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THE EFFECT OF INVESTOR SENTIMENT ON STOCK MARKET RETURNS

Master Thesis

by

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MSc in Business with Major Finance

Supervisor: Patrick Konermann

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ABSTRACT

In this Master Thesis, we study whether the effect of market sentiment on stocks that possess certain characteristics is still present. Additionally, we study whether the information is tradeable by defining three degrees of tradeability. We test whether portfolios that hold certain stocks are affected by changing market sentiment in general and in the cross-section. Our findings suggest that high investor sentiment is followed by low returns and vice versa. Importantly. the relation holds when using readily available data to construct the sentiment index. We conclude that investor sentiment has predictive power in the cross-section of returns.

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1 Introduction and motivation

The efficiency of capital markets has been discussed for a very long time. Supporters of the Efficient Market Hypothesis Fama (1970) say that investors react rationally to news that affect asset prices. Although there is support for the hypothesis, there are several examples of evidence that tell us that behavioral finance has a place in asset pricing. Within behavioral finance, investor sentiment and its effect on asset prices has been discussed extensively and contributed to how we evaluate asset prices.

If financial markets are efficient, market prices should perfectly reflect systematic risk. Thus, the return one can expect to gain, is proportional to the amount of systematic risk that is taken on. Behavioural finance, however, suggests that there are explanations other than systematic risk that explain returns in financial assets and allow for over- and underreactions to news that affect the price of financial assets. Within the topic, *Investor sentiment* connects the aggregated beliefs of market participants to consequent returns and describes a psychological phenomenom in asset pricing.

In a significant contribution, Baker and Wurgler (2006) posited that stock market return risk factors are influenced by investor sentiment. They observed that some stocks exhibit abnormal subsequent returns following periods of either higher-than or lower-than-average investor sentiment levels. Some factors that seemingly have minimal impact on asset returns can show strong predictive power when conditional on investor sentiment. They categorise stocks by some certain properties: They are relatively hard to value and thus prone to a wide range of valuations, while also difficult to arbitrage. They conduct their research by constructing an investor sentiment index using several proxies for sentiment.

This thesis aims to assess the predictive ability of the Baker and Wurgler (2006) sentiment index on cross-sectional returns using ex-ante available or *tradeable* data. Our research questions are:

"Does investor sentiment help explain cross-sectional stock returns?"

And

"Can the sentiment index explain cross-sectional returns when using tradeable data?"

The first research question is interesting to see if Baker & Wurgler's sentiment index *still* hold explanatory power over stock returns. To build on our first research question, we define *tradeable data* as data that is readily available to investors before making their investment decision. We also identify three degrees of data availability to create indexes that can answer our second research question.

As a measure of cross-sectional variance, we sort stocks from Nasdaq and NYSE based on their monthly trading volume and their market capitalization into quintiles to form portfolios. We perform regression analyses that are conditional on the investor sentiment index to see if it explains asset returns in our portfolios. By running regressions on the replicated sentiment index from Baker and Wurgler (2006), we answer the first research question. By running regressions on the indexes using *tradeable* data, we answer our second research question.

Understanding the effect of investor sentiment on stock returns is important for several reasons. Firstly, if investor sentiment can affect asset prices, it implies presence of irrational behaviour in financial markets. This adds to the need to research the topic further. Furthermore, if investor sentiment can be reliably quantified and predicted using tradeable data, it could offer a valuable tool for investment managers and other practiotioners. Institutional investors, whose decisions often have far-reaching impacts on the markets, can use these findings to refine their models and strategies, potentially enhancing returns and better mitigate risks. Private investors can also benefit from understanding investor sentiment's role in asset returns by enhancing their investment decision-making process.

2 Literature review

Literature which is relevant for the research question has been reviewed. Firstly, literature regarding the efficiency of capital markets has been considered, to lay the foundation for our research on investor sentiment's role on asset pricing. Secondly, the capital asset pricing model and models based on risk factors are discussed. Lastly, we have reviewed literature on how sentiment is found to affect asset prices in previous work, to address the relevancy of our research question.

2.1 The efficient market hypothesis

The efficient market hypothesis (EMH) proposes that financial markets are efficient and therefore that it is impossible to consistently outperform the market by using any information that is already available to the public Fama (1965). The theory was groundbreaking at the time of publication, but its validity has been scrutinised since it was published.

For reasons related to testing the hypothesis, three different forms of market efficiency has been specified; Weak, semi-strong and strong. Fama revisited the theory as well as the empirical evidence and found evidence for the weak and semi-strong form of efficiency when reviewing the literature available at the time, meaning prices incorporate public information and past prices Fama (1970). Fama (1991) reviews literature some 20 years later and again finds that markets are quite efficient when faced with firm-specific news. However, Grossman and Stiglitz (1980) presents the Grossman-Stiglitz paradox: A truly efficient market removes the incentive for investors to conduct research of available information, which in turn results in an inefficient market, since no-one will bother to conduct the necessary research.

Numerous papers have been published challenging the efficient market hypothesis. De Bondt and Thaler (1985) and De Bondt and Thaler (1987) present evidence that investors tend to overreact to surprising and dramatic news, resulting in past losers outperforming past winners. Results in Chopra et al. (1992) coincide with this finding, even after adjusting for size and beta, while

Jegadeesh and Titman (1993) finds that in a 3-12 month period, past winners outperform past losers, indicating a momentum effect in stock returns. Furthermore, Chan et al. (1996) conclude that the stock market responds only gradually to new information. Also, several considerations such as shorting constraints from Frazzini and Pedersen (2014) can explain how the market is in fact inefficient. On the other hand, Schwert (2003) discusses the possibility that anomalies are more apparent than real and uses the empirically evident phenomenon that a broad range of anomalies have disappeared after its discovery as basis for their argument. Additionally, several papers question the methodologies used in research concluding that markets are inefficient, such as Barber and Lyon (1997), Kothari and Warner (1997) and Lyon et al. (1999).

