three factors are expressed in two different currencies, the direction of the currency translation may affect the results by either increasing or decreasing the level of benchmark-adjusted returns. To avoid this eventual bias, a robustness check – similar to the one previously described in section 5.7 – has been conducted (Section 6.5), leading to the conclusion that currency translation does not affect the overall level and significance of benchmark-adjusted returns.

Therefore, consistent with these three observation, the Swedish base sentiment index is derived following a three-step procedure[5], which leads to a final sentiment index with two properties. Firstly, thanks to the Principal Component Analysis, the index considers the actual common sentiment component of the two sentiment proxies. Secondly, for each proxy, the index includes the lag predicting changes in the sentiment most appropriately.

In formula, the final Swedish base sentiment index is the following.

$$FINALSENT_t = -0.582DIVPREM_{t-1} + 0.582TURN_t \qquad (5)$$

[5] The whole detailed procedure for the base sentiment index is described in the Appendix – Section 9.4, page 46.

It is worth noting that the final base sentiment index shows two interesting features, consistent with the underlying theory and the results obtained by Baker and Wurgler (2006). Firstly, as shown in Table 7 (Appendix), there is a negative correlation of -0.47 between the first lag of dividend premium and the turnover. Secondly, as expected, the turnover gives a positive contribution to the sentiment index, while the lagged dividend premium gives a negative contribution to the sentiment index.

6.3.2 How the IVOL Effect Varies in High- and Low-Sentiment Periods

Starting from the base sentiment index derived in section 6.3.1, this section addresses the second research question by assessing if changes in investors' sentiment influence the IVOL effect. Indeed, the objective is to investigate whether:

i. A greater positive IVOL effect is observed for underpriced stocks following low-sentiment periods.

ii. A greater negative IVOL effect is observed for overpriced stocks following high-sentiment periods.

In other words, it should be determined whether the overall negative IVOL effect, which is very weak across the sample period (sections 5.3 and 5.4), is more negative and statistically stronger in high-sentiment periods, as opposed to low-sentiment periods.

Table 3 presents the differences in the IVOL effect between high-sentiment months and low-sentiment months, where high-sentiment month is defined as a month when the value of the sentiment index is greater than the sample average. The portfolios considered in the Table are the following.

i. The highest-IVOL and the lowest-IVOL portfolios within each level of mispricing
ii. The portfolio formed from the value-weighted differences between the highest-IVOL and the lowest-IVOL portfolios within each level of mispricing
iii. The two portfolios (Highest IVOL and Lowest IVOL) formed by simply sorting on IVOL across the stock universe
iv. The portfolios formed from the value-weighted differences of the returns of the overpriced and underpriced portfolios for both high and low IVOL.

In particular, as in Stambaugh, Yu and Yuan (2013), Table 3 reports benchmark-adjusted returns calculated separately after high- and low-sentiment months, for portfolios containing either the highest-IVOL stocks or the lowest-IVOL stocks, computed from the following regression.

$$R_{i,t} = a_{H,i}d_H + a_{L,i}d_L + \beta_i MKT_t + \gamma_i SMB_t + \theta_i HML_t + \varepsilon_{i,t} \qquad (6)$$

In particular, the benchmark-adjusted return associated with high-sentiment periods is the coefficient a_H of the dummy variable d_H, which takes a value of 1 when the preceding month is a high-sentiment month and 0 in the opposite case. Vice versa, the benchmark-adjusted returns associated with low-sentiment periods is the coefficient a_L of the dummy variable d_L, which takes a value of 1 if the preceding month is a low-sentiment month and 0 in the other case.

As above, all the portfolios' returns used in the regressions are value-weighted, and the t-statistics are reported in the parentheses below the coefficients. For each regression, the Breusch-Pagan test for heteroscedasticity of the residuals is conducted. Thus, in the eventual presence of heteroskedasticity, the heteroskedasticity-consistent standard errors of White (1980) are used to derive the t-statistics for the estimators of the monthly benchmark-adjusted returns. The stars show the level of statistical significance (one star for 90 percent confidence level, two stars for 95 percent, and three stars for 99 percent).

Table 3. IVOL Effects in High-Sentiment versus Low-Sentiment Months (Base Index)

	High-Sentiment Periods $a_{H,i}$			Low-Sentiment Periods $a_{L,i}$		
	Highest IVOL	Lowest IVOL	Highest minus Lowest IVOL	Highest IVOL	Lowest IVOL	Highest minus Lowest IVOL
Underpriced Stocks	0.36 (0.62)	0.19 (0.50)	0.01 (0.02)	1.20* (1.83)	0.45 (1.16)	0.70 (0.96)
Overpriced stocks	-0.37 (-0.72)	-0.07 (-0.20)	-0.45 (-0.80)	0.58 (0.72)	0.51 (1.11)	0.02 (0.02)
Overpriced minus Underpriced	-0.88 (-1.39)	-0.41 (-0.78)	-0.61 (-0.77)	-0.66 (-0.90)	0.01 (0.03)	-0.73 (-0.80)
All Stocks	0.12 (0.28)	0.28 (0.98)	-0.31 (-0.67)	0.85 (1.35)	0.42 (1.22)	0.38 (0.59)

After this premise, the following paragraphs analyze the results.

