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M.Sc. in Finance and Banking - Financial Analysis for Executives

Master Thesis

"The predictive ability of a sentiment index. A comparison across time and economic regions"

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Abstract

Investor sentiment in the stock market constitutes a highly appealing field, in the area of modern finance the last years. Many researchers have already attempted to connect the inability of capital market prices as derived from standard Capital Asset Pricing Model to equal the present value of expected future cash flows with the sentiment effect in combination with limits to arbitrage. In order to explain and analyze the sentiment effect, the first thing required, is to fairly measure this factor called "sentiment". It follows that the second step, is to explain the sentiment effect on current prices by using this measure. Lastly, as can be expected, investor sentiment measure can be effectively used as a tool for prediction of future returns and guidance of trading strategy. Correspondingly to Baker and Wurgler latest analysis on investor sentiment, this thesis discusses possible methods of measuring investor sentiment and deals with the sentiment effects on two different stock categories. Last but not least, it provides an attempt to investigate whether the measured investor sentiment is an appropriate forecast tool for future returns.

Key Words: Sentiment, Investor sentiment, Sentiment index, Sentiment proxies, Sentiment changes, Stock market, Stock returns.

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1. Introduction

Early as in 1776, the famous economist Adam Smith wrote in his book "Wealth of Nations": "The chance to win is overestimated by all people. The chance to lose is underestimated by most people." something that was probably not taken into account by Markowitz and the other introducers of CAPM in 60's and something that inspired researchers of modern finance to form alternative models that will include investor's sentiment.

It is a well-known fact that the CAPM, in which capital market prices are forced to equal the present value of future cash flows, is highly criticized mainly due to its inputs and assumptions. Also there is evidence that this model cannot apply in cases of crashes and bubbles in stock markets.[1] Behavioral finance proposes an alternative approach, regarding asset pricing, commonly based on two assumptions.

The first one implies that investors are subject to sentiment. To begin with the definition of investor sentiment, it's actually the measurement of the mood of a given investor or the overall investing public, either bullish or bearish.[2] In other words, it can be a "feeling" about the future cash flows or investment risks that is not explained by recent facts. But can it really affect asset prices? And this is exactly the second assumption. According to standard theory, irrational speculators, who buy when prices are high and sell when prices are low, driven by a special "feeling", exist, but on average are quickly eliminated by the market – rational speculators - . However, there is evidence against this elimination, due to the fact that the rational speculators do not take large positions because of risk aversion. That is to say that there are limits to rational arbitrage, because of high risk and unaffordable costs. As a result these traders, called "noise traders" can really affect asset prices and earn higher expected returns than normal. [3]

In particular, there is a special behavior observed in financial markets, which is called, positive feedback trading. According to this trading, when rational speculators receive for example good news they overtrade (buy more than expected) and drive prices in higher levels than expected, driven by their belief that positive feedback traders, will be willing to buy the next day. On the other

hand, the positive feedback traders buy in response to this increase and keep prices above fundamentals, even as rational speculators are selling out and stabilizing prices. Therefore, there is an increase in prices that departs from the rational speculators' behavior and the positive feedback traders' reaction.

So, given the fact that investor sentiment affects stock prices, the main question that arises is how this investor sentiment is measured and whether and how can we quantify its effects. Many researchers of modern finance have been engaged with this issue the recent years, following different approaches every time.

One approach is the "bottom up" approach. In psychology and neurosciences bottom – up approach is a progression from the individual elements to the whole.[4] In the same way, behavioral finance uses the biases in an individual investor's psychology to explain how individual investors in total underreact or overreact to past returns or fundamentals. Barberis, Shleifer and Vishny in 1998, developed a model consistent with this approach, to explain how investors form beliefs and how this is transferred as an overreaction or underreaction of prices to public information.

According to their study, they created a model about the investors' expectations for future earnings based on two main psychological behaviors: conservatism and representativeness heuristic.[5] Conservatism is related with underreaction and representativeness heuristic with overreaction. Using evidence from investors' reactions in past events, like earnings' announcements they proposed a model in order to make predictions about stock prices. This model is based on events classification by event's strength in terms of evidence on one hand and event's statistical weight on the other hand. They conclude that if the news' classification is feasible a priori, then the model the presented can give a testable prediction on future prices.

The alternative approach is the "top down" approach. According to this approach, in contrast with "bottom up", is not stimulus oriented but it focuses on stimulus results. Baker and Wurgler, in their paper "Investor sentiment in the stock market" in 2007, which is the main reference of this work, follow this macroeconomic approach. As a rule, they return to the two basic assumptions of behavioral finance as referred above: the fact that investors are subjected to sentiment and the

fact that there are limits to arbitrage for rational investors, so that asset prices do not actually reflect the present value of expected future cash flows. The difference in this approach is that, it tries to find out, which stocks or assets in general, are more likely to be affected by investor sentiment, given the fact that investor sentiment destabilizes stock prices. Conversely with the previous approaches that given the investor sentiment and the reactions followed, demonstrated the assets' "misvaluation" and resulted in models that give testable predictions about the future prices.

In this case, researchers tried to split the "sentiment effect" between stocks that are in general difficult to price and stocks that are "safe" or easy to arbitrage. In the first category, the stocks usually belong to "young" or no-dividend paying or unprofitable companies and of course are stocks that present high volatility in returns. For the second category stocks of large capitalization indexes are more representative. The results of the work of Baker and Wurgler, propose that prices of "difficult to arbitrage" stocks are more exposed to destabilization due to sentiment.

This thesis is actually an effort to measure investor sentiment and mainly quantify its effects in London Stock Exchange the last seventeen years. Admittedly there is high need for strong statistical evidence, regarding the effects of sentiment in stock market returns. Most studies before 2006 and Baker and Wurgler first work, usually did not express directly the meaning of sentiment. In other words, the mispricing of stock market was approached in total and explained by simple valuation ratios.[6] A main characteristic of these studies is the statistical weakness and the unclear economic explication.

Contemporary studies on market mispricing are seriously taking into account modern theories of behavioral finance and discussing the effects of sentiment after providing strong statistical results. In this way, this research concedes that two types of investors exist: rational and irrational. Rational traders are considered as non-subjective to sentiment in spite of irrational ones, inclined to sentiment. Just like in recent "top down" studies, market mispricing is also taken as a result of two basic grounds: Sentiment variation for the part of irrational traders and limits to arbitrage for rational traders. To put it more simply, theory implies that prices

meet the expectations about the present value of future cash flows, as a result of competition between rational and irrational investors. [7] On the contrary, in reality rational investors do not act as expected, due to high transaction costs in short time horizon or high risk of trading in short selling and irrational traders do not act as expected due to sentiment changes. Therefore, sentiment and limits to arbitrage compose the main factors of current analysis, as well.

As far as sentiment is concerned, in order to examine how its variation influences stock prices, we have to observe investor behavior changes around stocks. We can easily perceive that investors, driven by their sentiment, change their trading behavior in stocks that usually belong to young firms – no earning history, non-dividend paying and smaller, currently unprofitable, high growth potential - . These stocks' difficulty to price is actually the main reason that makes them speculative. In other words, speculation is inextricably linked with sentiment.

Turning to limits to arbitrage, now, it is perfectly reasonable and already proved in theory that arbitrage is avoided by rational investors in stocks that are difficult to price - belong to young or unprofitable or non-dividend paying or small with high growth potential firms – due to high risk and high cost in short term horizon. This implies that speculation is strongly related to limits to arbitrage as well.

Under these circumstances, in order to examine investor sentiment effect in stock market mispricing, we have to observe separately its effects on speculative or difficult to price stocks and on stocks that are less subjective to sentiment. These stocks seem to be more safe and easy to arbitrage.

Overall, to begin, we have to measure the factor that this thesis is dealing with and is called "investor sentiment". But how is actually investor sentiment defined? We can describe it as the feeling tone of investor or the psychology as revealed through the activity and as follows through the price movement of the traded securities. The overall attitude of trading investors toward a financial market forms the market sentiment.[8]

Surely, sentiment which is an attitude cannot be measured directly. Many indicators have been used in several studies overtime and across regions, as described analytically in the next chapter. Namely, these proxies are: investor

surveys, investor mood, retail investor trades, mutual fund flows, trading volume, dividend premium, closed-end fund discount, option implied volatility, IPO first-day returns, IPO volume, equity issues over total new issues, insider trading, Consumer Confidence Index, Intrest Rate and performance of similar equity markets. In this research we have to combine these useful indicators with data availability for London Stock Exchange, for the period 2000 – 2016, on a monthly basis.

From all these variables, finally the trading volume, dividend premium, Consumer Confidence Index, Interest Rate and US stock market performance were selected as proxies of sentiment. A sentiment index was finally derived from principal components analysis as a real measure of sentiment in the region and time we analyze.

Secondly, as we have already quantified the concept "sentiment", we had to search for extra statistical evidence regarding its effects in stock prices categories. In other words, we had to examine if difficult to price stocks, in London Stock Exchange, for the period 2000 - 2016 are disproportionately affected by sentiment rather than safe – easy to arbitrage stocks.

To complete this test, first of all, we had to create the two stock categories. For the "difficult to price" category we used the FTSE Small Cap Index while for the "safe" category we used as blue chips FTSE 100 Index.[9] Next we have to investigate the relationship between sentiment changes based on sentiment index that we have already composed and the returns of the two portfolios. So we applied two regressions, one for each portfolio. The dependent variable is the monthly return of each index while the independent the sentiment changes index.

The results strengthen the opinion that investor sentiment changes influences more the "difficult to price" stocks than blue chips. Sentiment betas are positively related with returns of difficult to price and hard to arbitrage stocks in contrast with the returns of blue chips.

As far as the predictive ability of this sentiment index is concerned, as the results showed that sentiment is unable to explain monthly returns of the FTSE 100 Index but it can only explain the FTSE Small Cap Index returns we used this sentiment

index to predict future returns of the FTSE Small Cap Index only. In particular, using the previous month's measure of sentiment level we split the time series into two periods; low and high sentiment. Next, we computed average returns of the portfolio, for the two separate periods and overall, based on the regression model that we have used earlier. Accurate predictions are presented in the fourth chapter of this thesis.

2. Literature Review

2.1 Quantify Investor Sentiment

Recent studies present several efforts for measuring investor sentiment by creating a sentiment index. In our days the changes of this index are seriously taken into account by financial analysts all over the world[10], so there is no doubt that sentiment can be described in the field of financial analysis by some proxies. Different proxies have been used in every study. This of course influences the issued explanations regarding the current changes on prices and affects the predictions about the future.

2.1.1 Potential Sentiment Proxies

In the most examined papers we found that researchers use between others the below common proxies, on which we are going to focus. These are:

- Surveys
- Mood Proxies
- Retail Investor Trades
- Mutual Fund Flows
- Trading Volume
- Premia on dividend-paying stocks
- Closed-End fund discounts
- Option Implied Volatility
- First days returns on Initial Public Offerings
- Volume of Initial Public Offerings
- Insider Trading

Investor Surveys

Early as in 1989, Robert Schiller has conducted a survey looking for the proportion of irrational investors in total investors. [11] Schiller, found evidence that the way the investors are communicating in order to form the perfect investment decisions is correlated with the performance of the invested stocks every time. To

put it more simply, when the investment decision is the outcome of an analysis taking into account only publications and direct information by brokers the performance of the stock seems to be systematic, while when the decision comes from a chain of communications from one investor to another the performance of the stock seems to be systematic. By questioning both individual and institutional investors about specific stocks that they have already purchased, Schiller attempts to explain the social psychology effects in financial markets. The research concludes in significant indications that the contagion of interest is important in describing the investors' behavior.

Later in 2005, Brown and Cliff, used only direct surveys as a measure of investor sentiment to explain at first the asset stock price deviations from fundamental values with the deviations in sentiment and secondly to predict future market returns on this assets (stocks).[12] The measure of sentiment, as highlighted, was survey data regarding market newsletters. They separate the newsletters as bullish, bearish or neutral and at the end they take the bull – bear spread as an independent variable because the majority of newsletters examined were bullish. In a bullish sentiment period the market is predicted to experience lower subsequent returns. And really it is significant to say that this research provides additional evidence that market pricing deviations as they come by an independent valuation model, are strongly explained by sentiment.

An alternative approach in using investor surveys as a measure of investor sentiment includes the consumer confidence measure as well. Especially, Qiu and Welch in their recent research[13] compared investor sentiment measures based on consumer confidence surveys with measures including the Closed-End Fund Discount. Their outcome shows that changes in consumer confidence is highly correlated with changes in small firms' returns while there is actually not significant correlation between market returns and Closed-End Fund Discount. In other words, they found evidence that sentiment affects stock prices, and they proved that Closed-End Fund Discount is inappropriate measure of sentiment.

Mood Proxies

In other works we have seen that stock prices are connected to human emotions. In particular Kamstra, Kramer and Levi in their publication in American Economic Review in 2003, pointed out that stock prices remain low in periods that depressive disorder is observed in high levels. Such periods are fall and winter seasons in which daylight is limited, compared to spring and summer. Accordingly they tried to model differences in human sentiment by capturing the influence of daylight on investors across countries. Then they found strong evidence that stock returns are subsequent to human sentiment measured by that mood, especially in the Southern Hemisphere.[14]

In the same way Edmans Garcia and Norli in 2007[15], combined international soccer results with stock market returns and found strong evidence that there is correlation. Mainly they found that losses in significant games are related with poor next day returns for the losing country. Again the results seem to be stronger for small firms. In brief, taking as a fact that human emotions are strongly connected with stock returns, we can use the investor mood as a potential proxy in order to measure investor sentiment.

Retail Investor Trades

It is observed that all the results from the papers referred so far; seem to be stronger were investors are not institutional but individual or not experienced but young in the field. Correspondingly, as inexperienced is the investor, as likely is to be subjected to sentiment. In the paper of Greenwood and Nagel in 2009[16], the assumption above is proven. As can be expected new individual investors are more subjective to sentiment than experienced mutual fund managers. The research was conducted on data regarding the 1990 technology bubble and especially on younger mutual fund managers' actions at the peak of the bubble. The fact that this category of investors is willing to buy stock in the peak of the bubble, with inflated prices shows that they are driven by a speculative trend at the one hand or by a sentiment of inexperience on the other; the two main pillars of this study. This implies that the measure of retail investor trades in every period can fairly represent a measure of investor sentiment for the same period as well.