2.2 Asset pricing models and established risk factors

At the heart of asset pricing theory, we have the discussion of the relationship between risk and returns. The Capital Asset Pricing Model (CAPM) was first proposed as a model that captures the linear relationship between expected returns and market volatility by Sharpe (1964) and Treynor (1961). The theory has been revised repeatedly, leading to a fruitful discussion of its validity and drawbacks. Lintner (1965) clarifies the theory by adding that the risk premium one can expect for a security is determined by both its variance *and* by its covariance with the portfolio it is in.

Several assumptions are made in the theory and even under these assumptions, the theory has been critiqued. Famously, Roll (1977) presents issues when testing the hypothesis. Firstly, no correct and unambiguous test of the theory has appeared in literature and secondly, there is no posibility that such a test can be accomplished Roll (1977). Banz (1981) argues that Roll's critique leads to wrongful rejection of the theory, if the market portfolio used in hypothesis tests is not the true market portfolio.

An extension to the CAPM by a set of common risk factors were developed by Fama and French (1993). They found after ideas from Fama and French (1992) on how fundamentals relate to stock size and book-to-market, that these can proxy for common risk factors in equities. The research was based on data collected from NYSE equities from 1963 until 1991. The authors found that market return, SML and HML does a good job explaining common variation in stock returns.

The Small Minus Big (SMB) factor abbreviates the size effect in financial markets. This effect is characterized by the observation that smaller firms, in terms of market capitalization, tend to yield higher returns than larger firms, often termed "big" stocks. This phenomenon is rooted in the economic rationale that smaller firms are usually associated with higher risk and uncertainty.

The High Minus Low (HML) factor encapsulates the value effect in financial markets. This effect manifests as the tendency for stocks with high book-to-market ratios, typically classified as "value" stocks, to yield higher returns than stocks with low book-to-market ratios, often termed "growth" stocks. This distinction mirrors the economic rationale that companies with high book-to-market ratios are usually more distressed and therefore carry higher risk. Investors, in turn, demand a higher rate of return for bearing this increased risk as with SMB.

This three-factor model represents a significant leap forward in our understanding of equity return variations. It suggests that company size and book-to-market values, along with market risk, are critical determinants of stock returns as an extent to CAPM. This acknowledgement of multiple sources of market risk marked a significant shift in asset pricing theory, emphasizing the complex, multi-faceted nature of risk in financial markets.

Momentum, as a risk factor, has been the subject of substantial academic investigation ever since it was identified by Jegadeesh and Titman (1993). This empirical regularity reflects the tendency for stocks with high returns over the past 3 to 12 months to continue to perform well in the near future, and conversely, for stocks with low past returns to continue to perform poorly. This phenomenon of past returns predicting future performance contradicts the efficient market hypothesis, leading to a wealth of research into its causes and implications.The authors found significance in their analysis, thereby extending the commonly used risk factor models.

2.3 The role of sentiment in asset pricing

Classical financial theory would suggest, as presented above, that there is no room for sentiment when determining financial asset prices. The field of sentiment has been researched multiple times and in the following, we discuss its role in answering our research question.

There is no straight forward solution to defining investor sentiment. Baker and Wurgler (2006) shows that investor sentiment can be quantified to an index, providing a relatively precise and practical way of estimating investor sentiment levels. They perform principal component analysis on factors such as closed-end fund discount, trading volume of stocks on NYSE, number of IPOs, (volume), returns on the first day of IPOs, dividend premium (log difference of average BM ratios between payers and non-payers) and share of equity in new capital issues.

Evidence in Baker and Wurgler (2006) support the prediction that investor sentiment has large effects on difficult-to-arbitrage stocks and uncertain valuation securities.

The authors no longer incorporate NYSE turnover as a measure due to the radical shifts in the trading landscape over recent years. The advent and proliferation of institutional high-frequency trading has significantly altered the trading velocity and volume, making measures like NYSE turnover potentially less representative of the overall market behavior. Additionally, the migration of trading to a multitude of venues, including various alternative trading systems and electronic communication networks, has fragmented the marketplace.

Earlier research presented in Brown and Cliff (2004) suggests that past returns have some sentiment incorporated which can be extracted. They use factors like CEFD first presented in Lee et al. (1991), as well as introducing derivatives variables. Derivatives variables is defined as net position in SPX futures where non-commercial trades represent institutions and small traders for individual sentiments. Resulting tests indicate that sentiment has little predictive power over short-term future returns and small stocks.

Building on ICAPM from Merton (1973) suggesting macroeconomic factors should be priced in the stock market, Shen et al. (2017) proposes there is predictability from defining a sentiment proxy. The study uses different macroeconomic factors such as consumption growth, TFP growth, industrial production growth, term -and default premium, changes in expected inflation, aggregate market volatility, market returns and labor income growth as proxies for investor sentiment. The authors conclude with high-risk portfolios earn significantly higher returns than low-risk portfolios following low-sentiment periods.

Da et al. (2011) explores the role of attention as a facet of investor sentiment, positing that stocks receiving higher media coverage generate higher returns due to increased investor attention. Stambaugh et al. (2012) also built on the theme of investor sentiment, linking it to the explanation of stock market anomalies. Their research suggested that high sentiment predicts low future returns in speculative stocks. Baker et al. (2012) extended the discussion to a global context, creating sentiment indices for six major markets and finding that local sentiment is an important driver of local market returns. Huang et al. (2015) refined the measurement of investor sentiment, proposing a new index that combines six existing measures. They found this combined sentiment index to be a powerful predictor of future stock returns. Cen et al. (2013) delved into anchoring bias, a specific behavioral finance concept, and found it impacts equity market dynamics, influencing both analysts' earnings forecasts and stock returns. Lastly, Glaser and Weber (2017) took an innovative approach by examining the role of entertainment and sentiment in financial markets, discovering that entertainment can induce trading activity and impact prices. These papers underscore the significance of investor sentiment in financial markets and its pervasive influence on asset pricing.

