Investor Sentiment and Asset Returns on the Johannesburg Securities Exchange

Cameron Singh (SNGCAM001) and Jonty Doyle (DYLJON001)

Supervisor: Associate Professor Edward Chamisa

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ABSTRACT

This study investigates the relationship between investor sentiment and asset prices on the Johannesburg Securities Exchange in South Africa. Previous literature suggests that a significant relationship exists, and periods of high sentiment are followed by periods of low returns for assets of specific characteristics, namely those most susceptible to noise-trader sentiment. Three proxies for sentiment are considered from 2007 to 2019: The Consumer Confidence Index, Business Confidence Index and a market developed sentiment index using principle component analysis of salient sentiment characteristics. Our findings note that survey sentiment indices have little to no predictive power in asset return while the developed sentiment index shows some forms of significance, particularly in portfolios of distressed firms. Additionally, a systematic endogenous model between sentiment and returns on small stocks relative to larger ones, is developed; showing short-run momentum and long-run mean-reversion effects of sentiment on small stock returns.

Keywords:

Investor Sentiment, Asset Prices, Johannesburg Securities Exchange, Business Confidence, Consumer Confidence, Sentiment Index, Cross-Section, Size Premium

1. INTRODUCTION

Traditional finance theory affords no opportunity for asset mispricing. When markets are efficient, and arbitrage is limited, asset prices will follow the fundamental valuations of discounted cash flows and capital asset pricing models. However, recent financial market failures have subsequently shown traditional models failing and have allowed for systemic mispricing to occur. Behavioural finance theory has thus developed to find reason behind such market anomalies, with investor sentiment providing increasing evidence for such (Baker & Wurgler, 2006)

Defined broadly, investor sentiment "is a belief about future cash flows and investment risks that is not justified by the facts at hand" (Baker & Wurgler, 2007: 129). Underlying assumptions of investor sentiment are twofold. Firstly, investors are prone to sentiment and secondly, arbitrageurs (rational investors) find it costly to bet against such sentiment. This results in market pricing reverting to fundamentals significantly less rapidly than traditionally thought (Baker & Wurgler, 2006). From such assumptions, research has developed from questioning its effects to quantifying these effects. The behavioural nature of sentiment has given rise to a significant number of models, proxies and indices attempting to explain it empirically. This can then be separated into two main categories, direct and indirect investor sentiment. Direct investor sentiment refers to the expectations about the future and is usually measured in the form of surveys. Indirect investor sentiment encompasses economic variables that are perceived to act as proxies (Bolaman & Mandaci, 2014). The objective of this study is to examine the effects of both direct and indirect investor sentiments on asset pricing using the data of firms listed on the JSE from 2009 to 2019.

The effects of investor sentiment are not uniform among all assets. Initially, many authors supported assumptions of the effects of sentiment on aggregate stock prices (Barberis, Shleifer & Vishny, 1998), however, Baker and Wurlger (2006) found such mispricing to be significantly evident on stocks which are both difficult to value and harder to arbitrage. This allows for the assumptions on investor sentiment to be maximised and is discussed in detail in our review of literature.

This study is motivated by the factors regarding the prevalence of investor sentiment and the asset prices it affects. Firstly, emerging countries have been shown to have a significantly larger portion of noise-traders to arbitrageurs than those of developed countries, coupled with higher transaction costs (Philpott & Firer, 1995; Rabinovitch, Silva & Susmel, 2003). These factors for market inefficiency open significant opportunity for the impact of investor sentiment. Secondly, the assets susceptible to sentiment show potential for high prevalence on the Johannesburg Securities Exchange (JSE) due to the lower market capitalization, higher transactions costs and low liquidity. From this, there is a high potential for systemic mispricing due to investor sentiment on the JSE (Philpott & Firer, 1995). Furthermore, previous studies on this topic conducted in South Africa are perhaps too broad in nature their explanatory return variables, as Solanki and Seetharam (2014) only consider the JSE All Share Index (ALSI) or consider quarterly deltas ranging from events prior to the global financial crisis (Dalika & Seetharam, 2015). The consideration of such events therefore serves as additional motivation for this study.