Starting from underpriced stocks, consistent with Stambaugh, Yu and Yuan (2013), it is immediately evident that the IVOL effect is more positive in low-sentiment months, as opposed to high-sentiment months.

Indeed, on the one hand, for the highest-IVOL portfolios, the monthly benchmark-adjusted returns after low-sentiment months is equal to 1.20, and statistically significant at 90 percent confidence level. Moreover, it is much higher than the one observed after high-sentiment months, which is equal to 0.36 and not statistically significant.

On the other hand, for the lowest-IVOL portfolios, benchmark-adjusted returns are higher after low-sentiment months, but neither the coefficients for low-sentiment months nor the difference with high-sentiment months are significant.

This first set of results shows that, within the group of underpriced stocks, a higher IVOL – thus higher arbitrage risk – deters arbitrageurs from exploiting mispricing to greater extent in low-sentiment months than in high-sentiment months. This implies higher future returns for high-IVOL portfolios following low-sentiment periods. Instead, when arbitrage risk is lower (low-IVOL portfolios), arbitrageurs can correct prices more easily, thus preventing abnormal future returns.

Moving to overpriced stocks, the IVOL effect seems still influenced by sentiment, although the results are less significant.

For the highest-IVOL portfolio, the estimate for the average benchmark-adjusted return has a negative sign (-0.37) after high-sentiment periods, and a positive sign (0.58) after low-sentiment periods, despite low levels of significance.

For the lowest-IVOL portfolio, instead, benchmark-adjusted returns following high-sentiment periods are less negative than they are for the highest-IVOL portfolio (-0.07), and the difference with benchmark-adjusted returns following low-sentiment periods is thinner.

Therefore, in the case of overpriced stocks, the data still indicate a difference between high- and low-sentiment periods. During high-sentiment periods, high arbitrage risk prevents arbitrageurs from exploiting overpricing by short-selling stocks, determining lower future returns for high-IVOL portfolios, as opposed to low-sentiment periods. However, the findings are weaker than in the case of underpriced stocks.

Overall, the time variation of arbitrage risk in causing mispricing is clear from the analysis of highest-minus-lowest-IVOL portfolios. After high-sentiment months, the alpha coefficient is negative for overpriced stocks (despite being statistically not significant), while it is substantially zero for underpriced stocks. On the contrary, after low-sentiment months, the estimate of alpha coefficient is positive for underpriced stocks (despite being statistically not significant), while it is substantially zero for overpriced stocks.

Finally, by looking at highest-minus-lowest-IVOL portfolio across the entire sample, it is indeed evident that the net IVOL effect varies over time. Despite low levels of significance, the estimate of the benchmark-adjusted returns is negative (-0.31) following high-sentiment periods, while it is positive (0.38) following low-sentiment periods. Compared with the aggregate estimate presented in section 5 (0.01), it may be concluded that the IVOL effect is more negative during high-sentiment months, when the short-sale constraints are more binding, than during low-sentiment months. This finding is consistent with the underlying theory and the work by Stambaugh, Yu and Yuan (2013).

However, as already noticed, the results are not always strong due to the low level of statistical significance. This may be a consequence of fact that, differently from Stambaugh, Yu and Yuan (2013), only large-cap liquid stocks are considered, for which the market tends to be less inefficient.

6.3.3 How the Base Sentiment Index Explains the Time-varying IVOL Effect

To deepen the analysis, given the behavior of portfolios' returns after high- and low-sentiment periods, it is now useful to study whether the sentiment index can be used as an additional factor predicting future returns for different portfolios. To this extent, the next paragraphs comment Table 4, which reports the value of the sentiment beta, i.e. the coefficient of the lagged sentiment index in the following regression, with the usual notation.

$$R_{i,t} = \alpha_i + \beta_{sent,i} FINALSENT_{t-1} + \beta_i MKT_t + \gamma_i SMB_t + \theta_i HML_t + \varepsilon_{i,t} \qquad (7)$$

where FINALSENT is the final standardized base sentiment index, as derived in section 6.3.2, and the other variables have the same meaning as in Table 2.

As in Table 3, the portfolios considered in the table are the following.

i. The highest-IVOL and the lowest-IVOL portfolios within each level of mispricing
ii. The portfolio formed from the value-weighted differences between the highest-IVOL and the lowest-IVOL portfolios within each level of mispricing
iii. The two portfolios (Highest IVOL and Lowest IVOL) formed by simply sorting on IVOL across the stock universe

iv. The portfolios formed from the value-weighted differences of the returns of the overpriced and underpriced portfolios for both high and low IVOL.