Past research suggests that investor sentiment has a place in asset pricing models. The goal of this thesis is to identify whether or not *tradeble*, as defined later in the paper, can predict abnormal stock returns for certain stocks.

3 Testable hypothesis

Our hypothesis states that investor sentiment does *not* help explain cross-sectional variations in the importance of firm characteristics on stock returns.

We will answer our research question by running characteristics regressions like in Baker and Wurgler (2006):

$$E_{t-1}[R_{it}] = \alpha + \alpha_1 T_{t-1} + \boldsymbol{\beta_1^T} \boldsymbol{x_{it-1}} + \boldsymbol{\beta_2^T} T_{T-1} \boldsymbol{x_{it-1}} \tag{1}$$

Where t denotes time, i indexes portfolios of stocks, T represents investor sentiment and $\boldsymbol{x}$ is a vector of well-established risk factors, namely the Fama French 3-factor model (FF3). The model connects the expected next-period return of a portfolio to today's level of investor sentiment through the overall level as well as the cross products with the FF3 factors. The different characteristics of stocks should be contained in the portfolios, making it a simple matter to test different the effect of investor sentiment on different stock characteristics.

Stating the general equation (1) allows us to answer both of our research questions by running regressions on four different indexes. It also allows us to control for generic effect of sentiment on *all* stocks as well as for the effect on the cross-section of returns. The focus for our thesis is on α_1. Equation (1) leads us to the null- and alternative hypothesis:

$$H_0: \ \alpha_1 = 0 \qquad \text{vs.} \qquad H_A: \ \alpha_1 \neq 0$$

If α_1 is different from zero, the returns of portfolio i, containing stocks characterised by the same common metric, are affected by changing levels of investor sentiment. Thus, our hypotheses answer whether investor sentiment can help explain cross-sectional stock returns. Furthermore, by running the general equation on investor sentiment indexes constructed using ex ante available data, we can infer whether said index can predict abnormal stock returns.

4 Methodology

In order to answer our research questions, we begin by replicating the investor sentiment index from Baker and Wurgler (2006). The replicated index can be used to answer our first research quesiton. However, the replicated index has a problem concerning the availability of data to answer our second research question. Therefore, we define *tradeable data* as data that is readily available to any investor before making an investment decision. To build our analysis we identify three degrees of *tradeability*:

- 1st degree - In-sample "simple" data
- 2nd degree - Out-of-sample full data
- 3rd degree - Out-of-sample "simple" data

In-sample "simple" data is defined as the two proxies concerning IPOs using the full dataset, namely the number of IPOs and the first-day returns of IPOs. Out-of-sample full data is defined as all five proxies, but where the proxies are out-of-sample. Finally, out-of-sample "simple" data is defined as the proxies concerning IPOs, only using out-of-sample data. The third degree of availability is key to answer our second research question, as it is truly *"tradeable"* and readily available to any investor before their investment decision is made. The proxies are defined and discussed in greater detail in part 4.1.1.

4.1 Replicating the original investor sentiment index

4.1.1 Proxies for sentiment

To replicate the sentiment index from Baker and Wurgler (2006), we use five proxies for investor sentiment:

- The number of IPOs
- First-day returns of IPOs
- Value-weighted dividend premium
- Closed-end fund discount
- The equity share of new issues

In their original paper, Baker and Wurgler (2006) also used NYSE turnover as a sixth proxy. However, due to the increase in the share of turnover that is related to high-frequency trading, they no longer use the proxy in their updated dataset.

4.1.2 Principal component analysis

The index from Baker and Wurgler (2006) uses principal component analysis (PCA) to create the first principal component of the proxies. To obtain the first principal component of the proxies, we perform the following steps:

1. Standardise the variables by subtracting their mean and dividing by their standard deviation
2. Construct the correlation matrix Π
3. Decompose Π to the eigenvalues λ and eigenvectors c

$$\underset{n\times n}{\Pi} = \underset{n\times n}{c^{-1}} \underset{n\times n}{\lambda} \underset{n\times n}{c} \tag{2}$$

where

$$\lambda = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda 2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix}$$

and

$$c = \begin{bmatrix} c_{1,1} & c_{1,2} & \dots & c_{1,n} \\ c_{2,1} & c_{2,2} & \dots & c_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n,1} & c_{n,2} & \dots & c_{n,n} \end{bmatrix}$$

4. Sort the eigenvalues to obtain the eigenvectors by solving the relation for c

Eigenvalues are sorted in descending order. Thereby, the first eigenvalue equals the first principal component, and so on. We use the first principal component as the sentiment index and compute it as

$$pc_{1,t} = c_{1,1}\frac{x_{1,t} - \overline{x_1}}{\sigma_1} + c_{2,1}\frac{x_{2,t} - \overline{x_2}}{\sigma_2} + \cdots + c_{n,1}\frac{x_{n,t} - \overline{x_n}}{\sigma_n}$$

For each observation t. As a measure of how much of the variation in the data that is explained by the first principal component, we have that

$$\phi_1 = \frac{\lambda_1}{\Sigma_{j=1}^{n}\lambda_j}$$

Where λ_1 is the eigenvalue corresponding to the first principal component. ϕ_1 is computed as the amount of explained variation in the first principal component can impact final results.

4.2 The index using only IPO data - In-sample

Using the same methodology as when replicating the Baker and Wurgler (2006) index, we create an index using only the two proxies relating to IPOs. The resulting index represents the first degree of *tradeability* defined earlier and serves as a comparison to the replicated index.

4.3 The indexes using out-of-sample data

To see whether the index can predict asset returns, we need a methodology that uses *tradeable* data as defined earlier. The in-sample index uses the correlation matrix of the full sample to create a timeseries of the first principal component. In order to obtain a value for the sentiment index using only ex-ante available data, we perform the following steps:

1. Define a time window size for which the index should use data
2. At each period t in the remaining dataset, run PCA on observations t - window size $\rightarrow t-1$

3. Define the latest observation $t-1$ of the resulting time series as period t's value for the out-of-sample index value.