Additional evidence regarding the number of retail investor trades as a measurement of investor sentiment is seen in the work of Barber, Odean and Zhu in 2009[17], in which the individual trading is analyzed in comparison with institutional. In more details, it comes out that individual investors not only exist but also their irrational behavior influences stock returns. It is also proven that their sentiment oriented investment behavior is systematic. Individual traders are observed to sell stocks with strong past returns and buy stocks with high abnormal trading volume. This trade is known as disposition trade and these individual traders are also called "noise traders". After all, as the effect of individual – noise traders on stock market in undoubtable we can surely use the measure of retail investor trades as a measure of investor sentiment.

Mutual Fund Flows

One study that represents evidence that daily mutual fund flows can correctly be used as a measure of investor sentiment is the study of Brown, Goetzman, Hiraki, Shiraishi and Watanabe in 2003[18]. Their region of research was USA and Japan, two of the most important stock markets of the world something that makes the outcome undeniable. In more detail, they used daily panel datasets of mutual fund flows of these markets. In Japan, the daily flows of bull and bear funds are negatively correlated with the according stock returns. The main reason they propose is the sentiment factor. They argue that this is the "priced" factor that caused the prices deviation in the Japanese stock market. Accordingly the same result is observed and in the US stock Market. Under these circumstances this team proposed the "mispricing" of mutual fund flows as the best instrument for measuring investor sentiment.

In the same way, an earlier work published in 1995 in Journal of Financial Economics, by Wartner provides evidence that aggregate security returns are strongly positively correlated with the abnormal cash flows into mutual funds and negatively correlated with the expected cash flows.[19] This research required the fund flows allocation into expected and unexpected using time-series analysis to find the expected. The results of this research agree with the previous ones that the abnormal mutual fund flows explain the unexpected stock prices. For this reason, mutual fund flows data can be used to quantitate investor sentiment.

Similarly, in the work of Frazzini and Lamont in 2008, we found evidence that mutual fund flows can totally represent an investor sentiment for individual retail investors. In this paper we came up against the phrase “dump money” which of course refers to the aimlessly invested money of individual investors. As this money does not add value to investor position, someone can easily conclude that this loss comes by investor sentiment. By observing the movements of this money among stocks and afterwards relating the returns of this stock with this “movements” we can find the positive reliance. Furthermore, in this research it was find out that the stock that individual invest the “dump money” are often the growth potential stocks – the stocks that are now difficult to price - .[20] After these results there is no reason to not include mutual fund flows changes as a measure of investor sentiment.

Trading Volume

Trading volume can be used as a proxy for investor sentiment due to the fact that it implies the liquidity of the market. In other words, in periods with high liquidity, we assume that the market is dominated by irrational investors who underreact to the information contained in order flow, so the stocks are overvalued. In the paper of Baker and Stein in 2004, this focuses exactly to market liquidity as sentiment measure; they explained that market liquidity changes are strongly related to the changes of returns, both of total market and of each firm.

Especially, Baker and Stein[21] create one model, based on two basic assumptions. The first one is that short-sale constrains exist in the market and the second is that irrationally overconfident investors. The scenario implies that irrational investors overestimate private signals, so that they cause “sentiment shocks” that boosts liquidity of the market. For example when irrational investors observe the trading decisions of others, they underestimate these decisions, due to the fact that they believe that they gain more information, wrongly. So this aspect of overconfidence when is taken into account with market short sales constraints boosts liquidity because of the decline of the price impact of trades. After all, in this paper it is shown that the change in market liquidity is negatively related with the change of stock prices (returns). Taken into account all the assumptions above

we can say that changes in market liquidity as given by trading volume can worthy represent investor sentiment.

An alternative approach to support the opinion that trading volume is correctly used as a sentiment proxy comes by the paper of Scheinkman and Xiong in 2003,[22] in which the changes of trading volume and liquidity, reflects the changes of investor opinion. By this work, there is strong evidence provided, the there is a negative relation between stock returns and changes in trading volume, taken into account that both irrational investors and short sales constraints, exist.

Overall, it must be noted that in both researches, the variable examined was market turnover which is equal to the ratio of trading volume to the number of shares listed, on the stock market.

Dividend Premium

Dividend premium is defined as the difference between the average market-to-book value ratios of dividend payers and non-payers.[23] For Baker and Wurgler as referred in their paper in 2004, dividend premium as a price based measure can be related to sentiment.

In particular, in their work it is argued that dividend policy is relevant to share value due to the weakness of efficient market hypothesis. It is mentioned that there is a demand dividend paying stocks that comes by psychological reasons of investors. Furthermore, high costs of arbitrage in short-term period, allow the effect of this demand on stock prices. Last but not list, it is said that rational managers usually pay dividends when investors demand dividend paying stocks and do not pay, when investors prefer non-paying stocks, respectively. For all these reasons, they assumed that dividends are related to the stock price, so they looked for statistical evidence to proof this assumption. Finally they really found that there is high relation between stock prices and dividend pay-out.

Taking also into account the fact that rational managers, care only for stock value maximization, anyone could conclude that these managers do cater to prevail sentiment on the desirable trend every time. For these entire reasons dividend premium can be a successful quantitative proxy for sentiment as well.

Closed-End Fund Discount

To begin with, closed-end fund are investment companies who issue a fixed number of shares, which then trade on stock exchanges.[24]The closed-end fund discount is defined as the difference between the net asset value of a fund's actual security holdings and the fund's market price. It is commonly argued, that when these funds are hold by retail investors, it can represent a sentiment measure.

As mentioned above, inexperienced retail investors are in majority subjected to sentiment. This means that the result of their investment effort usually reduce the value of their starting position. In this case we can say that the market value of the fund is usually less than the fund's net asset value of holdings, especially in bear trade. To put it more simply, the difference between the fund's market value and the net asset value of fund's holdings can fairly represent the inability of the inexperienced investors or in other words the factor that we call sentiment.

It follows that, many researchers have been looking for extra evidence to support the above logical assumption. Early as in 1973, Zweig developed a model using the changes in closed end funds premiums - the opposite sign of discounts - in order to explain the abnormal changes of stock prices, as a depiction of investor expectations, as comes out by their sentiment situation.[25] However, this model actually presented independence in stock market price changes. As far as the efficient market hypothesis is concerned regarding the price changes, it was empirically found that the random walk hypothesis is violated only when the response to an implied event is overwhelming but not actually total. Overall, based only on this research, closed end fund discounts/premiums cannot be used as a sentiment measure, as this difference cannot actually explain the changes on stock prices.

In the same way, Lee Shleifer and Thaler in 1991, taking into account that fluctuations in individual investor sentiment can lead to fluctuations in demand for closed end-fund shares which can be reflected to changes in closed end fund discounts, created a model to provide the required empirical evidence. Researchers finally found evidence that discounts are high when investors are pessimistic about future returns (so they sell) and low when investors are optimistic (so they buy). Therefore, according to this study[26] closed-end fund

discounts/premiums can correctly represent a measure of sentiment of individual investors.

Option Implied Volatility

Theory suggests that option prices rise when the value of the underlying asset has greater expected volatility.[27] Regarding the Standard and Poor's 100 stock index as an underlying asset, we can measure the implied volatility of the options on this stock using the Market Volatility Index, "VIX". According to Baker and Wurgler and our main reference paper, this index is practically used as investor fear gauge. Many recent studies as the one of Whaley in 2000 have been engaged with "VIX" trying to explain its construction to explain its history in relation with stock market returns. It follows that, by definition this index can perform an obvious measure of investor sentiment.

First days returns on Initial Public Offerings

It is common knowledge that, Intitial Public Offerings, known as "IPOs" of first trading day, earn higher returns than expected due to investor's sentiment and especially investor's enthusiasm. Contemporary researchers are trying to explain why IPOs are underpriced, since the starting prices integrate the information by investment bankers about market conditions. The only logical reason that can cause this increase to prices is the investor sentiment. And that's why this proxy can represent a measure of investor sentiment.

IPO Volume

If someone take a look at IPO Volume fluctuations will realize that IPOs represent an opportunity for speculation, for irrational investors, due to the fact that some periods there is excess underlying demand while other not. Ljungqvist, Nanda and Singh in 2006[28], tried to link some of IPO anomalies, such as underpricing and "hot issue" markets with irrational investors and investor sentiment. More specifically they claim and the show that the combination of this type of investors with short-sale restrictions results to the underperformance of shares after the first day, in long run period. Their model provides many interesting issues about IPO policy pricing, that are needless to represent in this thesis elaborately. They only thing that matters in our perspective is that IPO Volume, can represent a real

proxy of investor sentiment, as the fluctuations on its value are mainly caused by the unusual behavior of irrational investors.

Insider Trading

It is commonly accepted that corporate executives, of course have better information about the true value of their firms than outside investors. Because of that, their personal portfolio management decisions may show their opinion about the mispricing of the business share they work for. So, given the fact that the mispricing is also caused by insider trading, and this trading is caused by a change on investor sentiment, insider trading can really represent a proxy for investor sentiment.

2.1.2 Creating a Sentiment Index

Baker and Wurgler (2007)

Baker and Wurgler having experience in creating such indexes, in their work in 2007 they used some of the proxies above. They claim that, even though that sentiment may vary daily, major episodes could occur over years. As anybody can conclude, the most convincing tests of the effects of sentiment tare those in which it is used actually to predict long-horizon returns. As a result, proxies that include data that do not go so back as far as the stock returns they examined (1960's), are excluded. [29] These proxies are insider trading, micro-level data on trading behavior and implied volatility series.

Therefore, they constructed an index in the same way with their previous work in 2006, including the following sic proxies:

1. Trading Volume as measured by NYSE turn over
2. Dividend Premium
3. The closed-end fund discount
4. The number and the first day returns on IPO's
5. The equity share in new issues
6. Some mutual fund series

They observed that some of these variables contain idiosyncratic components that are unrelated to sentiment. For instance, the upward trend in turnover in 1975, is explained by the deregulation of brokerage commissions and the subsequent long decline in trading costs. For that reason they used, the log of turn over minus a five year moving average. In the same way, regarding close-end fund discounts, if the majority of individual investors have come to prefer open-end funds in recent years, the discount provides a less useful summary of the opinion of the marginal investor that it once did. However, both two proxies are significantly correlated in the expected directions.

What is more, they analytically represent that some of this proxies reflect economic fundamentals to some extent. They highlight the fact that IPO volume depends in part on prevailing investment opportunities. Under these circumstances, in order to remove such influences, they regress each proxy, on a set of macroeconomic indicators:

- Growth in industrial production
- Real growth in durable
- Real growth in nondurable
- Real growth in services consumption
- Real growth in employment
- NBER recession indicator

And they used the residuals from these regressions proxies for the sentiment.

The idea they based on is that, the six referred proxies have all in common the sentiment component, as macroeconomic influences have been removed. They used the principal components methodology in order to average the six proxies together into a sentiment level index. The levels index, they create is actually the first principal component of these six proxies. As they analyze they used the simple sentiment levels to test for return predictability conditional of the state of sentiment and also a sentiment changes index to test for return co-movement patterns associated with changes in sentiment.

Where:

- CEFD: Close-End Fund Discount,
- TURN: Detrended Log Turn Over
- NIPO: Number of IPO's
- RIPO: First Day returns on IPO's
- PDND: Dividend Premium
- S: Equity Shares

In the figures above we can see the sentiment indexes graphically, as presented in the published work of Baker and Wurgler in 2007. The first one represent the simple sentiment levels and the second one the changes of index. The signs of coefficients remain same in both panels, apart from equity share. They claim that this unexpected change of sign is explained by the fact that changes in high frequencies in equity shares are unrelated to sentiment. However they retained this variable as well in order to avoid data mining.

Last but not least, Baker and Wurgler also say that robustness is another concern in order to use as much proxies as possible in order to create the sentiment index. In response they highlight that the process of averaging these proxies is not crucial. It is believed that they are strongly correlated and if they were each studied as independent sentiment indexes some would display empirical results even stronger. Furthermore, by this way they claim that they used this approach in order to avoid to elevate individual proxies arbitrarily and to iron out idiosyncratic variation.

Of course the authors tested whether the index capture major fluctuation in sentiment, as well. They found that it lines up fairly well with the anecdotal accounts of bubbles and crushes written by various authors.30This is actually seen in both figures above. Especially in the second figure we can see that the volatility of sentiment rises in a speculative episode and this pattern suggest that the relative influence of fundamentals and sentiment on aggregate market returns, changes over time.

Brown and Cliff (2004)

Brown and Cliff's paper in 2004 was the first to explore the role of investor sentiment in the stock market, using a set of sentiment proxies including direct survey data on sentiment.

In more detail, as far as direct sentiment measures like surveys are concerned they used two surveys. The first one was conducted by American Association of Individual Investors. It was about a random sample that was polled to the members of the association each week. The sample size of the survey was between 125 and 500 participants, while only 140 on average really respond. Regarding the object of the survey, they asked each participant about their prediction for the stock market after 6 months; up, down or the same; in financial language bullish, bearish or neutral. It is really interesting that they found that on average the responses where 36% bullish, 28% bearish and 36% neutral. This actually was the prime measure of investor sentiment in their survey.

Another association also called Investors Intelligence, issued another weekly bull-bear spread by categorizing 150 market newsletters. In more detail the newsletters, were read and marked respectively as bullish, bearish or neutral, once a week. However, this is not as direct measure as the surveys above, due to the fact that many of the authors of the letters are retired market professionals.

But how Brown and Cliff quantified the answers of the surveys? They just used the percentage of bullish investors minus the percentage of bearish (bull-bear spread) as a measure of what we call investor sentiment. It is really interesting to quote the figures below, regarding the investor sentiment as measured either by the first or by the second direct measure, by Brown and Cliff.

Brown and Cliff analysis of course included and indirect measures, in other words proxies.[31]They categorize many market indicators into four maiun groups.