2. LITERATURE REVIEW

2.1 Studies using indirect (proxy) measures of investor sentiment

Prior literature has found significant empirical evidence on the effect of investor sentiment on asset return (Baker & Wurgler, 2006). Due to the limited access of direct sentiment measures, market indicators of the manifestation of sentiment have been established as proxies. Such proxies discussed in this paper are: trading volume, closed-end fund discount rates, initial public offering (IPO) volume and returns, equity issues over total new issues, dividend and volatility premia, mutual fund flows, consumer and business confidence indices, and option implied volatility.

2.1.1 Trading Volume

Market liquidity has been shown to exhibit significant time-variation and significant portions of such variation can be attributed to behavioural aspects (Douglas & Viswanathan, 1993). Trading volume, or total share turnover, is a signal for such liquidity and has been proven to indicate levels of sentiment in the market. Baker and Stein (2004) conducted a study on the New York Stock Exchange (NYSE) in which short-selling was constrained relative to opening and closing long positions, demonstrating a model in which a large portion of a highly liquid market is attributed to the irrational investor. Thus, high liquidity displays signals of high sentiment, with significantly lower expected returns. The model lacked empirical measures of sentiment as comparison and was subsequently followed by Liu (2015) who empirically tested sentiment, through survey data, and liquidity measures on the same exchange. Periods of high sentiment exhibited increasing liquidity and market trading volume.

2.1.2 Closed-end Fund Discount Rates

The discount at which a closed-end fund trades relative to its net asset value (NAV) has been a source of debate in modern finance. Lee, Shleifer and Thaler (1991) proposed that such changes in this relative price are motivated by individual sentiment, supporting their proposal by demonstrating how small stocks are subject to the same sentiment effects as closed-end funds on the NYSE. Chen, Kan and Miller (1993) disputed this claim, questioning the institutional ownership of small stocks after 1975, and showing that they had no statistical effect on the discount at which closed end funds traded. Chopra et al. (1993) then responded, presenting robustness in such a relationship and clarifying their methodology. The use of closed-end funds as an index for sentiment has followed since, either on its own or as part of a composite index. Prior use of such a proxy has predominantly been assessed on the NYSE (e.g., Neal & Wheatley, 1998; Baker & Wurgler, 2006). Studies in emerging countries are few and far between, due to the lack of prevalent closed-end funds. Canbaş and Kandir (2009) provide a use of such a proxy on the Istanbul Stock Exchange to effectively show prior returns influencing current sentiment levels over the period of 1997 to 2005.

2.1.3 IPO returns and volume

Fluctuations in the number of initial public offerings (IPOs) have shown to be subject to numerous factors, with investor sentiment being one of them. Lowry and Schwert (2002) concluded that adverse selection, opportunity for growth and investor sentiment, using the closed-end fund discount rate as a proxy, are all significant factors in determining aggregate volume. Ljungqvist, Nanda and Singh (2006) attributes the time-variation experienced with IPOs to “irrationally exuberant” investors, showing increased sentiment levels promoting more frequent IPOs. Furthermore, the existence of such investors, with equivalent short-sale limitations as Baker and Stein (2004) used in their analysis of the closed-end fund, was concluded to potentially explain long-run underperformance prevalent in the IPO market. Prior research linking sentiment and IPO volume/performance is almost entirely exclusive to the United States (US). From other markets, excessive underperformance and overperformance of technology-based IPOs on their first day on the Australian Stock Exchange was found to be positively linked to market sentiment, though individual investor sentiment was not considered (Ho et al., 2001).