That way, the correlation matrix used to perform PCA is based on ex-ante available data. For example, using a 240-period window, the first observation of the index would use observations $1 \rightarrow 240$ to create a time series of the first PC. Observation 240 would then be used as the first observation for the index. We perform this methodology using a rolling window of 240 periods to create the two remaining indexes based on second- and third degree *tradeable data* as defined earlier. The window size is picked while trying to strike a balance between stability and responsiveness. A larger window could provide more stable results, but at the expense of being slow to respond to changes in the underlying data.

4.4 Creating portfolios

Baker and Wurgler (2006) identify stocks that are hard to 1) Arbitrage and 2) Value and therefore relatively more prone to wide speculation are more affected by changing levels of investor sentiment. In line with the objective of this thesis, we categorise stocks on two *readily available* variables that are thought to be linked with these measures:

1. Their market capitalization
2. Their trading volume for the period

Low market cap. stocks are typically young companies that have an unproven record; Their valuations are more likely to be based on future earnings growth and thereby more prone to a wide range of speculation. Low volume stocks are thought to be hard to arbitrage as they pose relatively more liquidity risk than high volume stocks and therefore relatively more risk when shorting. We sort stocks into five portfolios based on their value in each of the variables. We create the following portfolios:

Portfolio	Description
P1 - Market cap.	Stocks with low market cap.
P5 - Market cap.	Stocks with high market cap.
P1 - Volume	Stocks with low volume
P5 - Volume	Stocks with high volume
P1 - P5 Market cap.	Long-short portfolio of P1 - P5 Market cap.
P1 - P5 Volume	Long-short portfolio of P1 - P5 Volume

Table 1: Portfolio sorts

Meaning we have portfolios for the two extremes as well as a long-short portfolio in each category. In order to capture the intended trading volume effect in the respective portfolio and to ensure a similar approach for both portfolios, we create equal-weighted portfolios of the selected stocks to compute the total returns of each portfolio.

4.5 Regressions

4.5.1 Model and variables

For each of the portfolios, we run regressions of the form of equation (1). The explanatory variables we use are the risk factors presented by Fama and French (1992), Mkt-Rf, SMB and HML (FF3). Additionally, we create variables of the products of the FF3 variables and the sentiment index. The regressions are run for all four of the sentiment indexes described earlier.

4.5.2 Interpreting the results

Running the regressions will output coefficients for each explanatory variable. Table 2 is a summary of our expectations for the coefficient signs for each portfolio, regardless of what index is used as the conditional variable.

Portfolio/Coefficient	$\alpha_1 T$	$\beta_1 smbxsent$	$\beta_2 hmlxsent$
P1 - Market cap.	-	-	-
P5 - Market cap.	+	+	+
P1 - Volume	-	-	-
P5 - Volume	+	+	+
P1 - P5 Market cap.	-	-	-
P1 - P5 Volume	-	-	-

Table 2: Our expectations for the main coefficients from our regression

Where *smbxsent* and *hmlxsent* are the products of the FF3 control factors and the sentiment index. Baker and Wurgler (2006) find that when beginning-of-period sentiment is high, subsequent returns are low for the selection of stocks we consider. This expectation is derived from the logic that when sentiment is high, asset prices are inflated above their fair value, leading to lower subsequent returns. Therefore, there should be a negative relationship between returns on speculative stocks and levels of sentiment.

5 Data

The data used for our analysis are divided into three main categories: 1) Sentiment-related data for the index, 2) Stock data for the full period and 3) Data on the FF3 factors. In the following, we describe the data, its origins as well as the necessary steps taken to make the data applicable to our analysis.

5.1 Proxies for investor sentiment

Raw data for the sentiment index is accessed from Wurgler's official research website. By using this dataset we ensure comparability of our results to theirs. The data contains the following proxies for investor sentiment:

- pdnd → Value weighted dividend premium

- ripo → First day return of IPO's
- nipo → Number of IPO's
- cefd → Closed-end fund discount
- s → Equity share in new issues

Table 3 displays the summary statistics of the proxies

Variable/Metric	Mean	Standard deviation	Max	Min	N	Frequency	Start	End
pdnd	-3.2175	15.0040	32.9000	-50.2300	738	Monthly	196101	202206
ripo	17.8603	20.1027	146.8000	-28.8000	723	Monthly	196001	202206
nipo	26.0693	23.7748	151.0000	0.0000	750	Monthly	196001	202206
cefd	8.9222	6.7569	25.2800	-10.9100	684	Monthly	196507	202206
s	0.1698	0.0825	0.4300	0.0400	763	Monthly	195812	202206

Table 3: Summary statistics

5.1.1 Data manipulation and handling

The dataset contains some missing values for variables 'pdnd', 'cefd' and 's'. In these instances, we have linearly interpolated the missing values to obtain values for the sentiment index throughout the full data sample. We deem linear interpolation as an appropriate method of dealing with missing values, weighed against the prospect of missing values for the index due to the nature of the variables. Furthermore, 'pdnd' is lagged by 12 periods and 'ripo' and 'nipo' is transformed to 12-,month averages to reduce the impact of short term trends. For 'nipo', we calculate a rolling cumulative sum. For 'ripo', we compute a weighted average over the past twelve months using the corresponding 'nipo' values as weights.

5.2 Stock Data

The primary data source for stock data is the Center for Research in Security Prices (CRSP) accessed via Wharton Research Data Services (WRDS). This dataset encompasses comprehensive information on all companies listed on the New York Stock Exchange (NYSE) from 1965 to 2022, including those that have been de-listed or gone bankrupt, thereby mitigating survivorship bias in our analysis.