In the first group they include variables connected with market performance. One of the most common technical indicators they used in this group is the ratio of the number of advancing issues to declining issues. Furthermore they used a modification of this ration which incorporates volumes (is the ration above

multiplied by volume). Another ration included in this group is also the new highs to new lows ratio, designed to capture the relative strength of the market.

The second group includes proxies regarding the type of trading activity. One main variable is the percent change in margin borrowing at a monthly level as reported by Federal Reserve Bank. It is said that the measure is seen as a bullish indicator because it presents investors using borrowed money to invest. Additionally they included the percent change in short interest as a bearish indicator. Furthermore, they regard the ratio of short sales to total sales on a weekly basis and the ratio of short sales to total short sales both on a weekly and a monthly basis. The idea they propose is that the specialists are well-informed and relatively savvy investors so when their sort-selling becomes relatively large the market is likely to decline. Last but not least, they included in this category also the ratio of odd-lot sales to real purchases as a bearish measure.

The third category is made only for derivatives variables. One ratio is the ratio equity put to call trading volume, as is widely taken as a bearish indicator. They also took into account the reported change in the net position of SPX Futures as calculated by Commodities Futures Trading Commission. What is more, data on non-commercial traders are used as a proxy for individual sentiment. In the same way, the forecasts of commodity market returns collected by Market Vane are regarded as a bullish predictor of futures market behavior that is derived by tracking the buy and sell recommendations of leading market advisers. Above all, in this category they include one measure of expected volatility to relative to current volatility, given by the equation:

$$VOL_t = \ln(VIX_t/SIG_{t)}$$

Where VIX is the S&P 500 Index Option Volatility and SIG is the realizes volatility calculated from Open – High – Low – Close data on the S&P100 Index. Accordingly a positive VOL measures higher anticipated volatility and can be interpreted as bearish.

The last category, include variables that do not suit at any of the categories above. One variable is the close-end fund discount, which has been deeply analyzed in papers as a measure of sentiment. Moreover Mutual Fund Flows

are included in this category, too. They found also and include data regarding the proportion of fund assets held in cash as a negative sentiment regarding the market direction, in the fields of institutional sentiment. Last but not least they manage to include data regarding IPO's first day returns and the number of offerings. Furthermore it is really worth to say that they collected data on several market factors and made an orthogonaliazation with returns on large stocks and returns on small stocks.

Brown and Cliff also used a principal components methodology to define a sentiment index. The first principal component of a set of time-series variables is simply the linear combination of the variable with coefficients, chosen to capture as much of the joint variation across the series possible. The second principal component performs the same analysis but defines the relevant series as the residual from the first principal component and so on.

To summarize, they exact the investor sentiment measure identifying a single state variable using the Kalman filter and the first two principal components of the selected series, both for monthly and weekly data. They found that the Kalman filter estimate tends to be highly correlated with the first principal component and less correlated with the second. Lastly a robustness check on their method suggests also that they have succeeded in measuring investor sentiment by that way.

Chen, Chong & Duan (2010)

Chen, Chong and Duan in their paper "Aprincipal component approach to measuring investor sentiment", propose a similar way to Baker and Wurgler and Brown and Cliff regarding measuring investor sentiment.

In more detail, they tried to construct a comprehensive market sentiment measure for the Hong-Kong stock market. Their method is more similar to Baker and Wurgler than Brown and Cliff. The factors the took under concideration were:

- The short-selling volume
- The Hong-Kong Inter Bank Offered Rate
- The relative strength index

- The money flow index
- The performances of Japanese and US equity markets
- The market turn-over

Equally to Baker and Wurgler 2006 and 2007 the stock market sentiment index is defined here as well, as the first principal component obtained from principal component analysis.

They begin with the turn-over of the market, based on the fact that a small turn-over is typically followed by a fall in price while a large turnover is related with a following rise in price. In other words, they claim that turn-over is high in bull markets and low in bear markets.

Second they include short-selling. They claim that abnormal returns are often due to temporary sentiment brought about short-selling activities around the event dates. They define so the short – selling ratio as the number of shares being short to the total number of shares traded. They plot the ratio as follows.

Third, they took into account the Hong-Kong Inter Bank Offered Rate, due to the fact that it reflects the cost of investments. When it is high investors leave the stock market and the profits of firms are decreased, too, something that will be reflected to the value of stocks in the future. For these reasons high rate is a sign of bear market.

Moreover, they added in the Relative Strength Index, as a market signal for oversell or overbuy mood. It is highlighted that the value of 80 in this index represents an overbought market. In the same way they subsumed Money Flow Index. This Index can take values from 1 to 100. As value turns near 100 it seem that the equity is overbought. On the contrary when the value comes near to one the equity is oversold. They analytical definition of this ratio is presented in their paper.

Last but not least they comprise as a sentiment proxy the performance of the US and Japanese Equity Markets. This implies that they wanted to examine how the performance of the world's two largest stock markets affects the Hong – Kong Market. In particular they comprised the returns of S&P 500 Index and NIKKEI 225, after taking the time-zone difference.

After applying the principal components analysis they found that the first principal component to represent the index is the market turnover. Also both Money Flow Index and Relative Flow Index are positively related while the Interest Rate is negatively related. The performance of US and Japanese stock markets are positively related. The equation is:

$$SMS_t = -4.90 + 1.23Rav_t + 0.03RSI_T + 0.05MFI_t - 1.03HIBOR_t - 16.79SR_t + 18.74SP_t + 14.77JAP_t$$

2.2 Using Investor Sentiment to Explain Current Returns

Baker and Wurgler (2007)

After constructing the index of sentiment and the index of sentiment changes as well, they proceed to examine whether sentiment affect stock returns. As we refer in the introduction it is better to separate the effect on bond-like stocks on the one hand and speculative of the other.

For that reason Baker and Wurgler sorted the stocks according to their difficulty to arbitrage. In order to apply this sort, one would have taken into account the dispersion of professional analysts' earnings forecasts for every company. But for the period that Baker and Wurgler analyze such data are not available. Another thing that could help this sort could be the transaction costs for every stock, but data unavailability is a constraint for this period, too. Under these circumstances they finally sorted stocks according to their recent return volatility, in particular the standard deviation of monthly returns over the prior year. They used data from (CRSP)[32]. High volatility is commonly accepted as a characteristic of stocks with strong speculative appeal while low is a characteristic for bond-like stocks. In the same way highly volatile stocks are generally riskier to arbitrage. For each month they placed each stock into one of ten portfolios according to their return volatility of previous year. Of course returns of portfolios were used to apply the cross – section analysis of sentiment changes on stock returns.

Sentiment Betas

This is actually the variable that gave the answer to Baker and Wurgler about the relationship between sentiment changes and stock returns. To put it more simply, the dependent variable of that model was the monthly return. The independent was the changes of sentiment index. The results are plotted below:

Needless to say that the coefficients or sentiment betas show the effect of one standard deviation difference in the sentiment measure on average returns in percentage points. Furthermore, the value weighted market return is also included in the model as a control variable, because it is said that speculative stocks are likely to have higher market betas and enable the risk of contamination of sentiment betas.

As shown in the plot, sentiment betas increase as stocks become more speculative or difficult to arbitrage or their return volatility is increasing. What exactly derives from the plot is that for example a one-standard deviation increase in the sentiment changes index increases the returns of the eighth volatile portfolio about one percentage point. The effect on the last portfolio is found two percentage points. On the contrary, low volatility - return stocks, represent negative betas, so are slightly unaffected by sentiment. This is absolutely consistent with the theory.

However, it is analyzed that sentiment changes index may include components like dividend premium which naturally lead to differences in the correlations between its changes and stocks. Furthermore, it is claimed that no-one ensures that the sentiment index is not contaminated by economic fundamentals which of course could affect returns independently. To sum up, it is believed that every analyst should take into account all factors that result in such effects.

From the regression Baker and Wurgler extract some results regarding the whole market’s effect by sentiment index. They found that the correlation between the market index and the sentiment index is described by a value +0.43 of the beta coefficient. This number is regarded as highly significant.

Brown and Cliff (2004)

These researchers, alternatively, estimated a set of VAR models with the sentiment series and market returns. They wanted to examine, similarly with Baker and Wurgler the way sentiment index (as they measured) and returns interact and in more detail identify the statistical causality between the two variables. Their model equation was:

$$Y_t = \mu + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t$$

Similar to Baker and Wurgler they estimated the effect on returns by using both levels and changes of sentiment index. Firstly they found that individual sentiment is strongly positively related to its past levels and positively related as well to large stock returns. Similarly strong relations are presented for institutional investors as well. However it is also highlighted that the effects of investor sentiment to subsequent returns is limited. To put it more simply changes in institutional sentiment are negatively related to future large stock returns about 1% level. Even though there is no significant explanatory power for returns as indicated by determinant factor (= 0.008). Moreover none of the coefficients reveal a significant relation between changes in sentiment and small stock returns.

To sum up, Brown and Cliff, using their own sentiment measure found strong evidence of co-movement of sentiment and returns, likewise theory and Baker and Wurgler. In addition, they analytically represent the strong relation between institutional sentiment and large stocks, something that implies that sentiment is not limited to individual investors. Consequently it comes out that "noise" traders are individuals who affect small stocks.

Chen, Chong & Duan (2010)

Chen, Chong and Duan in Hong-Kong, classify the stock market into bull and bear states. In order to achieve this, they applied a multivariate threshold model using the sentiment index as the threshold variable, in order to capture the non-linear movement of the stock index.

The model can be found in their paper in more details. Something that really matters and on which we are going to focus is that the stock market is finally classified into three regimes. In the figure below there is a comparison between sentiment index and Hong-Kong market index returns.

We can see clearly observe that when the index is rising the sentiment is also high and on the contrast when the market index represent a downward trend, the sentiment index is falling. Something compatible with the theory and the two previous studies as well.

2.3 Using Investor Sentiment to Predict Future Returns

Baker and Wurgler (2007)

As it is proved in their research that sentiment and returns are positively correlated, it is possible that someone can predict future returns on sentiment affected stocks. However these researchers remind always to the readers, to examine carefully the circumstances under which correlation found. For example is it real sentiment or index is contaminated by economic fundamentals.

In order to proceed to predictability tests our researchers created an empirical version of the theoretical sentiment seesaw. In more detail, firstly they kept the sorting between speculative and safer stocks. Secondly, they splited the sentiment level index into high and low sentiment periods. Lastly they estimated average returns for the ten portfolios they have previously created, for the two periods. As in the previous regressions for betas calculation, they kept also the market return as a control variable. They found the result as shown in the plot below.

It is clearly represented that when the sentiment is low, the average future returns of speculative stocks exceed those of safer stocks. When sentiment is high, the average future returns of speculative stocks are on average lower than the returns of bond-like stocks. It really interesting that difficult to price stocks sometimes earn lower expected returns, something that differs from the classical theory in which investors accept risk due to higher return expectations.

What is more is that unconditional average returns are lower for difficult to price stocks, similarly to behavioral models of disagreement among investors combined with short – sales constraints. It is also presented that the market adjusted returns are on average positive, which is a factor that increases the average return our equally related portfolios.

Regarding the whole market, it is actually shown that when sentiment is high subsequent market returns are low. In the figure below, Baker and Wurgler claim that just as the correlation between sentiment changes and returns, is higher for an equal related index of returns, so is the correlation between sentiment levels and subsequent equal weighted stock returns. This gap between equal-related and value-related markets returns proves the strongest impact of sentiment on small, riskier, and difficult to price stocks. [33]

Brown and Cliff (2004)

Brown and Cliff in their VAR model show that their sentiment variable is a strong predictor for itself. However, this sentiment index does not predict large stock returns, something in agreement with theory and Baker and Wurgler paper. Moreover, they found limited evidence that sentiment may predict small stock returns due to its strong negative correlation. Furthermore they found that speculators are driven by market performance. All these results came from level sentiment index.

As far as their sentiment index with changes is concerned, they claim that it is a powerful predictor of itself. However, they did not found evidence that changes in this kind of sentiment influence either of return variables. They analyze also that institutional sentiment can be a strong predictor for individual sentiment but there is no evidence for the opposite.

Last but not least they found limited evidence that sentiment may predict subsequent market returns. They argue that the Granger-Causality tests fail to reject the null hypothesis of no predictability in returns for all. Institutional sentiment however appears positively related to subsequent large stock returns.

Nevertheless they did not actually found any relationship between investor sentiment and stock returns they argue that this limited predictability could be also

used as a profitable trading tool. They suggest that the measure of sentiment they have already constructed can be used as an indicator of the optimal level of sentiment in the whole market. For all these reasons they conducted a test if sentiment can provide information about the level of trading in the market. Practically they tried to extract a stochastic discount factor from a set of basis assets in order to use this factor as a calculator of the fair price of the asset. Finally they compare the derived price with the real one.The results of their last test, do not suggest any abnormal performance to the sentiment trading strategy even for safe or for small stocks at short horizons.

Chen, Chong & Duan (2010)

As far as Chen, Chong and Duan models' forecasting performance is concerned, it seems that there is high predictive power regarding the existing models. In particular they found small Forecast Errors in general. Mainly in their multivariate TAR model [34] they found the smallest forecast error and mean absolute forecast error.

They also used the Mean Forecast Trading Return as a tool to evaluate their models, because they claim that the primary objective of investors is to maximize trading returns rather than to minimize the forecast errors. This tool is actually a measure of trading profits.

In more detail, they were looking for different implications of their conducted sentiment index for stocks with different market capitalizations and for that reason they applied a trading rule to the two different market indices. According to their rule they buy when the sentiment is under 1.47 and they sell when the sentiment take prices above 1.47. Finally they show that according to their trading strategy, including sentiment level, higher profits can be earned and this effect is more significant for small stocks, due to the fact that they are more subjected to sentiment.

3. Proposal of Empirical Study

As it was previously mentioned, in this thesis we are trying to answer the following questions:

- How investor sentiment can be empirically measured?
- Whether and how can we quantify its effects on different stock categories?
- Can we use investor sentiment on order to predict future stock returns for different stock categories?