As above, all the portfolios' returns used in the regressions are value-weighted, and the t-statistics are reported in the parentheses below the coefficients. For each regression, the Breusch-Pagan test for heteroscedasticity of the residuals is conducted. Thus, in the eventual presence of heteroskedasticity, the heteroskedasticity-consistent standard errors of White (1980) are used to derive the t-statistics for the estimators of the sentiment beta.

Table 4. The relation between Investors' Sentiment and IVOL Effects (Base Index)

	Highest IVOL	Lowest IVOL	Highest minus Lowest IVOL
Underpriced Stocks	-0.70 (-1.45)	-0.32 (-1.22)	-0.43 (-0.86)
Overpriced stocks	-0.67 (-1.01)	-0.33 (-0.94)	-0.38 (-0.56)
Overpriced minus Underpriced	-0.02 (-0.03)	-0.06 (-0.15)	-0.01 (-0.01)
All Stocks	-0.66 (-1.36)	-0.24 (-1.00)	-0.47 (-0.98)

The sentiment beta actually shows the role of sentiment index in predicting future portfolios' returns. Consistent with financial literature and previous results, the sentiment beta should be overall negative, since high-sentiment periods are usually followed by lower returns, at an aggregate level. Furthermore, it should be more negative for high-IVOL stocks than for low-IVOL stocks, especially within the overpriced category, since a higher sentiment should make short-selling riskier for arbitrageurs.

As a matter of fact, the sentiment beta is generally negative and more negative for high-IVOL stocks than for low-IVOL stocks, for both the underpriced and overpriced category. Indeed, despite low levels of significance, the sentiment beta for high-IVOL overpriced portfolios is equal to -0.67, more negative the -0.33 of the low-IVOL, overpriced portfolios. A similar pattern is observed within the underpriced category. However, inconsistent with the theory, the sentiment beta does not differ so much across the different levels of mispricing, with the estimate of sentiment beta being only slightly more negative for high-IVOL overpriced stocks than for high-IVOL underpriced stocks.

Finally, and most importantly, despite low levels of significance, the sentiment beta for the highest-minus-lowest-IVOL portfolio across all stocks is negative (-0.47). Consistent with the previous observations and with the underlying theory, this result further indicates that a higher investors' sentiment generally has a more pronounced negative influence on the subsequent returns of the stocks with higher arbitrage risk. Besides, this also confirms that the IVOL effect changes over time, being more negative after high-sentiment months than after low-sentiment month.

6.3.4 Conclusions from the Base Sentiment Index

Consistent with Stambaugh, Yu and Yuan (2013), the data show a negative relation between investors' sentiment and subsequent returns, especially for the highest-IVOL portfolios, which are the riskiest to arbitrage.

As a matter of fact, at an aggregate level, high sentiment causes a more pronounced negative IVOL effect, with lower predicted returns for higher-IVOL stocks than in the whole sample period. Indeed, high sentiment, combined with arbitrage risk, makes it riskier to correct mispricing through short-selling. Likewise, at an aggregate level, low sentiment causes a positive IVOL effect, with higher predicted future returns for higher-IVOL stocks than in the whole sample period. Indeed, low sentiment, together with arbitrage risk, makes it riskier to correct mispricing through stocks' purchasing, leading to higher future returns.

6.4 Adjusted Sentiment Index: Methodology, Results and Discussion

Following Stambaugh, Yu and Yuan (2013), this section introduces a further refinement to the sentiment index. Indeed, although the base final sentiment index runs out the idiosyncratic component of each individual indicator by capturing only the common component, it may fail to distinguish between the actual sentiment component and the business-cycle component.

6.4.1 Methodology: Adjusted Sentiment Index Derivation

To control for changes in the overall level of the economy, a similar procedure to the one of Baker and Wurgler (2006) is implemented. The two raw indicators, turnover and dividend premium, are regressed on the contemporaneous monthly growth in industrial production and the contemporaneous monthly growth in the Swedish composite leading indicator derived from the OECD Database. The residuals of the two regressions are used as the new proxies for sentiment, since they should express the true sentiment component embedded in the two indicators.

Once the two new proxies for true sentiment are derived, an adjusted sentiment index is computed following the exact same procedure as the one for the base sentiment index[6]. This leads to the following Swedish final adjusted sentiment index, which considers only the common variance component, employs the most explanatory lag for each sentiment proxy, and controls for macroeconomic-related components.

$$FINALSENT_{a,t} = -0.597DIVPREM_{a,t-1} + 0.597TURN_{a,t} \qquad (6)$$

As above, it is worth highlighting that, consistent with the theory, there is a negative correlation of -0.44 between the first lag of dividend premium and the turnover (Table 7 b). This result is very similar to the case of the base sentiment index. Moreover, as expected, while the lagged dividend premium enters with a negative sign, the turnover gives a positive contribution to the index.