The dataset contains data on identifiers such as company names, tickers, PERMNOs as well as financial metrics such as total return, market capitalisation and trading volume. To ensure we avoid spurious results, missing values are removed from the dataset. The frequency of the dataset is monthly for all variables.

5.3 FF3

The Fama-French three-factor model data was obtained directly from the official research website of Kenneth French. Their three-factor model serves as control variables for our regressions, to control for risk factors embedded in said factors.

6 Results and Analysis

In the following, we present our analysis in the relevant stages. We replicate the sentiment index from Baker and Wurgler (2006) and extend the analysis by creating the three additional indexes. The in-sample index based on only the IPO data retain a lot of the variation from the original index. The out-of-sample indexes are clearly affected by not having the full sample to be constructed on, but retain some of the variation from their in-sample counterparts. These results are encouraging for the main analysis and lead to our results in large parts aligning with the ones from Baker and Wurgler (2006) for the in-sample data. For the out-of-sample data, the results are less stable: For some tests, our alternative hypothesis is confirmed, but not with the same significance as for the in-sample data.

6.1 The indexes

Based on the previously defined degrees of *tradeablility*, four indexes have been constructed and compared to each other as well as to the original index by

Baker and Wurgler (2006). In the following, we compare the indexes, as it adds to the final results and can help in the discussion of potential deviations from our expectations.

6.1.1 The replica index

The replica index has a correlation of 0.96 with the index from Baker and Wurgler's dataset. The disparity from the original index origins from missing datapoints in our dataset. Baker and Wurgler report index values for periods where they don't report values for the proxies in their dataset. In these cases we have interpolated the dataset linearly between datapoints. Figure 1 shows us the replicated index across the data sample.

Figure 1: The index from Baker and Wurgler (2006) replicated

As an ad-hoc test of the validity of the index, we refer to the chain of arguments made by Baker and Wurgler (2006): The sentiment index seems to line up very well with historic examples of bubbles and crashes.

6.1.2 1st degree tradeability: The simple index on in-sample data

As a test on whether easily obtainable data can help explain much of the variation, we construct the index using only the IPO data, the 2nd degree tradeability. The IPO data is deemed easily obtainable as it is available right from market places such as stock broker platforms. Figure 2 displays the index.

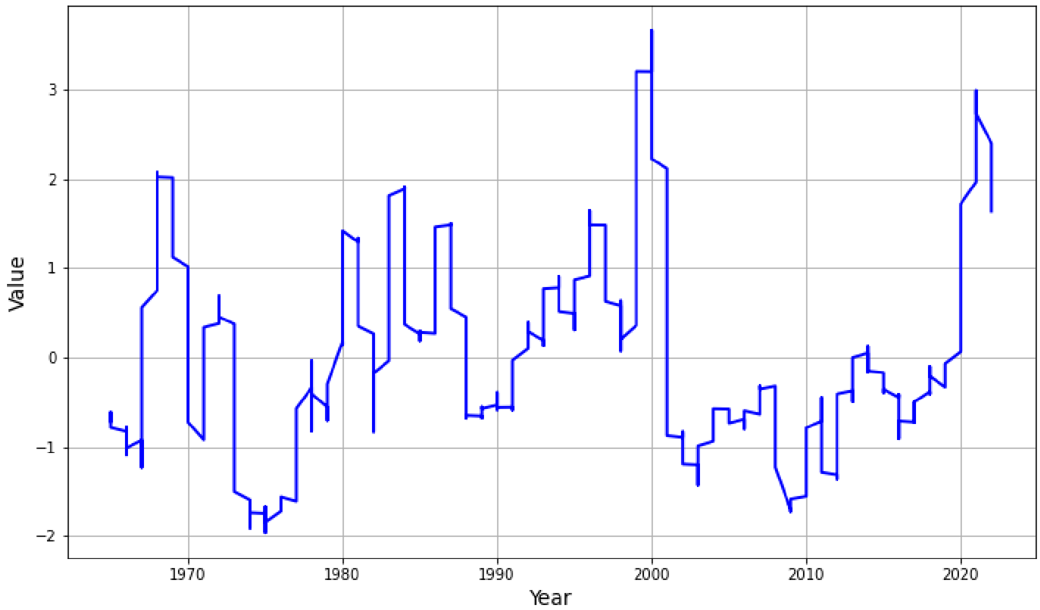

Figure 2: The index using only IPO data

A first-glance test suggests that the simple index retains most of the variation of the replica index, however that there are differences in the two.

6.1.3 2nd degree tradeability: The replica index on out-of-sample data

Using the methodology from part 4 of the thesis, we construct the replica index based on 2nd degree tradeable data. Figure 3 displays the index.