2.1.4 Equity Issues over total New Issues

Firms' financing choices, through either debt or equity, have the propensity to indicate levels of investor sentiment. Baker and Wurgler (2000) found that high equity financing lead to abnormally low returns and debt financing predicted higher returns. This was further expanded to allow for such results to exhibit characteristics of sentiment through the market-timing effect of equity issuance (Baker & Stein, 2004; Baker & Wurgler, 2006).

2.1.5 Dividend and Volatility premium

Dividend premium is defined as the "difference of the average market-to-book ratios of dividend payers and nonpayers" (Baker & Wurgler, 2004:1126). Baker and Wurgler (2004) developed this concept to exhibit investor demand for dividends, which was subsequently proven to potentially indicate investor sentiment in the construction of powerful sentiment indices by Baker and Wurgler (2006) and Huang et al. (2015).

In their study of Global, local and contagious sentiment, Baker, Wurgler and Yuan (2007) found significant differences in valuations of firms with high volatility relative to those with low volatility in times of high empirical and anecdotal sentiment. From such findings, they defined the volatility premium as the Price-to-Earnings ratios of high volatility stocks relative to low volatility stocks.

2.1.6 Mutual fund flows

Mutual fund inflows and outflows can be an indicator of investor sentiment (Jiang & Yuksel, 2014). Prior literature suggests that there is a strong positive relationship between past mutual fund performance and subsequent fund inflows. Frazzini and Lamont (2006) found empirical evidence that when funds - holding a stock - experience large inflows, the performance of that stock is relatively poor in subsequent years. Jiang and Yuksel (2014) used such fund flows to examine the behaviour of investors during periods of high and low sentiment. The results show that the performance of new money flows is consistent with investor sentiment on stocks.

Specifically, with retail funds, new money inflows earn higher returns than outflows during low sentiment periods.

2.1.7 Option implied volatility

The Chicago Board Options Exchange Implied Volatility Index (VIX) is widely regarded as one of the best measures of future market performance. In a developing country like South Africa, with the financial system still imperfect, the VIX is very important (Baker & Stein, 2004). Ruan (2018) conducted research to explore the influence of market volatility on stocks. The empirical results show that the VIX index has a significant impact on the stock market. The VIX index is easy and more intuitive to obtain and can provide useful guidance for investors (Baker & Stein, 2004). This is one of the few studies that analyses the VIX in such detail. However, the shortcoming of this study is that is uses only the VIX as a proxy for investor sentiment, without considering any other effects.

Further research conducted at the University of Pretoria attempted to apply a new method of quantifying investor sentiment on the JSE (Adamson, 2017). This made use of the South African Volatility Index (SAVI) as a market-timing tool. Synthetic portfolios were constructed and analysed. No significant relationship was established between investor sentiment as a leading indicator with short-term returns. There was however a significant interaction between investor sentiment and long-term returns (Adamson, 2017). Even though this study resulted in interesting findings, there was a major shortcoming. The SAVI was only introduced in 2009, meaning that the sample size was not sufficiently large. This may have impacted the quality of results. Mean reversion, a technique used in this study, relies on large sample sizes for accuracy (Mokete, 2015).

2.2 Relevant Studies using direct (survey) measures of investor sentiment

Prior empirical research has found that consumer confidence and business confidence can be used to explain returns on stock markets across countries in both developed and developing countries (Lemmon & Portniaguina, 2006; Ayuningtyas & Koesrindartoto, 2014).

In United States of America, Lemmon & Portniaguina (2006) investigate consumer confidence and asset prices on the New York Stock Exchange. While they initially find no significance, they then split sentiment into two components: expected sentiment due to business cycle conditions and excess optimism/pessimism regarding future economic conditions using residuals from a regression of fundamental macroeconomic variables on confidence measures. They find a significant relationship between high values of these residuals and lower subsequent returns in assets of smaller size and with larger individual holdings.