3.1 Quantify Investor Sentiment in UK Market

The abnormality of stock prices, seem to be well explained by sentiment factors, and this is the reason why it is really significant to measure these factors and carefully examine the effects in real trading. Everyone can find a variety of different approaches in quantifying investor sentiment in recent studies. In our research we found that Baker and Wurgler approach as performed in their study in 2007 is widely used and accepted. For these reason, we are going to follow the main steps of this approach in quantifying investor sentiment, adjusted into our region, period of time and data availability.

This implies that, we are going to construct a sentiment index, based on some main proxies that have been used even by Baker and Wurgler or by other analysts. We had to choose from a large variety as analytically described in literature review. However, data availability plays the role of constraint for the region and time we focus.

The region we analyze is United Kingdom and especially the London Stock Exchange market. The data in this study are monthly ad refer to the period between 01/01/2000 and 31/12/2016. After a deep research for the appropriate proxies of our sentiment index, we will finally use:

- Trading Volume
- Dividend Premium
- Consumer Confidence Index
- Official Interest Rate

- Performance of US Equity Market

Trading Volume: Trading Volume represents liquidity for every stock or index or fund. It is found as a sentiment proxy at least in the work of Baker and Wurgler in 2007 and in the work of Chen, Chong & Duan in 2010. It is claimed that irrational investors are willing to take short selling positions when this is less costly than taking long positions. Taking this into account, anyone could result that irrational investors add liquidity when they are optimistic and betting on rising stocks rather that when they are pessimistic. So, actually we used as proxy the market turnover ratio of trading volume to the number of shares listed on London Stock Exchange, for FTSE 100 on monthly basis, for period 01/01/2000 – 31/12/2016. Date was taken from THOMSON-REUTERS DATASTREAM database.

Dividend Premium: Baker and Wurgler have deeply discussed in their works in 2004 and 2007 the dividend premium as a sentiment indicator. They define this as the difference of the average price to book value ratio for dividend payers and non-dividend payers. They argue that when this difference is positive (premium), managers are more willing to pay dividends rather than when it is negative (discount). So this indicator is connected to sentiment, as it is connected to the investors' reaction to the managerial decision making regarding dividends.

In this case, firstly we downloaded data for price to book value ratio, for the constituents stocks of FTSE 100 and FTSE Small Cap, of London Stock Exchange for the referred period. Secondly, we downloaded data for dates of dividend payment for the same stocks for the same period. Thirdly, we counted for each stock the number of dividend payment dates. Then we ranked the stocks from the one that had the more dividend payment dates to the one that had the less dividend payment dates in these 17 years. It is reasonable that, no zero dividend paying stocks were found as the examining period is quite large. For this reason, stocks with less than ten dividend dates within 17 years were taken as non-dividend paying. Lastly, we take the difference of the average price to book value ratio for dividend payers and non-dividend payers

and we regard this difference as dividend premium or discount. Data were found on THOMSON-REUTERS DATASTREAM database.

Consumer Confidence Index: Nobody disagrees that investors surveys regarding their mood, is the most direct measure of investor sentiment. It has been found in previous studies that there is strong correlation with the index constructed by the results of direct studies and the consumer confidence index. Furthermore, it has been found that strong correlation exists between CCI and returns of small stocks, as they seem to be more subjected to sentiment in the recent studies. Undoubtedly, CCI can reflects in a direct way the investor sentiment. It has been used also in Qiu and Welch and in Lemmon and Portniaquina in studies 2006. For this reason, we collected data for this index, for United Kingdom, on a monthly basis, for the period between 01/01/2000-31/12/2016, from Eurostat on-line database.[35] It is really worth to note that we used both seasonally and calendar unadjusted data.

Official Interest Rate: The Official Interest Rate of each central bank reflects the cost of investments. When the rates are high, it is probable that investors cannot afford the cost and will leave the market. Furthermore, high rates on the other side are connected with lower profits for firms which are going to be reflected to stock prices in long term period. For all these reasons, high rates can indicate a bearish period while low rates can indicate a bullish period. Official Interest Rate of central bank has been used as a sentiment proxy in the very recent study of Chen, Chong & Duan in 2010 in the region of Hong-Kong. In this thesis data was found for Official Bank of England Interest Rate, on the website of Bank of England[36] for the period of 01/01/2000 – 31/12/2016 on a monthly basis.

Performance of US Equity Market: Chen, Chong & Duan in 2010 have taken into account the performance of the world's two largest stock markets as a sentiment indicator for the limited Hong-Kong market. In more detail they used the returns of the two basic indices of these stock markets: S&P 500 and NIKKEI. Finally they found strong positive relationship between US and Japanese and Hong-Kong Stock Market.

Regarding the market we examine, we assume that there is strong positive relationship with the US market performance. Therefore, we regard the returns of the world two most popular stock indices S&P 500 and NASDAQ, as a sentiment proxy for UK FTSE 100 and UK Small Cap stock returns. Data can be easily found on yahoo finance website[37], on a monthly basis for the period referred below. Note that there is no need for taking time-zone differences for these markets.

Principal Components Analysis

All these six referred proxies have in common the sentiment component and are highly correlated in the expected direction. Principal Components Analysis will indicate as the more important proxies that will form finally our index, in order to proceed to further explanations and predictions afterwards. Consequently, Principal Components Analysis was applied on Minitab statistics software. From this point forward we will occasionally refer to these proxies as TrVol, DivPrem, CCI, BOEBR, S&P 500, and NASDAQ, respectively.

Firstly, we formed a sentiment-levels index, which is actually the first principal component of the six proxies. In order to test for return predictability conditional on the state of sentiment changes as well, we constructed also a sentiment changes index which is actually the first principal component of the changes of the six referred proxies. [38]

3.2 Using Investor Sentiment to Explain Current Returns in UK Market

In the same way with the main reference of this thesis we constructed two portfolios. The first one represents the "bond-like" stocks in other words the blues chips of UK Stock Market. This portfolio is the UK FTSE 100 index. The second portfolio represents the more speculative and harder to arbitrage stocks. This portfolio is the UK FTSE Small Cap Index.

For each of the portfolios we run a time-series regression in SPSS Statistics software. In the first regression model, the dependent variable is the monthly returns of the FTSE 100 Index and the independent variable is the sentiment

changes index. In the second regression model, the dependent variable is the monthly returns of the FTSE Small Cap Index and the independent variable is as previously the sentiment changes index. Both regression models also include the monthly returns of the FTSE All-Share Index as a control variable.

As can be expected, we asked whether more speculative and difficult to price stocks are more sensitive to sentiment. To put it more simply, we asked whether these returns co-move more with an index of sentiment changes than the returns of safe stocks. Practically we expect positive sentiment betas on the regression between FTSE Small Cap returns and sentiment changes and negative sentiment betas on the regression between blue chips' returns and sentiment changes index as can be implied by theory and previous studies.

3.3 Using Investor Sentiment to Predict Future Returns in UK Market

Naturally, the FTSE 100 returns should not be related to sentiment betas. Under these circumstances the sentiment changes index is unable not only to explain monthly returns of FTSE 100 Index but also to predict these returns. Consequently, we will use this sentiment index as a forecast tool only for the returns of FTSE Small Cap Index.

The regression model will contain the returns of FTSE Small Cap Index returns as dependent variable, the sentiment changes index as main independent variable and the FTSE ALL Share Index returns as a controlling variable.

Firstly, using the previous month's measure of sentiment level we split the time series into two periods; low and high sentiment. Next, we compute average returns of the portfolio, for the two separate periods and overall, based on the regression model that we have used earlier.

4. Empirical Study

4.1 Quantify Investor Sentiment in UK Market

As mentioned earlier, in the present study the construction of the sentiment index was based on the six following proxies: Trading Volume, Dividend Premium, Consumer Confidence Index, Official Bank of England Interest Rate, and returns of the indices S&P 500 and NASDAQ. We will occasionally refer to these proxies as TrVol, DivPrem, CCI, BOEBR, S&P 500, and NASDAQ, respectively.

According to Table 1 moderate to high correlations exist among the six proxies. In particular, TrVol, DivPrem, CCI, S&P 500, and NASDAQ are positively correlated to each other, whereas BOEBR is negatively correlated with the rest of the proxies.

Since the six proxies are significantly correlated to each other, we then construct the sentiment changes index. Based on the Baker and Wurgler (2007) approach, the sentiment changes index is the first principal component of the changes in the six proxies. In further detail, the sentiment changes index's values are calculated according to the following equation:

$$\Delta SI = 0.08 \cdot \Delta TrVol - 0.06 \cdot \Delta DivRem - 0.02 \cdot \Delta CCI + 0.08 \cdot \Delta BOEBR + 0.70 \cdot \Delta S\&P500 + 0.70 \cdot \Delta NASDAQ$$

The sentiment changes index is then standardized to have zero mean and unit variance over the 17-year period. Figure 16 shows the index of sentiment changes index graphically.

4.2 Using Investor Sentiment to Explain Current Returns in UK Market

For each of the portfolios we run a time-series regression. In the first regression model, the dependent variable is the monthly returns of the FTSE 100 Index and the independent variable is the sentiment changes index. In the second regression model, the dependent variable is the monthly returns of the FTSE SmallCap Index and the independent variable is as previously the sentiment changes index. Both

regression models also include the monthly returns of the FTSE All-Share Index as a control variable.

The first regression model yields an R^2 of 0.96 ($F(2,200) = 2409.63$, $p < 0.001$). However, there is no statistically significant effect of the sentiment changes index on the monthly returns of the FTSE 100 Index (β = -0.004, p = 0.756), while controlling for the monthly returns of the FTSE All-Share Index.

The second regression model yields an R^2 of 0.51 ($F(2,200) = 102.93$, $p < 0.001$). Moreover, the sentiment changes index significantly affects the monthly returns of the FTSE Small Cap Index (β = 0.009, p = 0.002), while controlling for the monthly returns of the FTSE All-Share Index. For example, a one-standard-deviation increase in the sentiment changes index increases the monthly returns of the FTSE All-Share Index by 0.9 percentage point.

The results are as predicted. Sentiment beta is higher in the portfolio that represents the more speculative and difficult to price stocks, obviously because these stocks are presenting difficultly to arbitrage as well. On the other hand, the effect on sentiment changes in safe stocks' returns is slightly negative and this is consistent with Baker and Wurgler (2007) results and the theory.

4.3 Using Investor Sentiment to Predict Future Returns in UK Market

The analyses showed that sentiment is unable to explain monthly returns of the FTSE 100 Index, however it can explain monthly returns of the FTSE SmallCap Index, while controlling for the monthly returns of the FTSE All-Share Index. Particularly, an increase in the sentiment changes index increases the monthly returns of the FTSE All-Share Index. Based on this result, we will use sentiment in order to predict future returns of the FTSE SmallCap Index.

First, using the previous month's measure of sentiment level we split the time series into two periods; low and high sentiment. Next, we compute average returns of the portfolio, for the two separate periods and overall, based on the regression model that we have used earlier.

Figure 17 shows that when the sentiment level is below its 17-year average, monthly returns of the FTSE SmallCap Index average -0.386 percentage points,

whereas when the sentiment level is above its 17-year average, monthly returns of the FTSE SmallCap Index average -0.166 percentage points. The overall monthly returns of the FTSE SmallCap Index average -0.328 percentage points.

5. Conclusion

This work consists an approach to investigate what investor sentiment means for real trading world. To summarize, after a deep study of previous works around investor sentiment and in particular after analyzing the answers that have already be given by other analysts regarding the questions below:

- How investor sentiment can be measured?
- Are there any quantified effects on recent real trading?
- Can it be used as a forecast tool for future returns?

it comes that there is plenty space for extra statistical evidence in order to make this factor respected and calculated by more and more traders. It's one step that will move markets closer to the ideal situation of strong form of efficiency.

With reference to Baker and Wurgler analysis from 2007, in the US stock market, this research in an attempt for extra evidence in the London Stock Exchange Market the last 16 years.

Particularly, in the same way with the completed studies so far, this thesis represents firstly an approach to quantify investor sentiment, using a combination of already used proxies in the region and time of our focus. The method used; principal components analysis is widely accepted. The results of this analysis derived an index, which consists of the principal proxies that have been used as inputs.

What is more, with this index on hand, this work asks for extra evidence regarding the relation between sentiment changes index and UK stock returns. After constructing two portfolios; one which represented the safe stocks and one which represented speculative stocks and running one regression for each one with

independent variable the sentiment changes index, it came that there is positive correlation between speculative stocks and sentiment changes index. These results provide the extra evidence required and are consistent with the previous studies' results.

Last but not least, this thesis represents an approach to use the constructed sentiment index as a forecast tool for future returns. In particular based on the previous regression model of FTSE Small Cap and sentiment changes index, which shows the ability to explain current returns we computed average returns for this portfolio in two period of high and low sentiment.

In conclusion, similar to Baker and Wurgler (2007) approach, this thesis, consists an additional approach to quantify investor sentiment in an index based on various proxies at first. Secondly, it represents an approach to find extra evidence that speculative stocks are more subjective to sentiment and last but not least is performs a forecast for future returns of speculative stocks in periods of high and low sentiment.

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7. Tables

7.1 Table 1: Correlations between the six proxies

	1	2	3	4	5	6
1. CCI	1					
2. BOEBR	.230**	1				
3. TrVol	.252**	-.507**	1			
4. S&P 500	.435**	-.397**	.698**	1		
5. NASDAQ	.356**	-.466**	.627**	.956**	1	
6. DivPrem	.457**	-.232**	.367**	.477**	.455**	1

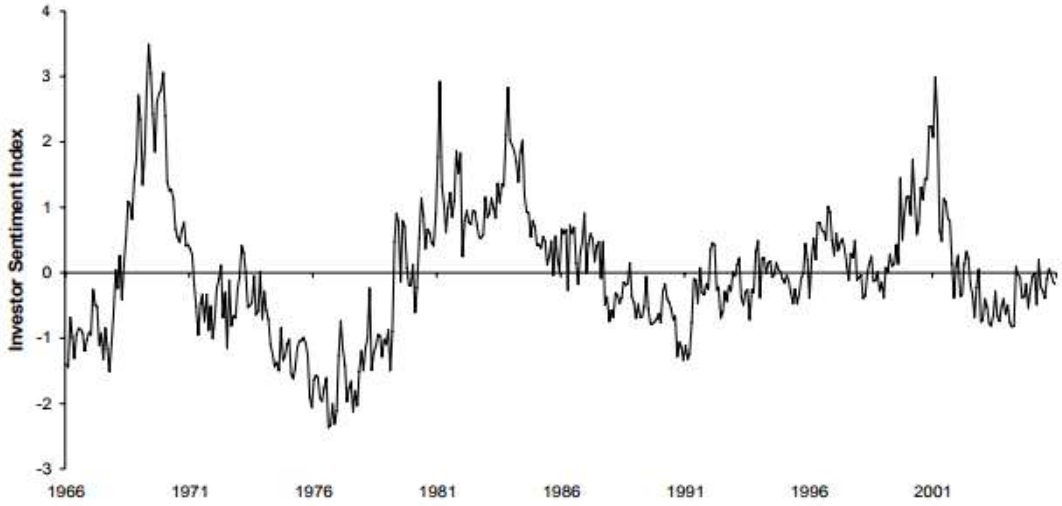
Note. ** $p < 0.01$.