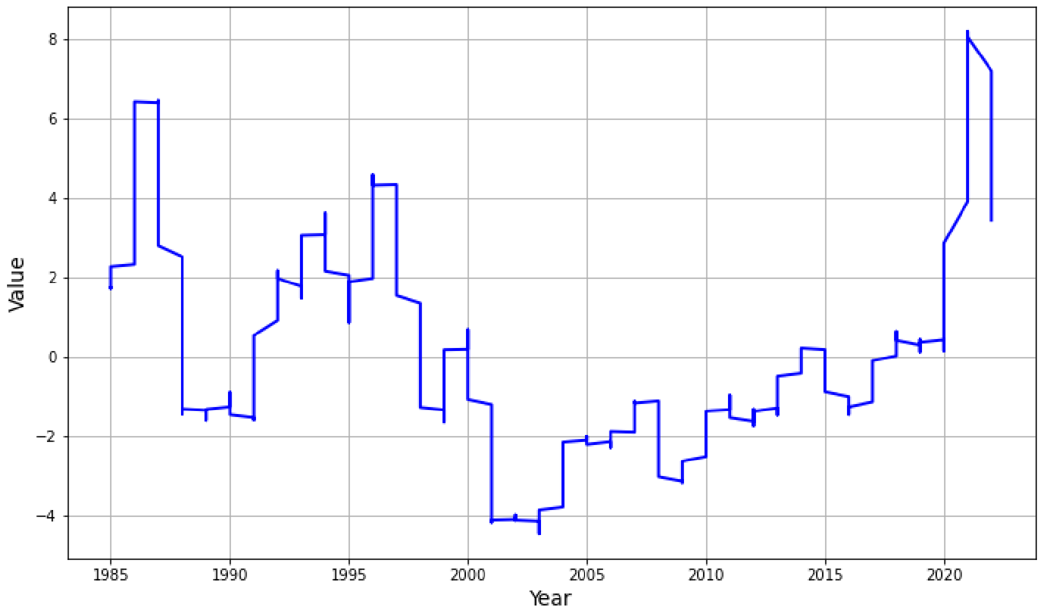

Figure 3: The index using five proxies

6.1.4 3rd degree tradeability: The simple index on on out-of-sample data

In-sample, the index retained almost all of its variation compared to the replica index. Figure 4 displays the index.

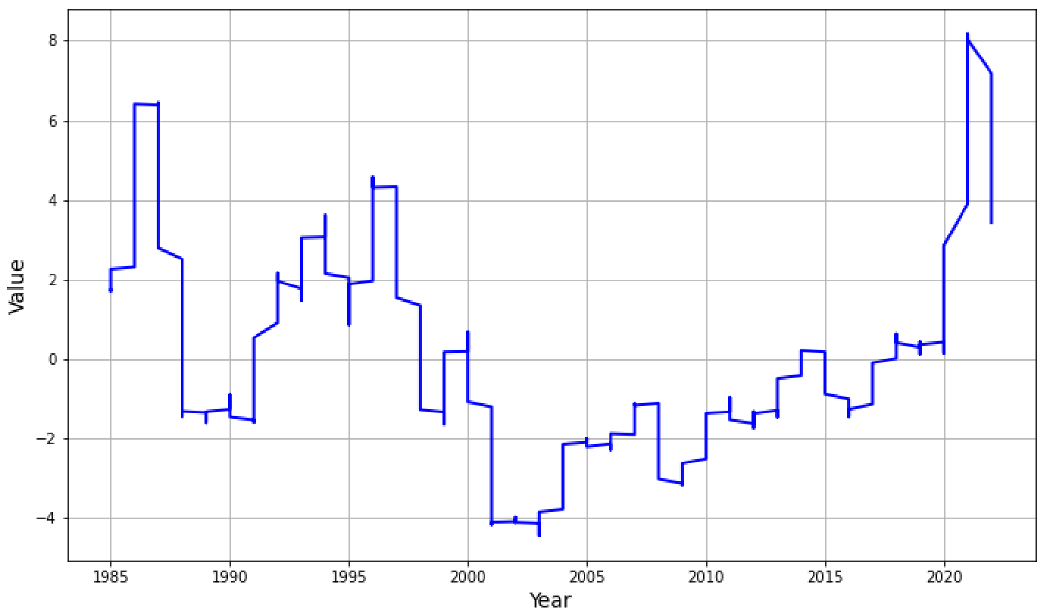

Figure 4: The index using only IPO data

6.1.5 Comparing the indexes

Figure 5 displays the four indexes for the part of the data containing the out-of-sample data.

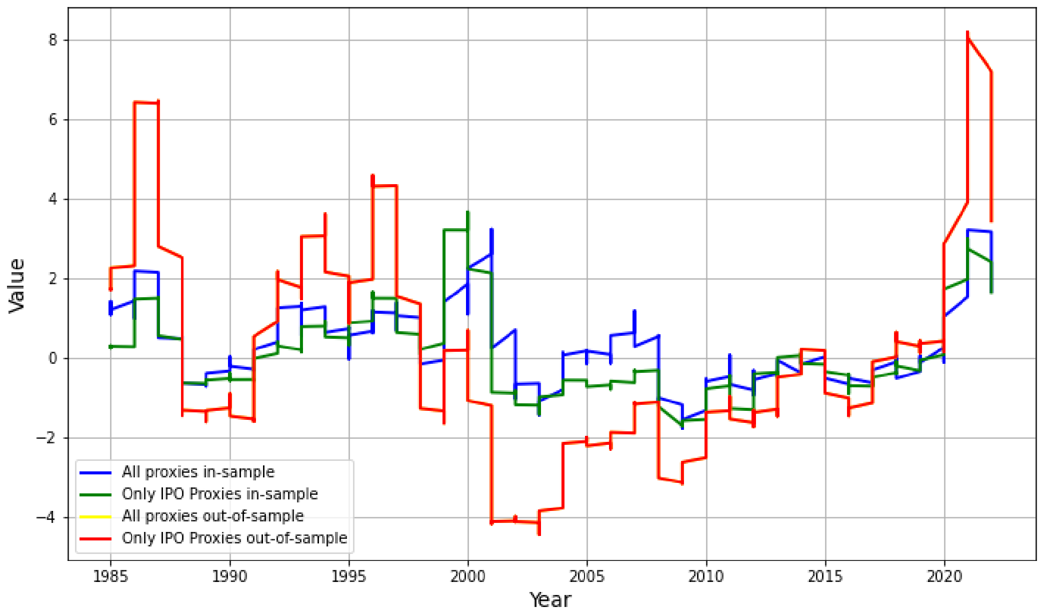

Figure 5: A comparison of all the indexes in the out-of-sample part of the data

The replicated portfolio using all five of the proxies for sentiment line up quite well. However, the IPO data don't seem to capture the volatility in sentiment levels as well as the original index. The two have a correlation of more than 0.8, meaning *most* of the variation is kept. The out-of-sample indexes have a correlation of close to 1, making it difficult to distinguish them in the plot. The finding of most importance is the fairly high correlation between the in-sample and out-of-sample indexes as can be seen in Table 4.