6.4.2 How the IVOL Effect Varies in High- and Low-Sentiment Periods

In this section, the results from the adjusted sentiment index are discussed and compared with the ones derived from the base index. The purpose is to answer the following two questions.

i. Whether the positive IVOL effect observed following low-sentiment periods is simply caused by fundamental macroeconomic components, or it depends on the actual investors' sentiment.

ii. Whether the greater negative IVOL effect measured following high-sentiment periods is simply due to fundamental macroeconomic components, or it depends on the actual investors' sentiment.

As in section 6.3.2, Table 5 reports the average benchmark-adjusted returns after high-sentiment months, a_H, and the average benchmark-adjusted returns after low-sentiment months, a_L, for the same portfolios as in Table 3. The methodology employed to derive benchmark-adjusted returns after high- and low-sentiment periods is the same as in section 6.3, except for the fact that the adjusted sentiment index is employed instead of the base sentiment index. A high-sentiment month is defined as a month when the value of the adjusted sentiment index is greater than the sample average.

As usual, all the portfolios' returns used in the regressions are value-weighted, and the t-statistics are reported in the parentheses below the coefficients. For each regression, the Breusch-Pagan test for heteroscedasticity of the residuals is conducted. Thus, in the eventual presence of heteroskedasticity, the heteroskedasticity-consistent standard errors of White (1980) are used to derive the t-statistics for the

[6] The whole detailed procedure for the calculation of the adjusted sentiment index is described in the Appendix – Section 9.5, page 47.

estimators of the monthly benchmark-adjusted returns. The stars show the level of statistical significance (one star for 90 percent confidence level, two stars for 95 percent, and three stars for 99 percent).

Table 5. IVOL Effects after High-Sentiment versus Low-Sentiment Months (Adjusted Index)

	High-Sentiment Periods $a_{H,i}$			Low-Sentiment Periods $a_{L,i}$		
	Highest IVOL	Lowest IVOL	Highest minus Lowest IVOL	Highest IVOL	Lowest IVOL	Highest minus Lowest IVOL
Underpriced Stocks	0.01	0.14	-0.28	1.48**	0.48	0.94
	(0.02)	(0.35)	(-0.41)	(2.45)	(1.27)	(1.38)
Overpriced stocks	-0.74	-0.14	-0.76	0.89	0.53	0.29
	(-1.44)	(-0.37)	(-1.24)	(1.15)	(1.19)	(0.37)
Overpriced minus Underpriced	-0.90	-0.43	-0.63	-0.65	-0.00	-0.71
	(-1.41)	(-0.77)	(-0.70)	(-0.89)	(-0.00)	(-0.87)
All Stocks	-0.31	0.11	-0.58	1.23**	0.58*	0.60
	(-0.71)	(0.39)	(-1.27)	(2.14)	(1.71)	(0.96)

The results of benchmark-adjusted returns from Table 5 appear similar to those from Table 3, signaling that the true sentiment component has a prime role in determining time-changes in the IVOL effect.

Starting with underpriced stocks, consistent with the theory, it is confirmed that a higher IVOL deters arbitrageurs from purchasing stocks more in low-sentiment months than in high-sentiment months. Indeed, the highest-IVOL portfolio experiences higher and statistically significant benchmark-adjusted returns after low-sentiment periods (1.48, significant at 95 percent confidence level). Moreover, the average benchmark-adjusted return on the value-weighted long-short highest-minus-lowest-IVOL portfolio is positive (0.94) after low-sentiment periods, while it is slightly negative (-0.28) and not statistically different from zero after high-sentiment periods. This clearly shows evidence of a more pronounced positive IVOL effect among underpriced stocks in low-sentiment periods.

Moving to overpriced stocks, despite lower statistical significance, it is confirmed that a higher IVOL – thus a greater arbitrage risk – deters arbitrageurs from short-selling stocks to greater extent in high-sentiment months than in low-sentiment months. In this case, the results are still weak, but generally more significant than in the case of the base index. As observed above, this signals that investors are influenced by actual sentiment even more than they are by fundamentals. As a matter of fact, for the highest-IVOL portfolio, the average benchmark-adjusted return is negative after high-sentiment periods (-0.74), while it is positive after low-sentiment months (0.89). For the lowest-IVOL portfolio, instead, the average benchmark-adjusted return after high-sentiment periods is less negative than it is for the highest-IVOL portfolio (-0.14), and the difference with benchmark-adjusted returns following low-sentiment periods is thinner. Consequently, consistent with Stambaugh, Yu and Yuan (2013), the benchmark-adjusted for the value-weighted difference between highest-IVOL and lowest-IVOL overpriced portfolios is negative after high-sentiment periods, as opposed to low-sentiment one (-0.76 versus 0.29).