8. Figures

Figure 1: Baker and Wurgler Sentiment Index, January 1966 through December 2005

Panel A: Index of Sentiment Levels

$$SENT = -0.23CEFD + 0.23TURN + 0.24NIPO + 0.29RIPO - 0.32PDND + 0.23S$$



Panel B: Index of Sentiment Changes

$$\Delta SENT = -0.17\Delta CEFD + 0.32\Delta TURN + 0.17\Delta NIPO + 0.41\Delta RIPO - 0.32\Delta PDND - 0{,}28S$$

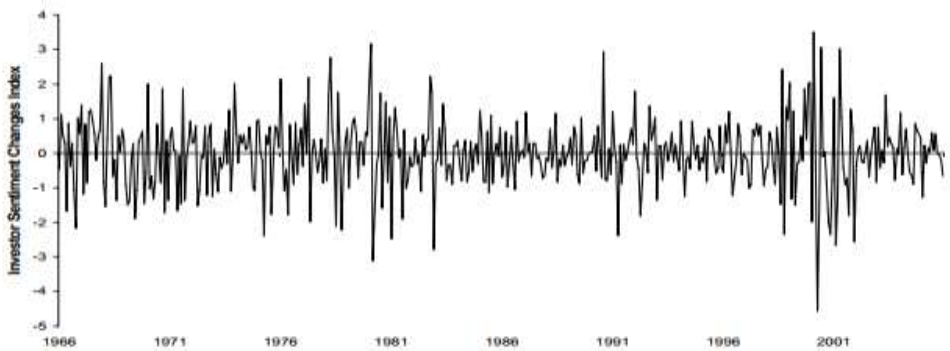


Figure 2: Brown and Cliff 2004 Survey Results

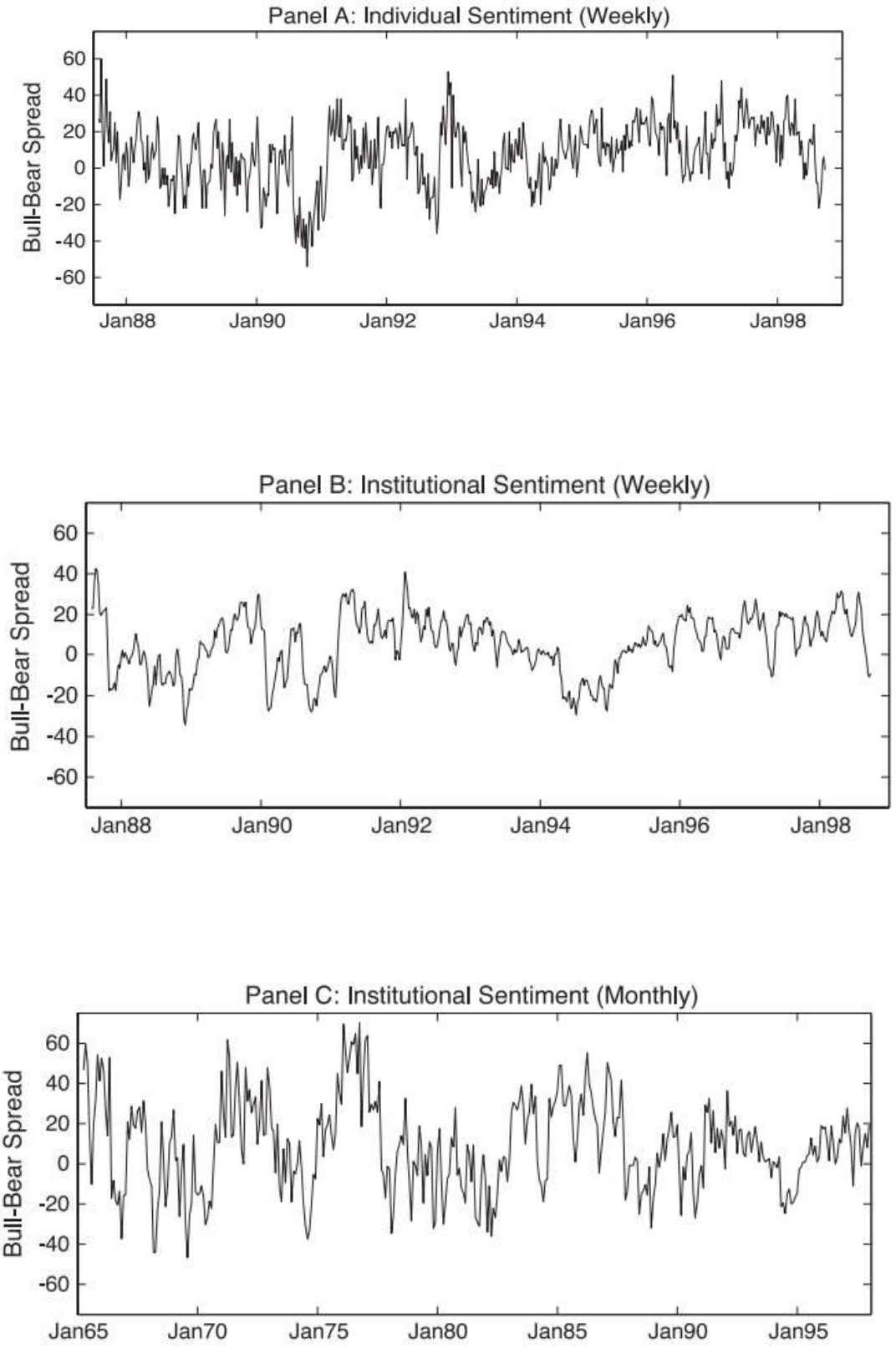


Figure 3: The Chen, Chon, Duan turnover ratio [33]

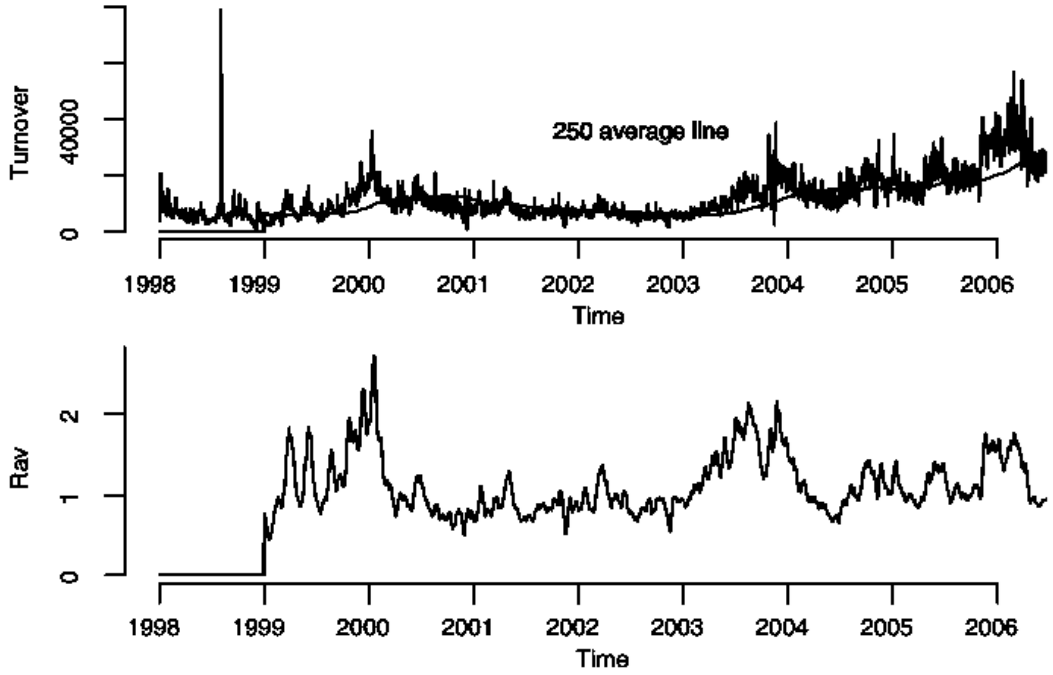


Figure 4: The Chen, Chon, Duan short-sell ratio

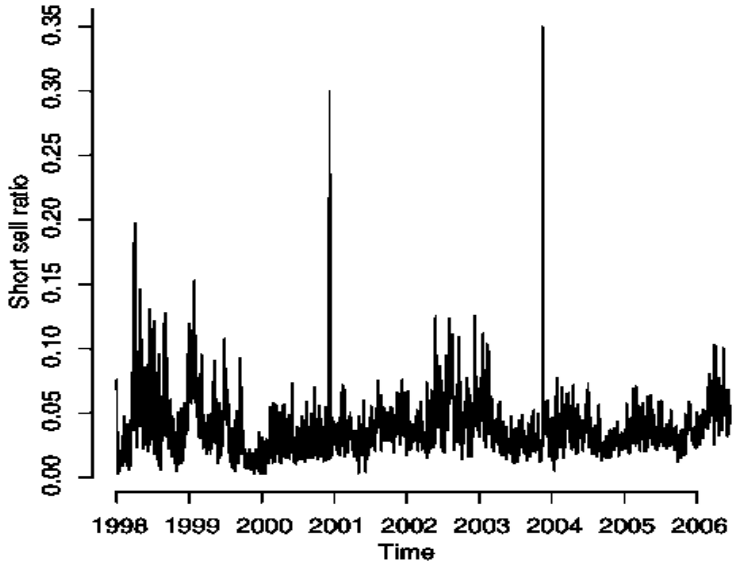


Figure 5: The Chen, Chon, Duan sentiment Index

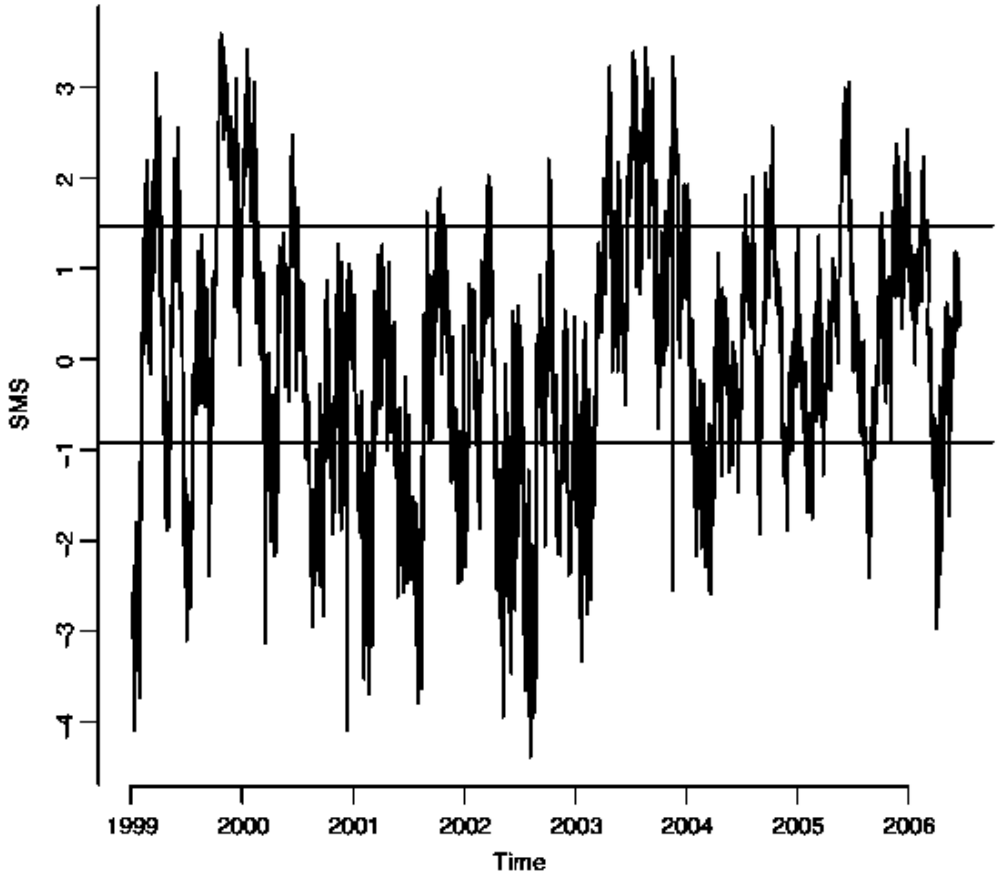


Figure 6: Baker and Wurgler sentiment betas based on a sentiment index

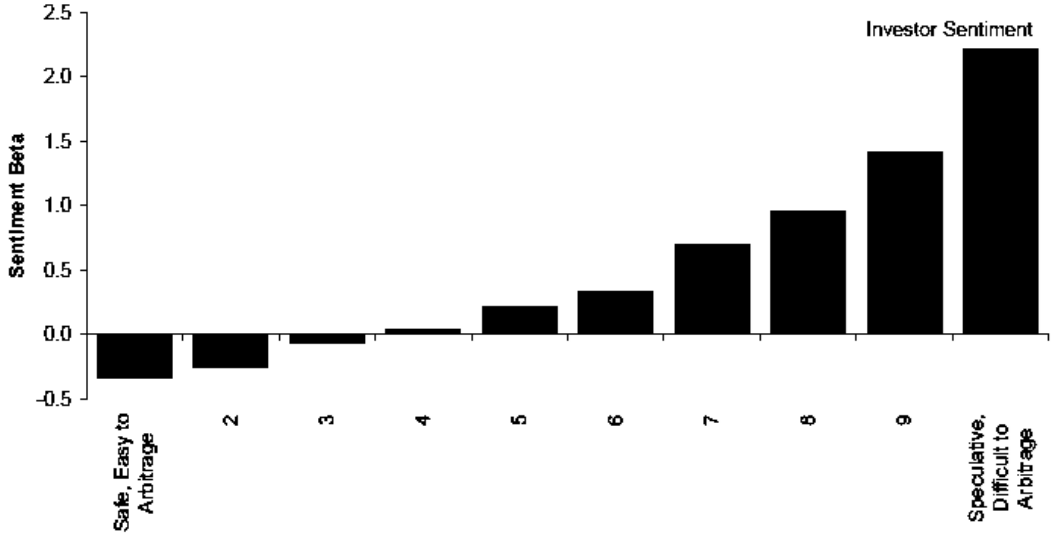


Figure 7: Chen, Chong & Duan sentiment index and Hong-Kong Market Index over time