	Replica index in-sample	Simple index in-sample	Replica index out-of-sample	Simple index out-of-sample
Replica index in-sample	1.0000			
Simple index in-sample	0.8277	1.0000		
Replica index out-of-sample	0.7050	0.7291	1.0000	
Simple index out-of-sample	0.7049	0.7292	1.0000	1.0000

Table 4: Correlation matrix

The fairly high correlations should mean the out-of-sample indexes should have close to the same explanatory power as their in-sample counterparts.

6.2 Regression results

In line with our null- and alternative hypotheses, we perform regressions of the form from equation (1). Our thesis is focused on whether varying levels of sentiment affects the cross-section of returns, proxying hard-to-arbitrage and hard-to-value stocks by low market capitalisations and -trading volume. Additionally, we check the *overall* effect of investor sentiment on stock returns by running regressions on both extremes of stocks. All four of the regressions we run suffer from heteroscedasticity and we therefore use White's heteroskedasticity-consistent standard errors when making inferences.

6.2.1 Results using the replica index in-sample

For the tests based on the indexes made with in-sample data, our findings line up with the ones from Baker and Wurgler (2006). Beginning-of-period sentiment has a significant and negative relationship with subsequent returns. Table 5 shows the regression coefficients and their p-values in parentheses. Our focus is on the effect of the index and the product of the factors and the index on the portfolio sort returns.

The sentiment index is only significant in the *smbxsent* variable, with a negative sign. Low-market cap.-stocks seem to be affected by sentiment as predicted. The overall sentiment index has a p-value of .0575 whereas the products *smbxsent* and *hmlxsent* are significant on the 5 percentage level. They also have negative signs, in line with our expectation. The long-short portfolios follow the same trend: Low-market cap.-stocks have a significant negative relationship with beginning-of-period sentiment. The effect is not significant for low-volume stocks except for the product *smbxsent*.

Table 5: Regression outputs

	p1 - MthVol Decile	p5 - MthVol Decile	p1 - MthCap Decile	p5 - MthCap Decile	p1 - p5 MthVol	p1 - p5 MthCap
const	-0.0065	0.0141	-0.0132	0.0103	-0.0207	-0.0235
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
mktrf	0.6196	1.2528	0.8765	1.0172	-0.6332	-0.1407
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
smb	0.5064	0.7319	1.0207	0.1811	-0.2255	0.8396
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)
hml	0.3396	0.0822	0.3663	0.0782	0.2574	0.2882
	(0.0000)	(0.0363)	(0.0000)	(0.0001)	(0.0000)	(0.0002)
index	-0.0002	0.0002	-0.0022	0.0009	-0.0004	-0.0030
	(0.7066)	(0.7004)	(0.0575)	(0.0080)	(0.5769)	(0.0099)
smbxsent	-0.0740	0.0991	-0.1203	0.0717	-0.1731	-0.1920
	(0.0225)	(0.0015)	(0.0255)	(0.0000)	(0.0006)	(0.0005)
hmlxsent	-0.0268	-0.0321	-0.1338	0.0169	0.0053	-0.1508
	(0.3234)	(0.1261)	(0.0046)	(0.2333)	(0.8808)	(0.0017)

6.2.2 Results using the simple index in-sample

The index using 2nd degree tradeable data retain a lot of the variation from the replicated index. Therefore, one should expect to see similar results. The results are overall very similar to the ones using the replicated index and generally in line with our expectations. However, there are also some important differences.

When using the 2nd degree tradeable index as the conditional variable, the long portfolios are not statistically significantly affected by the overall sentiment level. The short-leg of both portfolios are affected with a positive relationship to the sentiment index. The long-short portfolio returns for both market cap. and trading volume both have statistically significant negative relationships with investor sentiment. The *smbxsent* variable is generally statistically significant for all portfolios. Table 6 shows the results.

Table 6: Regression results

	p1 - MthVol Decile	p5 - MthVol Decile	p1 - MthCap Decile	p5 - MthCap Decile	p1 - p5 MthVol	p1 - p5 MthCap
const	-0.0032	0.0208	-0.0085	0.0157	-0.0240	-0.0242
	(0.0084)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
smb	0.8055	1.2284	1.4363	0.5896	-0.4229	0.8467
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
hml	0.1406	-0.3054	0.0976	-0.2384	0.4459	0.3359
	(0.0495)	(0.0134)	(0.3742)	(0.0147)	(0.0000)	(0.0000)
index2	-0.0003	0.0050	-0.0009	0.0037	-0.0053	-0.0046
	(0.8314)	(0.0380)	(0.6630)	(0.0471)	(0.0027)	(0.0126)
smbxsent	-0.2043	-0.1661	-0.3023	-0.1426	-0.0382	-0.1596
	(0.0000)	(0.0205)	(0.0000)	(0.0047)	(0.5397)	(0.0031)
hmlxsent	-0.0899	-0.2094	-0.2453	-0.1214	0.1195	-0.1239
	(0.0678)	(0.0095)	(0.0019)	(0.0635)	(0.0534)	(0.0700)

6.2.3 Results using the replica index out-of-sample

The correlation between the out-of-sample indexes with their in-sample counterparts are fairly high, which should be encouraging for their predictive power. Generally, the results are still in favour of our alternative hypothesis.

Low-volume stocks have a slight negative and significant relationship with the overall sentiment index. The same is true for the low-market cap. stocks.

For the long-short portfolios, only the low-volume portfolio has a significant relationship with sentiment. The relationship is negative, in line with our expectations. The *smbxsent* and *hmlxsent* variables are not statistically significant for neither the low-volume nor the low-market cap. stocks. Table 7 shows the results.