Therefore, also in the case of the adjusted index, from the highest-minus-lowest-IVOL portfolio across all stocks, it is evident that the net IVOL effect varies over time. Despite low significance, the estimate of the benchmark-adjusted returns is negative (-0.58) following high-sentiment periods, while it is positive (0.60) following low-sentiment periods. Compared with the aggregate estimate presented in section 5 (0.01), it may be concluded that:

i. The net IVOL effect is more negative during high-sentiment months, when the short-sale constraints are more binding, than during low-sentiment months.

ii. There seems to be an actual negative relation between pure investors' sentiment, controlled for the macroeconomic components, and the IVOL effect.

As pointed out in section 2.6, the second finding is particularly important in the framework of this thesis. As a matter of fact, it confirms the role of behavioral aspects in determining market inefficiencies. From a practical point of view, these inefficiencies are the result of both arbitrage risk – with the highest-IVOL portfolios presenting more extreme benchmark-adjusted returns – and arbitrage asymmetry, with the overall IVOL effect being negative. However, as noticed already, the results on arbitrage asymmetry are not very strong because of the characteristics (size and liquidity) of the stocks in the sample.

6.4.3 How the Adjusted Sentiment Index Explains the Time-varying IVOL Effect

As in section 6.3.3, further insights are derived from Table 6 reporting the value of the sentiment beta, which is defined in the same way. The sentiment index associated with the sentiment beta is the adjusted sentiment index, instead of the base one.

The portfolios analyzed are the same as in the case of the base sentiment index. All the portfolios' returns used in the regressions are value-weighted, and the t-statistics are reported in the parentheses below the coefficients. For each regression, the Breusch-Pagan test for heteroscedasticity of the residuals is conducted. Thus, in the eventual presence of heteroskedasticity, the heteroskedasticity-consistent standard errors of White (1980) are used to derive the t-statistics for the estimators of the monthly benchmark-adjusted returns.

Table 6. The relation between Investors' Sentiment and IVOL Effects (Adjusted Index)

	Highest IVOL	Lowest IVOL	Highest minus Lowest IVOL
Underpriced Stocks	-0.71 (-1.64)	-0.18 (-0.69)	-0.57 (-1.18)
Overpriced stocks	-0.99 (-1.58)	-0.44 (-1.51)	-0.60 (-0.91)
Overpriced minus Underpriced	-0.33 (-0.56)	-0.30 (-0.82)	-0.08 (-0.14)
All Stocks	-0.82 (-1.63)	-0.22 (-0.99)	-0.65 (-1.26)

The results show that the sentiment beta has the same features as in the case of the base index. In particular,

i. It is overall negative, since high-sentiment periods are followed by lower returns, at an aggregate level.

ii. It is more negative for the highest-IVOL stocks than for the lowest-IVOL stocks, especially within the overpriced category, since a higher sentiment makes short-selling riskier for arbitrageurs.

Indeed, the sentiment beta for high-IVOL overpriced portfolios is equal to -0.99 and at the border of 90-percent statistical significance, while it is less negative (-0.44) and not statistically significant for the low-IVOL overpriced portfolios. The same pattern is observed within the underpriced category. The size of the high-IVOL-portfolio coefficients is smaller, suggesting that the sentiment beta correctly predicts a greater price decrease for overpriced stocks.

Consequently, the sentiment beta for the highest-minus-lowest-IVOL portfolio across all stocks is negative (-0.65). Consistent with the underlying theory, this finding further indicates that a higher investors' sentiment generally has a more pronounced negative influence on the subsequent returns of the stocks with higher arbitrage risk. Most importantly, despite still generally low significance, the result is stronger than the one for the base sentiment index, suggesting that pure sentiment has a primary role in predicting future returns for high-IVOL stocks.

6.4.4 Conclusions from the Adjusted Sentiment Index

Consistent with the underlying theory, the data show a negative relation between the actual (adjusted for macroeconomic effects) investors' sentiment and the stocks' future returns, especially for the highest-IVOL portfolios, which are the riskiest to arbitrage.

Indeed, from an aggregate perspective, a high sentiment-level causes a more pronounced negative IVOL effect, with lower predicted future returns for higher-IVOL stocks. Indeed, high sentiment, combined with arbitrage risk, makes it riskier to correct mispricing through stocks' short-selling.

Likewise, from an aggregate perspective, a low sentiment-level causes a positive IVOL effect, with higher predicted future returns for higher-IVOL stocks. Indeed, low sentiment, together with arbitrage risk, makes it riskier to correct mispricing through stocks' purchasing, leading to higher future returns.

As already discussed in section 2.6, it is worth stressing one last time that this section results are particularly important because they reflect pure investors' behavior, with a control for business-cycle components. This means that the market inefficiencies observed in the data are actually due to arbitrage limits combined with psychological aspects, consistent with the underlying behavioral theory.