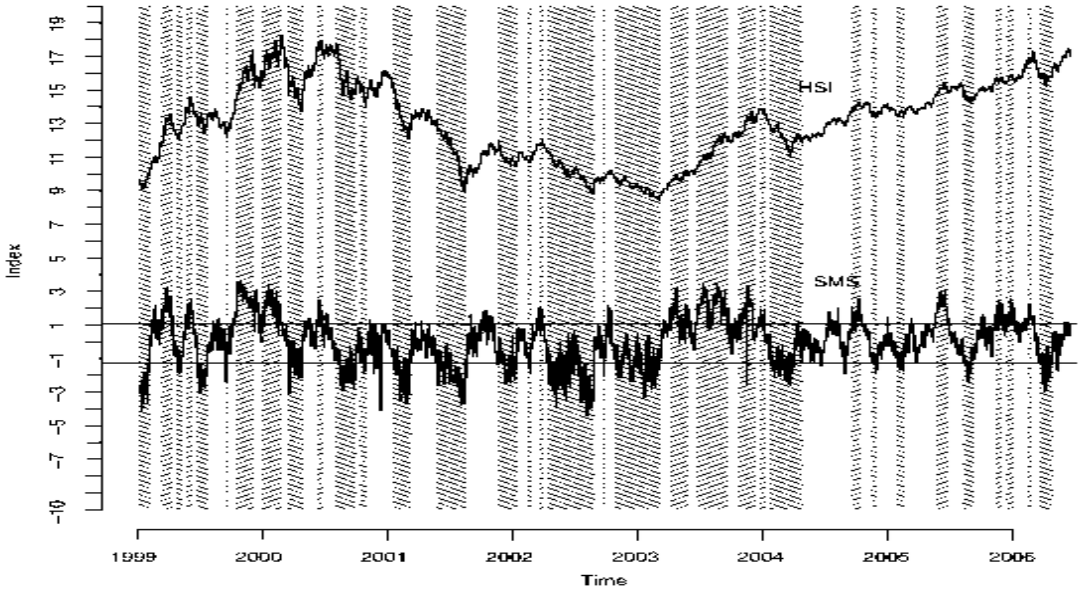


Figure 8: Baker and Wurgler sentiment and future returns

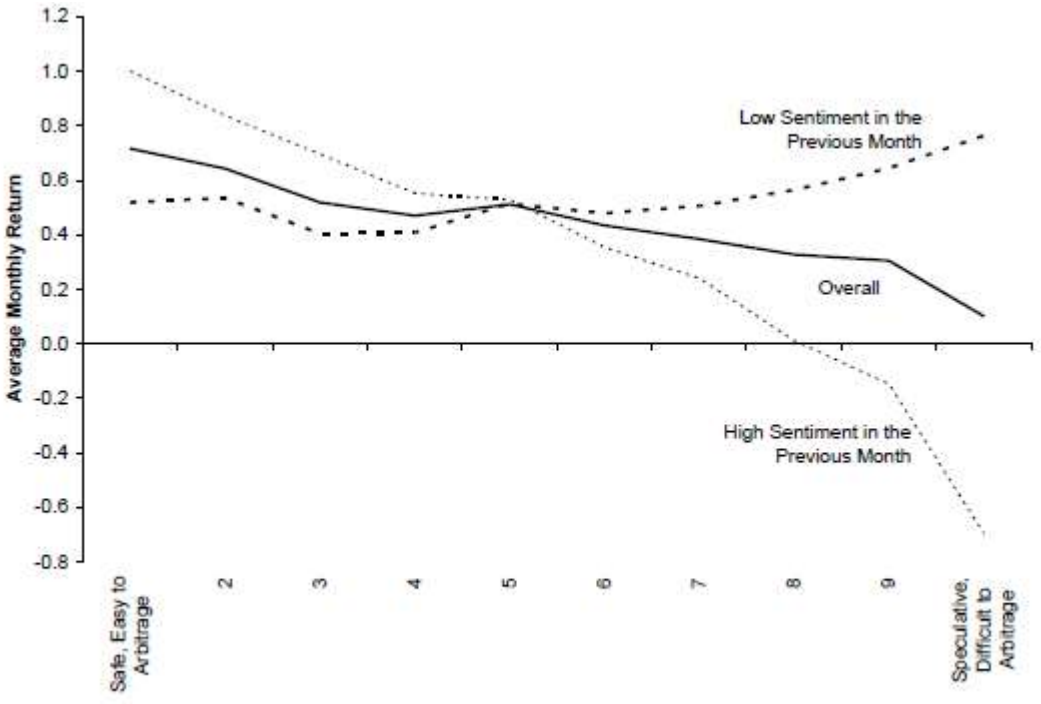


Figure 9: Baker and Wurgler sentiment and future market returns

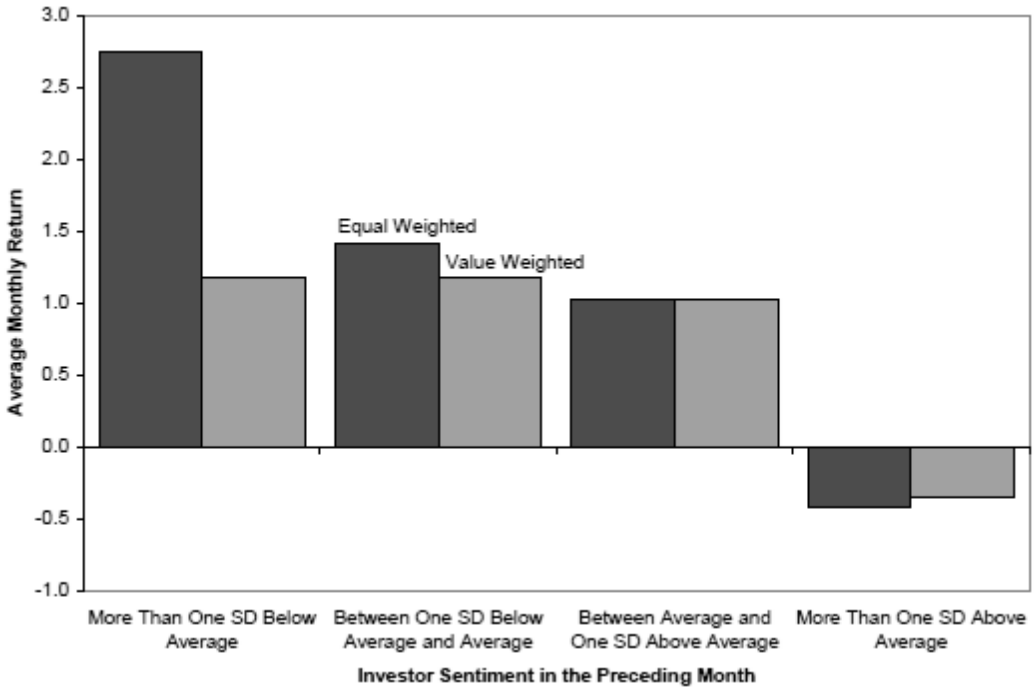
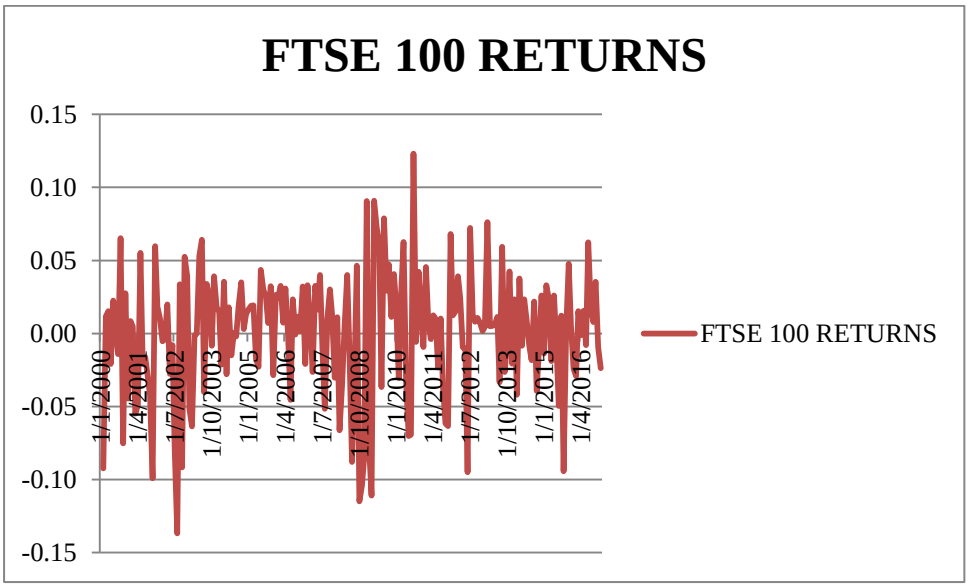
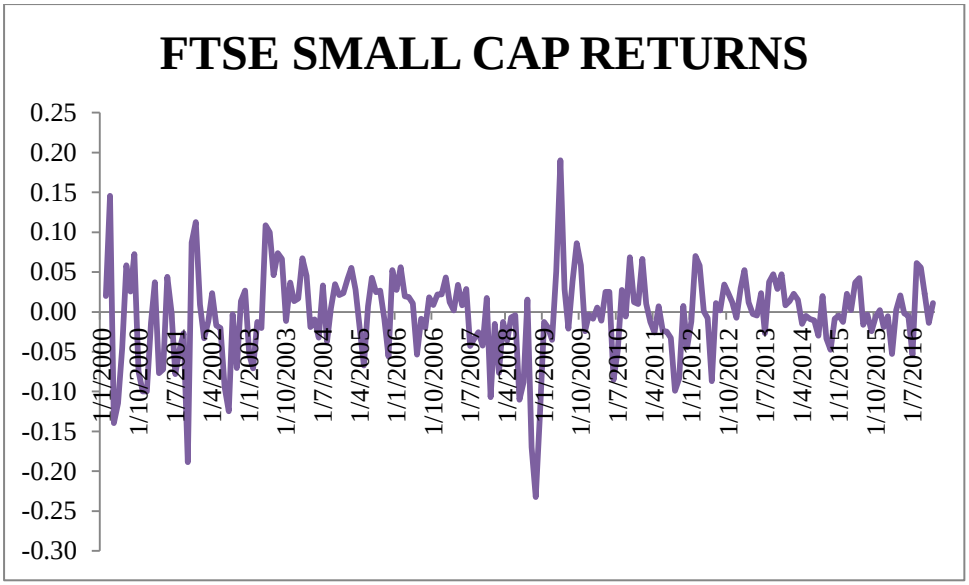