Ayuningtyas and Koesrindartoto (2014) examined the relationship between both consumer and business confidence on asset returns in Indonesia. There is a limited amount of research conducted on this topic in developing countries, this being the motivation behind this study. Using linear regression, the effect of consumer confidence and business confidence on various major Indonesian stock market indices was analysed. The results provide empirical evidence that business confidence has a strong positive relationship with quarterly returns, whilst consumer confidence was found to have a significant negative relationship with quarterly returns (Ayuningtyas & Koesrindartoto, 2014). The analysis was split by sectors which provides usefulness when being examined for further application. The reliability of the results is further strengthened by the fact that various indices were used as opposed to most other literature that considers the effect of only one index or the market as a whole (Ayuningtyas & Koesrindartoto, 2014).

The Consumer Confidence Index (CCI) and Business Confidence Index (BCI) have proven to be accurate indicators of economic growth and of the business conditions in South Africa, though their explanatory power in asset pricing is limited (Seetharam & Solanki, 2014). Their research, conducted at the University of Witwatersrand, examines effects investor sentiment on the JSE with sentiment proxied by the CCI. They found no causality of confidence on JSE ALSI returns, though found that ALSI returns had causal effects on confidence. Such insignificant effects of confidence could be due Solanki and Seetharam (2014) only considering ALSI and not specific portfolios. Furthermore, quarterly data restricted the number of observations used in the sample. Improvement could therefore be made by using a larger data set or using a higher frequency (Bolaman & Mandaci, 2014). Lastly, Granger causality tests do not result in the most robust results, and the use of other methods may lead to more reliable results (Lemmon & Portniaguina, 2006). Previous literature reveals that the decision regarding which test to use should reflect three areas, type of data used; frequency of the available data and the sample size (Dalika & Seetharam, 2015).

2.3 Characteristics of assets most susceptible to sentiment-based mispricing

A large body of previous research reveals that investor sentiment affects different stocks in different manners. The firms most sensitive to investor sentiment are younger, smaller, distressed and more volatile (Baker & Wurlger 2006; Lemmon & Portniaguina 2006). On the contrary, stocks of larger, more stable companies are less sensitive to investor sentiment (Brown & Cliff, 2005). Baker and Wurgler (2007) conducted research to attempt to empirically measure investor sentiment. The results further highlighted that investor sentiment has a relationship with stock returns, particularly on stocks that are young and difficult to value. This was done using a top-down approach whilst most previous literature used a bottom-up approach. The advantage of this approach is that it has greater potential to predict crashes, bubbles and regular patterns in stock prices (Baker & Wurgler, 2018). This diversity in methodology allowed the origin of investor sentiment to be taken as exogenous and focus was rather placed on the empirical effects, from a macroeconomic perspective. However, some of the proxies used when constructing the index contained parts that are not related to sentiment. This idiosyncrasy compromised the validity of the findings.

Dalika and Seetharam (2015) predicted a relationship between investor sentiment and stock returns in the South African Market. To test this prediction, the authors constructed an aggregate measure of investor sentiment from several proxies and then examined the impact that it has on stock returns from 1999 to 2009. The results indicate that investor sentiment has a strong impact on stock performance in South Africa. When sentiment is low, returns are relatively high on younger stocks with extreme growth potential. When sentiment is high, these patterns are inverted. The main shortcoming of the study by Dalika and Seetharam (2015) was that the period analysed did not capture the effect of the financial crisis. The condition of stocks on the JSE was greatly impacted by this and the period after 2008 is therefore important to consider. Given the many challenges caused by financial crises in the past, it worthwhile analysing if investor sentiment provides an indication as to when a stock market crash may occur.

Bolaman and Mandaci (2014) examined the relationship between investor sentiment and stock market prices. Although there are studies examining the same concept, this was the first to consider the impact of the financial crisis. Test with structural breaks were used rather than conventional tests used in most previous literature. The findings point in the direction of a long-term pattern between these variables. This is a significant insight, showing that consumer confidence interacts with stock markets in a significant way. While most of the prior literature focuses on developed markets, Bolaman and Mandaci (2014) is conducted in a developing market. The data period used is also longer than most other studies and it considers the latest financial crisis in a way that enabled the relationship between consumer confidence and stock market during the crisis period to be examined (Bolaman & Mandaci, 2014).