6.5 Robustness Check on Currency Translation

As in section 5.7, this section discusses the robustness test conducted on the direction of the currency translation. Indeed, it may be the case that the choice to convert the portfolios' excess returns from SEK to USD, rather than the Fama-French factors from USD to SEK, generates either higher or lower benchmark-adjusted returns due to the currency component.

Also in this case, the whole procedure presented in section 6 has been repeated by using the portfolios' excess returns expressed in SEK and computed over the Swedish 1-month risk free rate, and the Fama-French three factors converted in SEK, as well as the shares' turnover expressed in SEK.

Once more, this empirical check provides very similar results to the ones presented above, both in terms of size and significance, leading to the conclusion that currency translation does not affect the relevant findings on arbitrage risk and arbitrage asymmetry.

7 Conclusions

This thesis analyzes the effect of OMXS30 stocks' idiosyncratic volatility on their subsequent monthly returns, by exploiting the concepts of arbitrage risk, arbitrage asymmetry, and investor sentiment. In particular, the empirical study moves from two observations, based on Stambaugh, Yu and Yuan (2013).

Firstly, higher idiosyncratic volatility implies greater arbitrage risk, thus generating more pronounced mispricing. Therefore, subsequent returns of underpriced stocks should be positively related with their IVOL, while subsequent returns of overpriced stocks should be negatively related with their IVOL.

Secondly, short-sale constraints cause short sellers to have greater arbitrage limits than purchasers, meaning that arbitrage is asymmetric. As a result, the negative IVOL effect among overpriced stocks should be stronger than the positive IVOL effect among underpriced stocks: the net IVOL should be negative.

By studying the stocks constituting the OMX Stockholm 30 index, the empirical analysis finds evidence of arbitrage risk, but weak evidence of arbitrage asymmetry. Indeed, after employing a combined measure of mispricing built on three return anomalies, the study shows evidence a negative IVOL effect among overpriced stocks and a positive IVOL effect among underpriced stocks, suggesting arbitrage risk. Considering that portfolio returns are originally expressed in SEK while Fama-French factors in USD, this finding does not depend on the direction of currency translation. However, inconsistent with arbitrage asymmetry, the net IVOL effect is not statistically different from zero, although its estimate is slightly negative. This may be due to the fact that the sample includes only large-cap stocks, for which short-sale constraints are weak.

Moreover, the thesis finds evidence of a time-varying behavior of the IVOL effect, in the direction predicted by the underlying theory. Indeed, after building an investors' sentiment index for the Swedish stock market based on Baker and Wurgler (2006), the analysis finds that the IVOL effect depends on the level of investors' sentiment. Despite generally low levels of significance, the positive IVOL effect among underpriced stocks is stronger after low-sentiment periods, while the negative IVOL effect among overpriced stocks is stronger after high-sentiment period. Overall, the net IVOL effect is more negative after high-sentiment periods.

Most importantly, these results are confirmed even after netting the sentiment index from its macroeconomic elements, thus indicating that the actual behavioral component plays a primary role in determining the extent of arbitrage risk and arbitrage asymmetry in the Swedish market.

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9 Appendix

9.1 Appendix to section 3.1 (Note 1): Universe of Stocks and Sample Period

This section presents the changes in the OMX Stockholm 30 index constituents that have been considered when determining the composition of the stocks' universe.

i. January 2003: Alfa Laval AB (ALFA.SE) and Swedish Match AB (SWMA.SE) replace Pharmacia Corp. SDB (PHA.SE) and WM-data AB ser. B (WM-B.SE).

ii. July 2006: Boliden AB (BOL.SE) and Vostok Gas Ltd SDB (VGAS-SDB.SE) replace Skandia Försäkrings AB (SDIA-SEK.SE) and Fabege AB (FABG.SE).

iii. January 2007: Scania AB ser. B (SCV-B.SE) replaces Holmen AB ser. B (HOLM-B.SE).

iv. July 2007: SSAB AB ser. A (SSAB-A.SE) replaces Stora Enso Oyj ser. AE (STE-AE.SE).

v. January 2008: Lundin Petroleum (LUPE.SE) replaces Autoliv Inc (ALIV.SE).

vi. January 2009: Vostok Gas Ltd SDB (VGAS-SDB.SE) leaves the index.

vii. July 2009: Getinge AB ser. B (GETI-B.SE) and Modern Time Group MTG AB ser. B (MTG-B.SE) enter the index; Eniro AB (ENRO.SE) leaves the index.

viii. June 2014: Scania AB ser. B (SCV-B.SE) leaves the index;

ix. July 2014: Kinnevik AB ser. B (KINV-B.SE) enters the index.

Thus, over the period June 2002 – December 2015, the index is always composed by 30 stocks, except for the period January – June 2009, when Vostok Gas Ltd SDB (VGAS-SDB.SE) leaves the index without any replacement, and the month of June 2014, when Scania AB ser. B (SCV-B.SE) leaves the index without any replacement.