Figure 10: LSE Returns 01/01/2000-31/12/2016





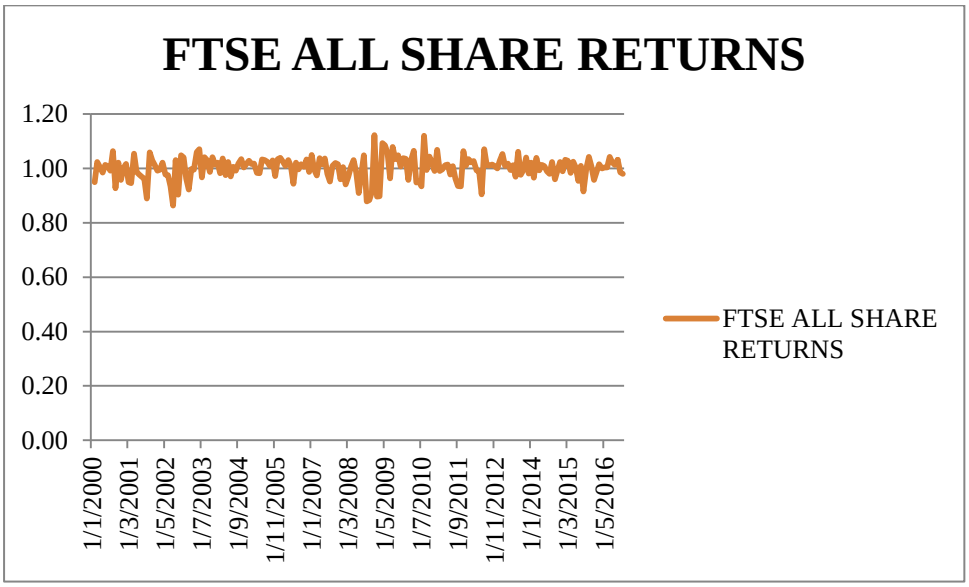


Figure 11: Trading Volume FTSE 100 01/01/2000-31/12/2016

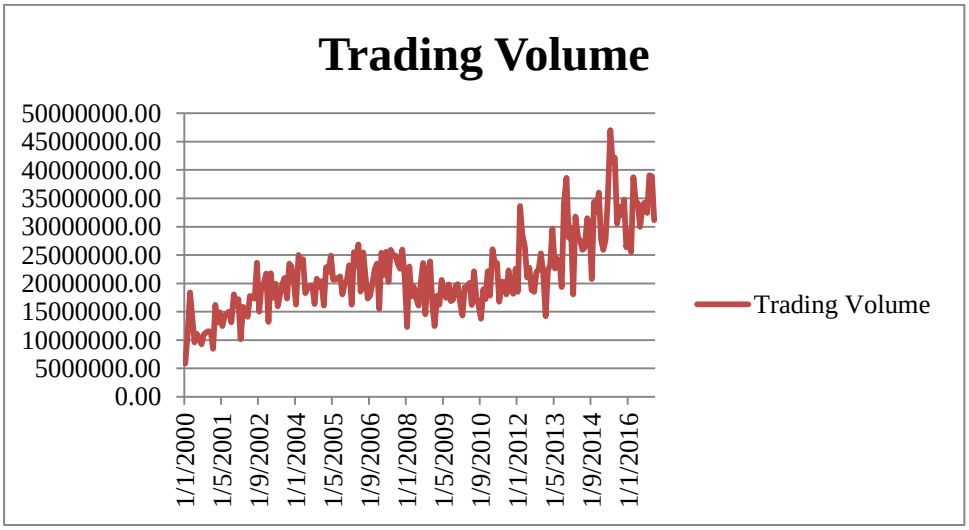


Figure 12: Dividend Premium LSE 01/01/2000-31/12/2016

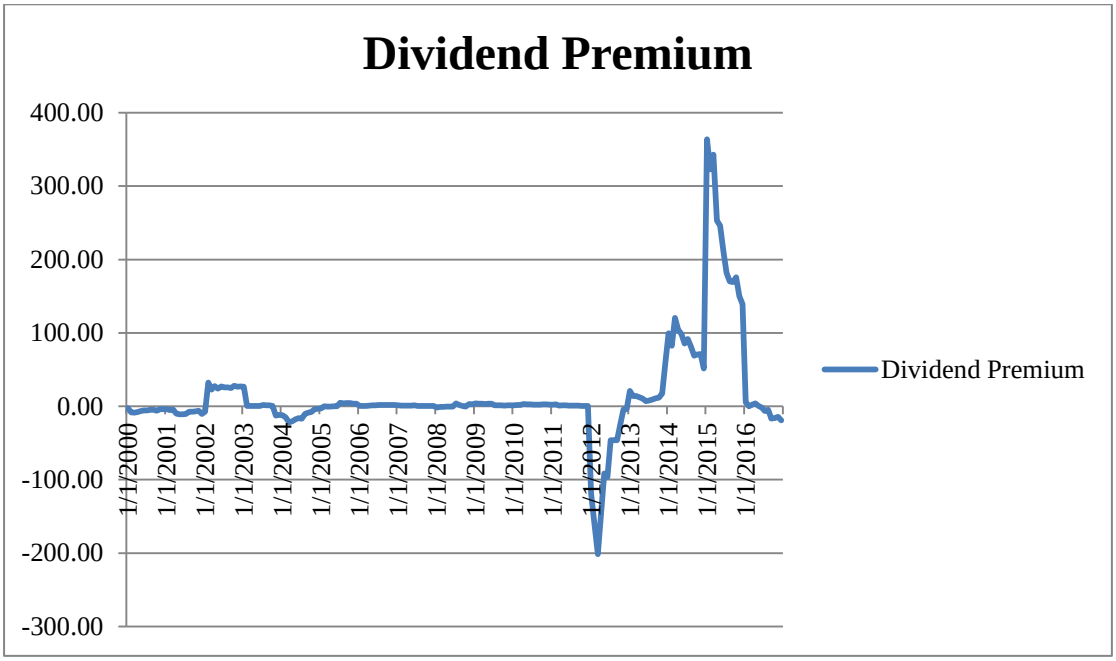


Figure 13: Consumer Confidence Index, UK 01/01/2000-31/12/2016

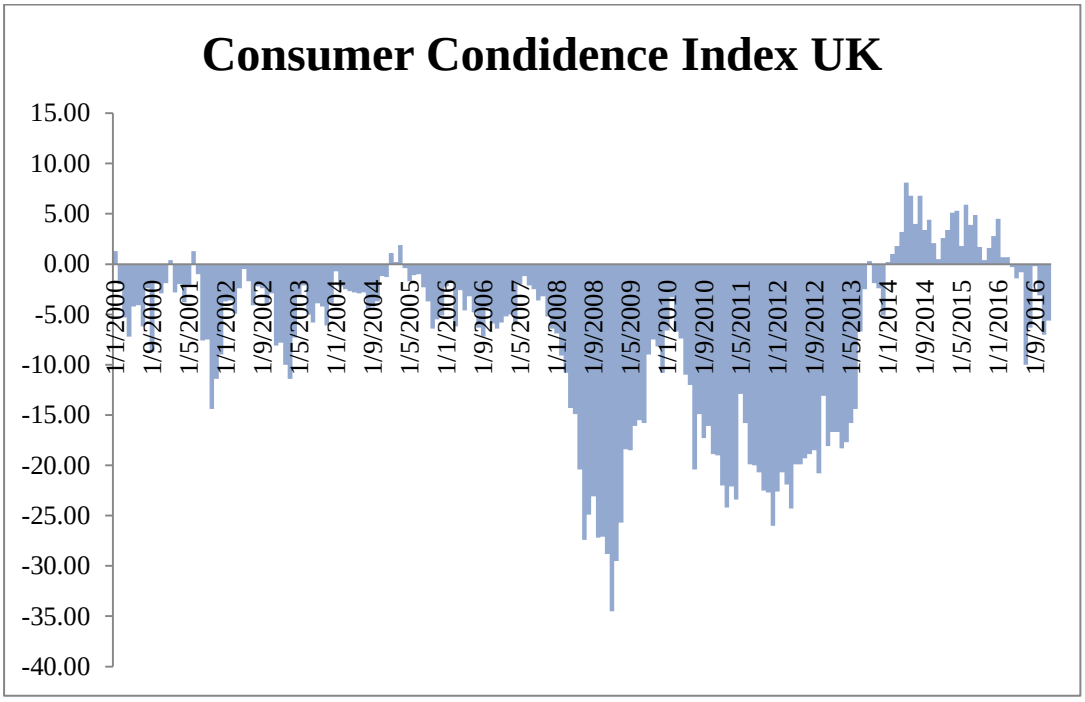


Figure 14: Interest Rate, UK 01/01/2000-31/12/2016

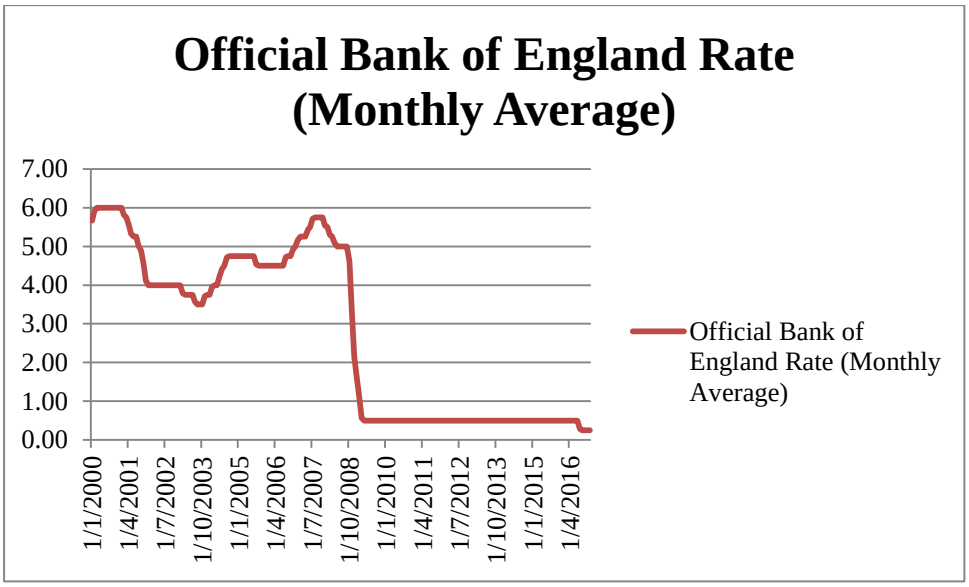


Figure 15: FTSE 100, S&P 500 & NASDAQ, 01/01/2000-31/12/2016

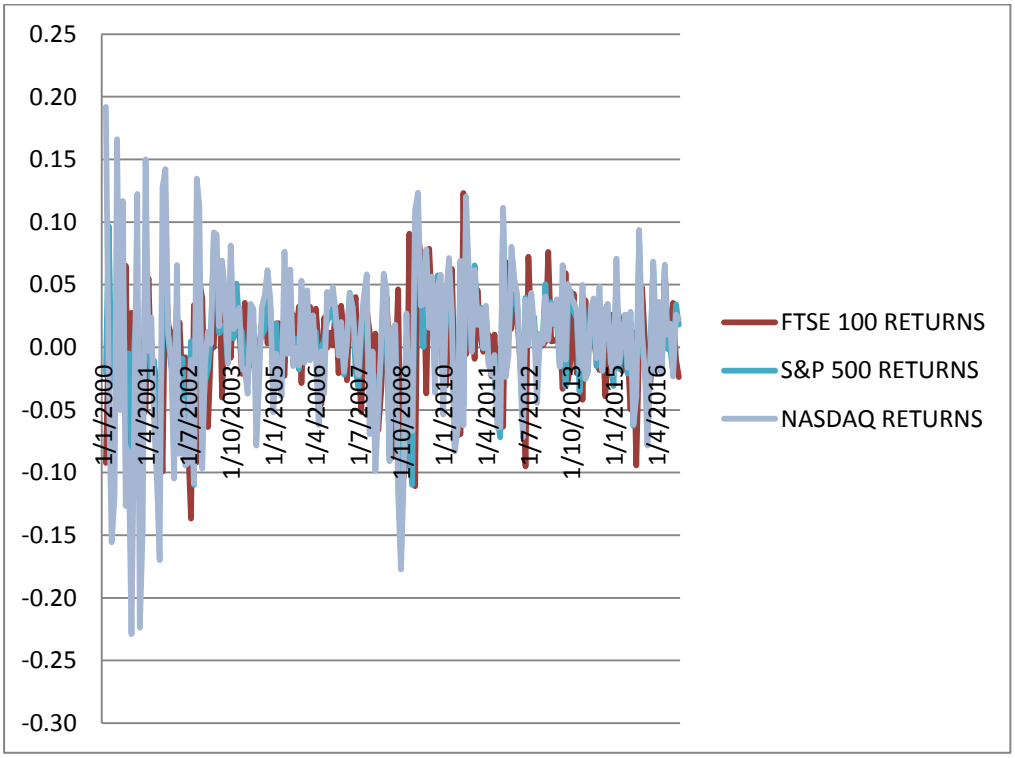


Figure 16: Index of sentiment changes, 01/01/2000-31/12/2016

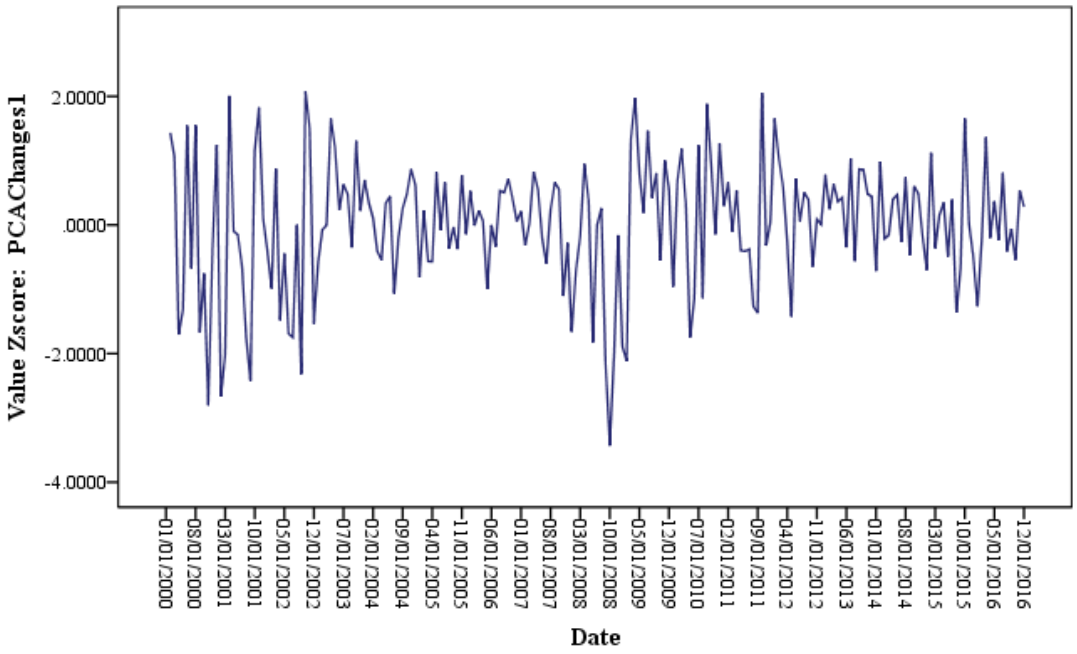
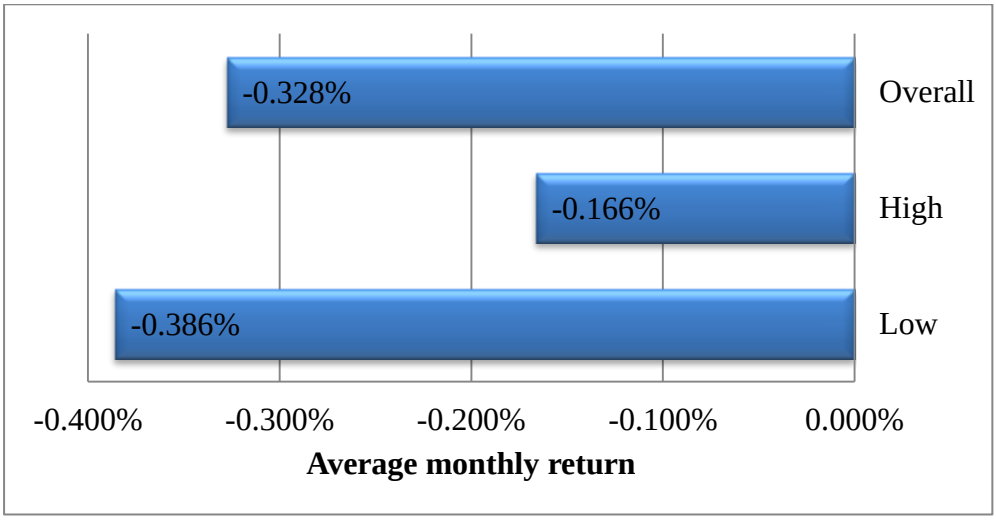