2.4 Conclusion

Overall, the majority of previous literature published on this topic has found that a significant relationship exists between investor sentiment and stock market returns. Investor sentiment affects different stocks in different ways (Brown & Cliff, 2005). The importance of analysing sentiment is often overshadowed by the complexity of quantifying this concept. However, there is no reason why one cannot find useful proxies. Most researchers have used the bottom-up approach due to the many advantages it has. However, limitations exist in most of the previous literature. This paper aims to make use of a top down approach to sentiment to build on prior successful models, by applying these to the JSE in South Africa, whilst trying to fill the gaps in previous literature.

3. DATA DESCRIPTION AND RESEARCH METHODOLOGY

3.1 Sample Period and Frequency

This study uses monthly observations ranging from January 2007 to December 2018, with a sample size of n = 144 observations. While survey confidence data was obtainable from as far back as 1982, limitations arose from portfolio analysis on Bloomberg L.P's terminal being historically capped from January 2007 onwards, thus enforcing this date as lower bound of our sample span.

To account for sample size issues, monthly data is considered. Furthermore, this period still encapsulates the events of the global financial crisis.

3.2 Economic Variables

Given the significant cyclical influence of economic conditions on measures of sentiment, as demonstrated by Lemmon & Portniaguina (2006), we consider two economic variables in this paper: namely the Composite Coincident Indicator (CI) and a recession indicator (REC).

Obtained from the South African Reserve Bank, the CI is a monthly weighted composite indicator of five South African business cycle variables, namely: gross value added (at constant prices), total formal non-agricultural employment, value of retail vehicle sales (at constant prices), the industrial production index and the utilisation of production capacity in manufacturing (South African Reserve Bank [SARB], 2015). Although more accurate business cycle data could be obtainable, it is predominantly in quarterly format. Additionally, CI has been shown to provide significantly accurate estimations of monthly coincident movements in the business cycle (particularly after its revision in 2004) (Venter, 2019).

Furthermore, REC is a dummy variable sourced from the Organisation for Economic Co-operation and Development (OECD) signifying monthly recessionary turning points in business cycle movements for South Africa (OECD Composite Leading Indicators, n.d.), this variable is only considered on for visual representation and qualitative analysis.

3.3 Sentiment Variables

Both survey and market derived proxies for sentiment (SENT) were considered in this paper. Furthermore, all sentiment proxies were regressed on CI, in which the residuals (denoted by the superscript $SENT^r$) from this regression were used to reflect sentiment values not attributable to business cycle conditions, in a manner equivalent Lemmon & Portniaguina (2006). Both raw and residual sentiment data was considered in our results, though further tests only use residual sentiment variables due to its more robust, standardized nature. In this paper, we consider the Consumer Confidence Index, Business Confidence Index and develop a market constructed sentiment index; all of which are discussed below.

3.3.1 Survey Sentiment Variables

Consumer Confidence Index (CCI)

The Consumer Confidence Index was obtained through the Bureau of Economic Research (BER), based in Stellenbosch with sample of 2500 households. It is the weighted combination of three questions asked to South African adults, namely:

- *"How do you expect the general economic position in South Africa to develop during the next 12 Months? Will it improve considerably, improve slightly, deteriorate slightly, deteriorate considerably or don't know?*
- *How do you expect the financial position in your household to develop in the next 12 months? Will it improve considerably, improve slightly, deteriorate slightly, deteriorate considerably or don't know?*
- *What is your opinion of the suitability of the present time for the purchase of domestic appliances such as furniture, washing machines, refrigerators etc. Do you think that for people in general it is the right time, neither a good nor a bad time or the wrong time?"* (Bureau for Economic Research [BER], n.d.).