9.2 Appendix to section 4.3 (Note 2): Sorting Methodology: Mispricing Measures

This section presents some additional details regarding the mispricing-based sorting procedures.

With respect to the sorting methodology based on the growth in outstanding shares, since most stocks present an equal growth in outstanding shares of 0 percent or, alternatively, a growth between -1 percent and +1 percent, a rank is assigned only to the stocks with a growth outside that interval. This is aimed at improving the precision of such mispricing measure and capturing only significant SEOs and share-buybacks. Therefore, for the stocks with a growth in outstanding shares between -1 percent and +1 percent, the growth in outstanding share is not included in the computation of the average ranking.

Concerning the operating profitability measures, the profitability of a company with a negative book value of equity is set to zero, in order not to alter the results. This takes place only when calculating the profitability of Swedish Match AB at the end of the years 2011 to 2014.

Regarding the changes in the index composition taking place in January *t+1*, the mispricing measures are calculated for both the stock leaving the index and the one entering the index. For each month, the ranking is then computed by considering only the stocks included in the index in that given month. This means that two different rankings are computed, one for the thirty stocks belonging to the index from July *t* to December *t*, the other for the thirty stocks included in the index from January *t+1* to June *t+1*. This involves three cases: January 2003, January 2007 and January 2008.

In relation to the changes in the index composition taking place in July *t*, the mispricing measure is computed only for the stocks entering the index in July *t*. This is observed in four cases: July 2006, July 2008, July 2009 and July 2014.

When the index is left with only 29 constituents (January-June 2009 and June 2014), it is assumed that the portfolios with the lowest mispricing counts only fourteen components. The choice of not adding a thirtieth component is consistent with the willingness not to alter the comparability and, most importantly, the accessibility for both domestic and international investors of the stocks in the sample.

9.3 Appendix to section 4.4 (Note 3): Sorting Methodology: Idiosyncratic Volatility

This section discusses further assumptions regarding the sorting methodology based on idiosyncratic volatility. In particular, with respect to the calculation of stocks' daily excess returns, two considerations should be made.

Firstly, stocks' returns in day t – expressed in SEK – are computed by using the last traded-price of the stock in each trading day. The stock prices are adjusted for corporate actions, as to make the prices in a time series comparable over time.

Secondly, the currency translation is implemented by using the percentage daily change in the USD/SEK exchange rate, from the previous day close to the current day close, consistent with the way the stocks' returns are calculated. Since the daily changes in USD/SEK are small (the 10^{th} percentile is equal -0.91 percent and the 90^{th} percentile is equal to 0.93 percent), for any given day, the difference between the stocks' returns (expressed in SEK) and the same-day change in the USD/SEK exchange rate is used as an approximation to compute the USD returns.

It is worth outlining that the choice to translate the stocks' daily returns from SEK to USD – rather than the Fama-French European factors from USD to SEK – is due to the willingness to obtain the most precise results possible, by applying only one currency translation. Indeed, as explained in section 3.3, the European Fama-French three factors are not originally expressed in SEK, since their calculation is derived from the stocks listed on the most relevant European markets, including Sweden.

Therefore, daily excess returns are computed over the U.S. one-month T-bill rate.

9.4 Appendix to section 6.3 (Note 5): Methodology: Base Sentiment Index

Referring to section 6.3.1, this section describes the entire three-step procedure employed to derive the base sentiment index. As discussed in section 6.3.1, this procedure ensures that the final sentiment index reflects the actual common component of the two indicators, includes the lags predicting changes in the sentiment most appropriately, and controls for eventual currency-translation biases.

The steps pursued in the index construction are the following.

i. The first step implies the construction of a raw sentiment index (RAWSENT) with four loadings – the first-principal-component coefficients of the two indicators and their respective first lags. As shown in Table 7 c, by estimating the first principal component of these four variables, it is possible to get the following raw sentiment indexes, with standardized coefficients to assure unit variance.

$$RAWSENT_t = -0.302DIVPREM_t - \ 0.307DIVPREM_{t-1} + 0.300TURN_t + 0.294TURN_{t-1}$$

Two important observations are discussed below.

Firstly, the first principal component explains 69 percent of sample variance, thus capturing the majority of the common variance (Table 7 c).