Table 7: Regression results

	p1 - MthVol Decile	p5 - MthVol Decile	p1 - MthCap Decile	p5 - MthCap Decile	p1 - p5 MthVol	p1 - p5 MthCap
const	-0.0063	0.0129	-0.0166	0.0103	-0.0192	-0.0270
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
mktrf	0.5626	1.3157	0.8833	1.0108	-0.7531	-0.1276
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0088)
smb	0.3775	0.9004	0.8352	0.3064	-0.5228	0.5288
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
hml	0.3198	0.0406	0.2181	0.0903	0.2793	0.1278
	(0.0000)	(0.4191)	(0.0322)	(0.0008)	(0.0000)	(0.2295)
index_roll	-0.0008	0.0006	-0.0017	-0.0003	-0.0014	-0.0014
	(0.0114)	(0.1990)	(0.0153)	(0.0676)	(0.0093)	(0.0530)
smbxsent	0.0105	0.0543	0.0331	0.0075	-0.0438	0.0256
	(0.3975)	(0.0912)	(0.2480)	(0.2331)	(0.2317)	(0.3681)
hmlxsent	0.0052	0.0373	0.0267	0.0078	-0.0321	0.0189
	(0.7005)	(0.0117)	(0.3062)	(0.1905)	(0.0666)	(0.4657)

6.2.4 Results using the simple index out-of-sample

The simple index using only the IPO data has a correlation of almost 1 with the replica index out-of-sample. Therefore, the results are almost identical as in 6.2.3. and the inferences are identical. For that reason we will not discuss them further, but present them in table 8.

Table 8: Regression results

	p1 - MthVol Decile	p5 - MthVol Decile	p1 - Mth-Cap Decile	p5 - Mth-Cap Decile	p1 - p5 MthVol	p1 - p5 Mth-Cap
const	-0.0063	0.0129	-0.0166	0.0103	-0.0192	-0.0270
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
mktrf	0.5626	1.3157	0.8833	1.0108	-0.7531	-0.1276
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0088)
smb	0.3775	0.9004	0.8352	0.3064	-0.5228	0.5288
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
hml	0.3198	0.0406	0.2181	0.0903	0.2792	0.1278
	(0.0000)	(0.4188)	(0.0322)	(0.0008)	(0.0000)	(0.2295)
index_roll_2	-0.0008	0.0006	-0.0017	-0.0003	-0.0014	-0.0014
	(0.0115)	(0.1989)	(0.0154)	(0.0677)	(0.0093)	(0.0532)
smbxsent	0.0105	0.0543	0.0330	0.0075	-0.0438	0.0255
	(0.3985)	(0.0912)	(0.2485)	(0.2333)	(0.2315)	(0.3687)
hmlxsent	0.0052	0.0373	0.0267	0.0078	-0.0322	0.0189
	(0.7010)	(0.0117)	(0.3065)	(0.1906)	(0.0665)	(0.4661)

6.3 The results in light of our research questions

Our results are in line with the ones found in Baker and Wurgler (2006). High beginning-of-period sentiment is connected to low subsequent returns for low-volume and small-cap stocks and vice versa. However, the results are not entirely unambiguous. The replicated sentiment index in itself is not significant for the portfolios other than the long-short portfolio sorted on market capitalization. Also, the *economic* significance cannot be considered to be large, although the index's effect is statistically significant. Somewhat surprisingly, the 2nd degree tradeable index outperforms the replicated index as the results are more in favour of our hypothesis. Both low-volume- and low-market cap. stocks hold a significant negative relationship with the sentiment index. The economic significance is also larger than for the replicated index.

For the test run on tradeable data, the relationships are in general not as strong as for their in-sample counterparts. However, there is still generally a significant negative relationship between the low-volume and low-market cap stocks and the sentiment index. In general, the products of sentiment and SMB and HML are not statistically significant when explaining returns. Importantly however, the results for the index itself are in favour of our hypothesis. There is a statistically significant negative relationship between beginning-of-period sentiment and low-volume and low-market cap. stocks even when using 2nd and 3rd degree tradeable data to construct the index. This is however not true for the long-short portfolio holding low-market cap. stocks, as its p-value is slightly above our accepted test alpha of 5%.

7 Conclusion

This thesis studies whether or not the sentiment index from Baker and Wurgler (2006) is still able to explain returns in stocks that are hard to arbitrage and thus hard to value. Additionally, the thesis extends the analysis to whether the index can be constructed using easily available or *tradeable* data. The original sentiment index can still explain subsequent returns in stocks characterised by 1) Low market capitalizations and 2) low trading volume. When extending the analysis to allow for indexes using tradeable data, the conclusion remains the same, but with slightly less statistical significance. Readily available data *can* predict stock returns in stocks that are prone to a wide range of valuations; Following periods of high sentiment, subsequent returns in these stocks are typically lower than otherwise.

The predictive power of our investor sentiment index using tradeable data adds to the discussion of market efficiency. It begs the question whether the index truly is a behavioural variable or whether there is incorporated unobserved risks in the index. From a practical standpoint, our results can be interpreted as an increased need for sentiment in asset pricing models. Incorporation of sentiment-inclusive models by institutional investors could contribute to making financial markets more efficient.

As discussed in the literature review of this thesis, more recent papers have built on and confirmed that the sentiment effect from Baker and Wurgler (2006) is still present in several forms. This thesis has the objective of being practical in its use of variables proxying sentiment to address whether tradeable data can explain subsequent returns. Our findings are in line with recent literature. Baker et al. (2012) extend their analysis and find that the sentiment effect can be contagious across markets. Importantly, our results are in line with results presented in Huang et al. (2015). They find that *aligned* sentiment is a powerful predictor of returns in stocks that are driven by high volume.

Although our results are conclusive for the stated research question(s), we see potential for further research. Using market capitalization and trading volume as variables to capture the degree of speculation in stocks should be challenged. The availability of reliable data for the two variables adds to this thesis's practicality. However, other characteristics are like likely to better describe stocks' propensity to be driven by speculation. Also, changing the way the out-of-sample index is constructed could make it a better proxy for investor sentiment. This would likely make the results more stable.

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