The BER then express the weighted combination of these answers provided as an individual expecting either an improvement or a deterioration. The results are provided quarterly and is measured as the net balance between the percentage of respondents expecting improvement less the percentage expecting a deterioration. The CCI variable is thus this percentage value represented as an integer. Figure 1 shows the values of CCI^r and CCI over the sample period, with the shaded areas denoting recessionary periods as defined by REC. Given that CCI data is quarterly and the delta of our research is monthly, monthly values have been interpolated using the cubic spline method.

Figure 1: CCI^r and CCI from 2007 to 2019

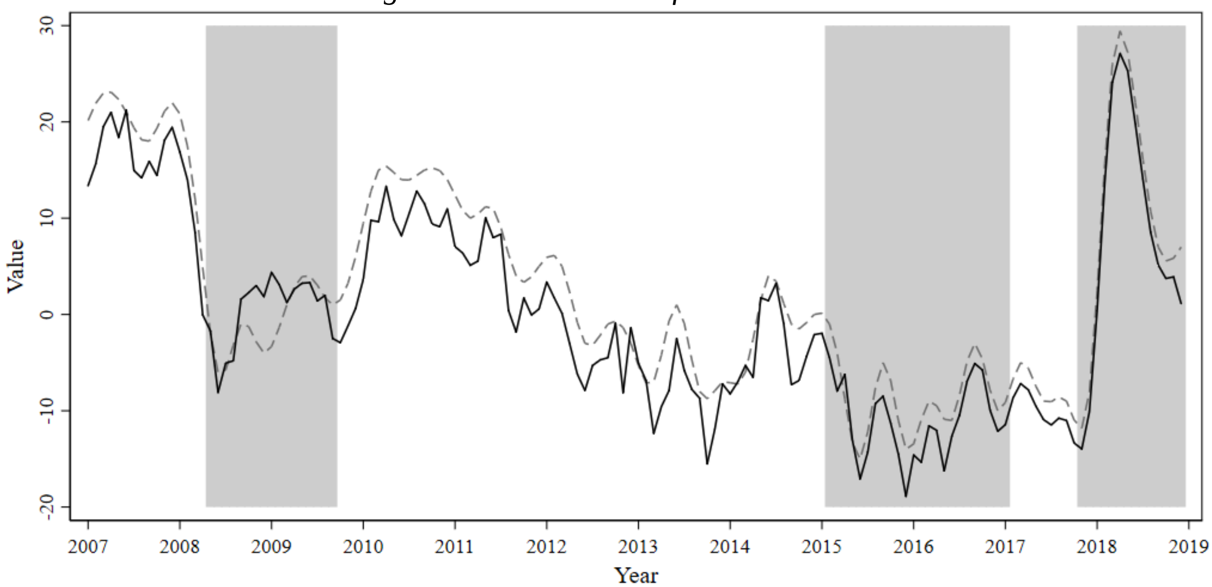

Figure 1 shows CCI^r (Solid Line) and CCI (Dashed Line) values, with grey areas denoting recessionary periods as defined by REC. CCI^r is defined as the residuals of the regression of CCI on CI.

Business Confidence Index (BCI)

Also obtained through the BER, the Business Confidence Index is a derived from set of qualitative questions posed to senior executives in trade, manufacturing and building sectors. Also compiled quarterly, the survey is sent to 3800 executives with about a 50% response rate. Unlike the CCI, this is defined as the gross percentage of respondents considering prevailing business conditions to be satisfactory or unsatisfactory and thus far more straightforward. A value of 50 is neutral, with unanimous confidence being 100. Figure 2 Shows the BCI^r and BCI over the sample. In order to centre this value around 0, the BCI variable is represented as 50 less the quarterly value, which has also been interpolated to reflect monthly values using the cubic spline method.