Secondly, as suggested by the theory, there is a negative correlation between turnover and dividend premium. For example, the current turnover has a correlation of -0.47 with the current dividend premium and -0.47 with the first lag of dividend premium (Table 7 a). Moreover, since economic intuition and financial literature suggest that higher share turnover mirrors higher investor sentiment, while higher dividend premium reflects lower sentiment, the sign of each coefficient is changed from the first raw result. Indeed, since Principal Component

Analysis is a simple linear transformation, by modifying the signs of all coefficients, the total variance explained by the first component does not change.

ii. The second step estimates the correlation between the raw sentiment index and each of the four variables – the two current variables and the two lags – to determine the lag with the higher correlation with the index (Table 7 a). The current turnover and the first-lagged dividend premium are the components with the stronger correlations with the raw index (0.83 and -0.85, respectively).

iii. The third step computes the actual final sentiment index by re-applying the Principal Component Analysis on the current turnover and the first-lagged dividend premium. The coefficients associated with each variable are the first-principal-component loadings, and are standardized to ensure that the index has a variance of 1. Once more, the first principal component explains a clear majority of the common variance (73 percent). In formula, the final sentiment index is equal to the following linear combination (Table 7 c).

$$FINALSENT_t = -\ 0.582DIVPREM_{t-1} + 0.582TURN_t$$

As predicted by underlying theory, it is possible to observe the negative correlation of -0.47 between the first lag of dividend premium and the turnover, as well as the positive contribution of the turnover and the negative contribution of the lagged dividend premium to the sentiment index. Furthermore, the correlation between the raw sentiment index and the final sentiment index is equal to 0.97, thus indicating that little information is lost after dropping the less correlated lag of each component.

9.5 Appendix to section 6.4 (Note 6): Methodology: Adjusted Sentiment Index

Referring to section 6.4, this section describes the entire three-step procedure employed to derive the adjusted sentiment index, following the same scheme as section 9.4.

After deriving the two proxies – adjusted dividend premium and adjusted turnover –, the same procedure as the one described above is implemented.

i. The resulting raw adjusted sentiment index is the following (Table 7 d).

$$RAWSENT_{a,t} = -0.311DIVPREM_{a,t} - 0.319DIVPREM_{a,t-1} + 0.310TURN_{a,t} + 0.303TURN_{a,t-1}$$

where the notation is the same as above, and the subscripted *a* stands for *adjusted*.

As above, two observations are now presented.

Firstly, the first principal component explains and 67 percent of sample variance (Table 7 d), still capturing most the common variance.

Secondly, as suggested by the theory, although the correlations are a little weaker than in the base case, there is a negative correlation between turnover and dividend premium. For example, the current adjusted turnover has a correlation of -0.45 with the current adjusted-dividend premium and of -0.44 with the first lag of adjusted dividend premium (Table 7 b).

i. As before, the current turnover and the first-lagged dividend premium are the components with the higher correlations with the index – 0.82 and -0.84, respectively (Table 7 b).

ii. The final sentiment index is calculated as in the base case and standardized to set its variance to one, giving the following result (Table 7 d).

$$FINALSENT_{a,t} = -\,0.597DIVPREM_{a,t-1} + 0.597TURN_{a,t}$$

Tables 7

Correlations between each of the Current and Lagged Sentiment Proxies and the Raw Sentiment Index

Tables 7 a-b report the correlations between each sentiment proxy (and its respective lag) and the raw sentiment index, in the two cases analyzed (base sentiment index, and adjusted sentiment index).

As pointed out, for each index, current turnover and lagged dividend premium presents the highest correlation with the raw sentiment index.

Base Sentiment Index	DivPrem	DivPremLag	Turn	TurnLag	RawSentIndex
DivPrem	1.00				
DivPremLag	0.87	1.00			
Turn	-0.47	-0.47	1.00		
TurnLag	-0.42	-0.47	0.82	1.00	
RawSentIndex	-0.83	-0.85	0.83	0.81	1.00

Adjusted Sentiment Index	DivPrem	DivPremLag	Turn	TurnLag	RawSentIndex
DivPrem	1.00				
DivPremLag	0.84	1.00			
Turn	-0.45	-0.44	1.00		
TurnLag	-0.38	-0.45	0.80	1.00	
RawSentIndex	-0.82	-0.84	0.82	0.80	1.00

Tables 7 c-d report the coefficients for the sentiment proxies in the raw and final indexes, as well as the proportion of variance explained by each principal component in the first-step and second-step analysis, for the two indexes considered: Base Sentiment Index (Table 7c), and Adjusted Sentiment Index (Table 7d).

Raw Index	Coefficients
Div Prem	-0.302
Div Prem Lag	-0.307
Turn	0.300
Turn Lag	0.294

Number PC	Proportion of Variance
1	0.6894
2	0.2326
3	0.0471
4	0.0310

Final Index	Coefficients
Div Prem Lag	-0.582
Turn	0.582

Number PC	Proportion of Variance
1	0.7345
2	0.2655

Raw Adjusted Index	Coefficients
Div Prem	-0.311
Div Prem Lag	-0.319
Turn	0.310
Turn Lag	0.303

Number PC	Proportion of Variance
1	0.6695
2	0.2416
3	0.0558
4	0.0331

Final Adjusted Index	Coefficients
Div Prem Lag	-0.597
Turn	0.597

Number PC	Proportion of Variance
1	0.7201
2	0.2799