Figure 17: The predictive ability of the sentiment index



9. Appendix

9.1 Quantify Investor Sentiment – PCA in Minitab

Results for: Minitab_data.XLS

Principal Component Analysis: PosMetCCI; PosMetBOEBR; PosMetTradVo; PosMetSP500

```
Eigenanalysis of the Correlation Matrix
203 cases used, 1 cases contain missing values

Eigenvalue  1.8585  1.0646  1.0348  0.9724  0.9157  0.1541
Proportion   0.310   0.177   0.172   0.162   0.153   0.026
Cumulative   0.310   0.487   0.660   0.822   0.974   1.000


Variable          PC1
PosMetCCI      -0.020
PosMetBOEBR     0.084
PosMetTradVol   0.084
PosMetSP500     0.702
PosMetNASDAQ    0.699
PosMetDivPrem  -0.062
```

Principal Component Analysis: Consumer Con; Official Ban; Trading Volu; S&P 500

```
Eigenanalysis of the Correlation Matrix

Eigenvalue  3.3139  1.3179  0.6405  0.4175  0.2786  0.0316
Proportion   0.552   0.220   0.107   0.070   0.046   0.005
Cumulative   0.552   0.772   0.879   0.948   0.995   1.000


Variable                            PC1
Consumer Condidence Index UK      0.264
Official Bank of England Rate (  -0.296
Trading Volume                    0.442
S&P 500                           0.516
NASDAG                            0.503
Dividend Premium                  0.357
```

9.2 Regressions – SPSS Outputs

Variables Entered/Removed[b]

Model	Variables Entered	Variables Removed	Method
1	PosMetFTSEall, Zscore: PCAChanges1	.	Enter

Variables Entered/Removed[b]

Model	Variables Entered	Variables Removed	Method
1	PosMetFTSEall, Zscore: PCAChanges1	.	Enter

a. All requested variables entered.

b. Dependent Variable: PosMetFTSE100

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.980[a]	.960	.960	.0084383

a. Predictors: (Constant), PosMetFTSEall, Zscore: PCAChanges1

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.343	2	.172	2409.626	.000[a]
	Residual	.014	200	.000		
	Total	.357	202			

a. Predictors: (Constant), PosMetFTSEall, Zscore: PCAChanges1

b. Dependent Variable: PosMetFTSE100

Coefficients[a]

Model		Unstandardized Coefficients	
		B	Std. Error
1	(Constant)	-.001	.001
	Zscore: PCAChanges1	.000	.001
	PosMetFTSEall	.968	.014

a. Dependent Variable: PosMetFTSE100

Coefficients[a]

Model		Standardized Coefficients Beta	t	Sig.
1	(Constant)		-1.470	.143
	Zscore: PCAChanges1	-.004	-.311	.756
	PosMetFTSEall	.980	69.201	.000

a. Dependent Variable: PosMetFTSE100

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT P_A
  /METHOD=ENTER ZP_J P_B.
```

Regression

Variables Entered/Removed[b]

Model	Variables Entered	Variables Removed	Method
1	PosMetFTSEall, Zscore: PCAChanges1	.	Enter

a. All requested variables entered.

b. Dependent Variable: PosMetFTSEsmall

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.712[a]	.507	.502	.0381097

a. Predictors: (Constant), PosMetFTSEall, Zscore: PCAChanges1

ANOVA[b]

Model	Sum of Squares	df	Mean Square	F	Sig.

1	Regression	.299	2	.149	102.933	.000[a]
	Residual	.290	200	.001		
	Total	.589	202			

a. Predictors: (Constant), PosMetFTSEall, Zscore: PCAChanges1

b. Dependent Variable: PosMetFTSEsmall

Coefficients[a]

Model		Unstandardized Coefficients	
		B	Std. Error
1	(Constant)	-.005	.003
	Zscore: PCAChanges1	.009	.003
	PosMetFTSEall	.864	.063

a. Dependent Variable: PosMetFTSEsmall

Coefficients[a]

Model		Standardized Coefficients		
		Beta	t	Sig.
1	(Constant)		-1.772	.078
	Zscore: PCAChanges1	.157	3.162	.002
	PosMetFTSEall	.681	13.680	.000

a. Dependent Variable: PosMetFTSEsmall

```
COMPUTE lagSentLevels=LAG(SentLevels).
EXECUTE.
EXAMINE VARIABLES=PRE_1 BY lagSentLevels
  /PLOT NONE
  /STATISTICS DESCRIPTIVES
  /CINTERVAL 95
  /MISSING LISTWISE
  /NOTOTAL.
```

Explore

lagSentLevels

Case Processing Summary

		Cases		
		Valid		Missing
	lagSentLevels	N	Percent	N
Unstandardized Predicted Value	1	153	100.0%	0
	2	50	100.0%	0

Case Processing Summary

		Cases		
		Missing	Total	
	lagSentLevels	Percent	N	Percent
Unstandardized Predicted Value	1	.0%	153	100.0%
	2	.0%	50	100.0%

Descriptives

	lagSentLevels			Statistic
Unstandardized Predicted Value	1	Mean		-.0038060
		95% Confidence Interval for Mean	Lower Bound	-.0105465
			Upper Bound	.0029345
		5% Trimmed Mean		-.0025360
		Median		.0035569
		Variance		.002
		Std. Deviation		.04220074
		Minimum		-.13829
		Maximum		.09256
		Range		.23085
		Interquartile Range		.05055
		Skewness		-.591
		Kurtosis		.644
	2	Mean		-.0016648
		95% Confidence Interval for Mean	Lower Bound	-.0084730
			Upper Bound	.0051433
		5% Trimmed Mean		-.0006448

		Median	-.0028292
		Variance	.001
		Std. Deviation	.02395581
		Minimum	-.08318
		Maximum	.04355
		Range	.12673
		Interquartile Range	.03131
		Skewness	-.676
		Kurtosis	1.648

Descriptives

	lagSentLevels			Std. Error
Unstandardized Predicted Value	1	Mean		.00341173
		95% Confidence Interval for Mean	Lower Bound	
			Upper Bound	
		5% Trimmed Mean		
		Median		
		Variance		
		Std. Deviation		
		Minimum		
		Maximum		
		Range		
		Interquartile Range		
		Skewness		.196
		Kurtosis		.390
	2	Mean		.00338786
		95% Confidence Interval for Mean	Lower Bound	
			Upper Bound	
		5% Trimmed Mean		
		Median		
		Variance		
		Std. Deviation		
		Minimum		
		Maximum		
		Range		
		Interquartile Range		
		Skewness		.337
		Kurtosis		.662

```
FREQUENCIES VARIABLES=PRE_1
  /FORMAT=NOTABLE
  /STATISTICS=STDDEV MEAN
  /ORDER=ANALYSIS.
```

Frequencies

Statistics

Unstandardized Predicted Value

N	Valid	203
	Missing	1
Mean		-.0032786
Std. Deviation		.03847271

```
RECODE ZP_L (Lowest thru -1=1) (-1 thru 0=2) (0 thru 1=3) (1 thru
Highest=4) INTO SI4levels.
EXECUTE.
COMPUTE lagSent4Levels=LAG(SI4levels).
EXECUTE.
SORT CASES  BY lagSent4Levels.
SPLIT FILE SEPARATE BY lagSent4Levels.
FREQUENCIES VARIABLES=PRE_1
  /FORMAT=NOTABLE
  /STATISTICS=STDDEV MEAN
  /ORDER=ANALYSIS.
```

Frequencies

lagSent4Levels = .

Statistics[a]

Unstandardized Predicted Value

N	Valid	0
	Missing	1

a. lagSent4Levels = .

lagSent4Levels = 1

Statistics[a]

Unstandardized Predicted Value

N	Valid	11
	Missing	0
Mean		-.0531148
Std. Deviation		.07928147

a. lagSent4Levels = 1

lagSent4Levels = 2

Statistics[a]

Unstandardized Predicted Value

N	Valid	142
	Missing	0
Mean		.0000137
Std. Deviation		.03563258

a. lagSent4Levels = 2

lagSent4Levels = 3

Statistics[a]

Unstandardized Predicted Value

N	Valid	11
	Missing	0
Mean		.0006077
Std. Deviation		.02179539

a. lagSent4Levels = 3

lagSent4Levels = 4

Statistics[a]

Unstandardized Predicted Value

N	Valid	39
	Missing	0
Mean		-.0023058
Std. Deviation		.02476040

a. lagSent4Levels = 4

```
SPLIT FILE OFF.
```

[1] Such cases are: the Great Crash of 1929, the Tronics Boom of the early 1960's, the Go-Go years of the late 1960's, the Nifty Fifty bubble of the early 1970's, the Black Monday crash of October 1987, the Internet or Dot.com bubble of the early 1990's or the rally of US stock markets after Trump's election.

[2] Definition as given by: http://www.investorwords.com/4491/sentiment.html

[3] Bradford Delong J., Shleifer A., Summers L., Waldman R., (1990) "Positive feedback investment strategies and destabilizing rational speculation", The Journal of Finance, Vol. XLV, No 2, pp. 379 - 395

[4] https://en.wikipedia.org/wiki/Top-down_and_bottom-up_design

[5] Barberis N., Shleifer A., Vishny R., (1998), "A model of investor sentiment", Journal of Financial Economics 49, 307-343

[6] This approach is commonly found in Fama – French Studies (1988&1989) and Campbell and Shiller(1988)

[7] As described in "bottom up" approach and Bradford Delong J., Shleifer A., Summers L., Waldman R., (1990) "Positive feedback investment strategies and destabilizing rational speculation", The Journal of Finance, Vol. XLV, No 2, pp. 379 - 395

[8]Definition as given: http://www.investopedia.com/terms/m/marketsentiment.asp

[9] Please turn to Chapter 3 for more elaboration.

[10] http://www.trade-futures.com/dailyindex.php

[11] Schiller J. Robert (1989), "Survey Evidence On Diffusion of Interest and Information Among Investors", Journal of Economic Behavior and Organization, Vol 12, pp. 47-66

[12] Brown W. Gregory, Cliff T. Michael (2005), "Investor sentiment and asset valuation", The Journal of Business, published by the University of Chicago Press, Vol. 78, No 2, pp. 405-440

[13] Qiu, Lily X., Welch Ivo, (2004) "Investor Sentiment Measures", NBER Working Papers, Working Paper 10794, http://www.nber.org/papers/w10794

[14] Kamstra Mark J., Kramer Lisa A., Levi Maurice D., (2003), "Winter Blues: A Sad Stock Market Cycle", The American Economic Review, Vol. 93, No. 1, pp. 324-343

[15] Edmans A., Diego G., Norli O., (2007) , "Sports Sentiment and Stock Returns" , The Journal of Finance, Vol 62, Issue 4, Pages 1529-2058

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[17] Barber Brad M., Odean T., Zhu N., (2009), "Systematic Noise", Journal of Financial Markets, Vol. 12, pp. 547-569

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[19] Wartner A. (1995), "Aggregate Mutual Fund Flows and Security Returns", Journal of Financial Economics, Vol 39, pp. 209-235

[20] Frazzini A., Lamont O. (2008), "Dump Money: Mutual Fund Flows and the cross-section of stock returns", Journal of Financial Economics, Vol 88, pp. 299-322

[21] Baker S., Stein J., (2004), Market Liquidity as a sentiment Indicator, Journal of Financial Markets, Vol 7, pp. 271-299

[22] Schneikman J., Xiong W., (2003) Overconfidence and Speculative Bubbles, Journal of Political Economy, Vol 111, pp. 1183-1219

[23] Baker M., Wurgler J., 2004b. "Appearing and disappearing dividends: The link to catering Incentives, "Journal of Financial Economics, Vol. 73(2), pp. 271-288

[24] The definition in the one given in the main reference of this work the paper of Baker M., Wurgler J., (2007), "Investor Sentiment in the Stock Market", Journal of Economic Perspectives, Vol 21(2), pp. 129-151

[25] Zweig M., (1973), "An Investor Expectations Stock Price Predictive Model Using Closed-End Fund Premiums" Journal of Finance, vol28(1), pp. 67-87

[26] Lee C., Shleifer A., Thaler R., (1991), "Investor Sentiment and the Closed-End Fund Puzzle", Journal of Finance, vol 46(1), pp. 75-79

[27] The definition in the one given in the main reference of this work the paper of Baker M., Wurgler J., (2007), "Investor Sentiment in the Stock Market", Journal of Economic Perspectives, Vol 21(2), pp. 129-15

[28] Ljungvist A., Nanda V., Singh R., (2006), " Hot Markets, Investor Sentiment and IPO Pricing" Journal of Business, vol 79(4), 1667-1703

[29] Baker M., Wurgler J., (2007), "Investor Sentiment in the Stock Market", Journal of Economic Perspectives, Vol 21(2), pp. 129-151

[30] Such as Brown(1991), Dreman (1979), Graham (1973), Malkiel (1999), Schiller(2000), Siegel (1998)

[31] Brown W. Gregory, Cliff T. Michael (2004), "Investor sentiment and the near – term stock market", The Journal of Empirical Finance, Vol. 11, No 1, pp. 1-27

[32] Center for Research in Securities Prices

[33] M., Wurgler J., (2007), "Investor Sentiment in the Stock Market", Journal of Economic Perspectives, Vol 21(2), pp. 129-151

[34]A model with past return as a threshold variable

[35] http://ec.europa.eu/eurostat/web/products-datasets/-/teibs010

[36]http://www.bankofengland.co.uk/statistics/Pages/default.aspx

[37] https://finance.yahoo.com/

[38] Change in proxies is calculated as: $(X_t - X_{t-1})/X_t$, where X the value of every proxie in time t