Figure 2: BCI^r and BCI from 2007 to 2019

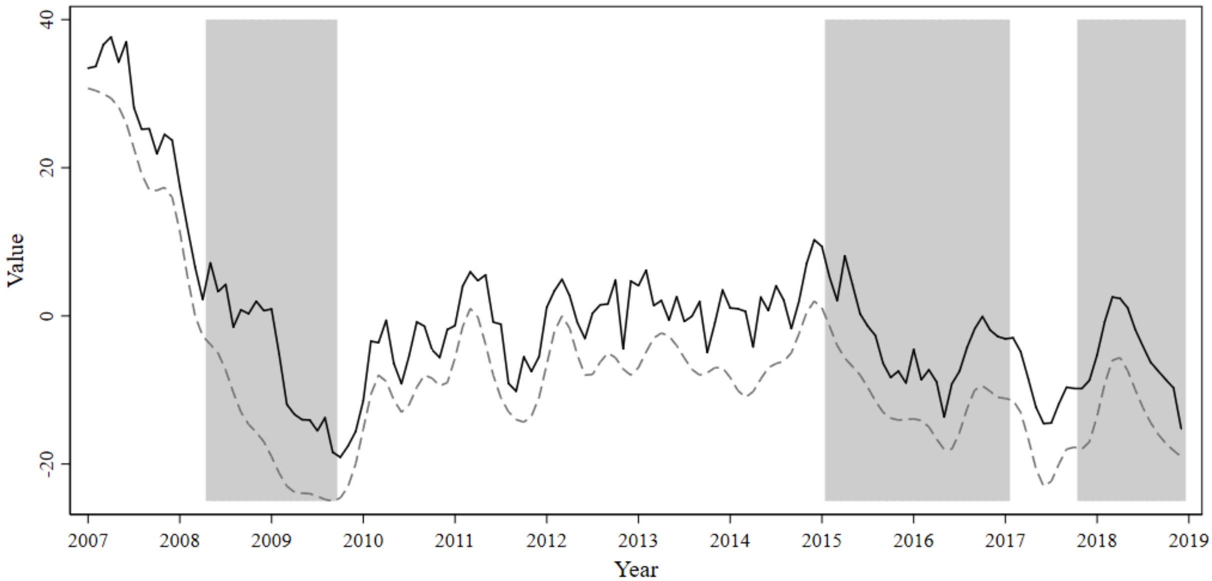

Figure 2 shows BCI^r (Solid Line) and BCI (Dashed Line) values, with grey areas denoting recessionary periods as defined by REC. BCI^r is defined as the residuals of the regression of BCI on CI.

3.3.2 Market Sentiment Variables and Sentiment Index

An index reflecting sentiment, analogous to Baker and Wurgler (2007), was constructed using the first principle component of four market variables from the Johannesburg Stock Exchange: Number of Initial Public Offerings (NIPO), Return on Initial Public Offerings (RIPO), Market Turnover (TURN) and Volatility Premium (VOLP). All market variables were sourced from Bloomberg L.P.

Number of Initial Public Offerings (NIPO)

This variable is the natural logarithm of the number of announced IPO's for each month of the sample span. NIPO was logged to better reflect normality in issuances. For example, 2007 saw 49 IPO announcements, which is 40 more than any other year in our sample period. As discussed in the review of literature, many IPO's over a certain period is a signal for high market sentiment on the basis that a factor of a companies' choice to issue is one of positive prevailing market conditions (Baker & Stein, 2004).

Return on Initial Public Offerings (RIPO)

Return is calculated as the difference between the closing price and the offer price, at the end of the first trading day after an Initial Public Offering. Similar to Baker and Wurlger (2007) and on the same basis of normality as NIPO, we take the natural logarithm of the monthly arithmetic mean return. Months in which no IPO's occurred have returns of zero.

Market Turnover (TURN)

Market Turnover is defined in the model of Baker and Wurgler (2006) as the natural logarithm of the total traded value divided by the number of shares traded during a certain time horizon. More specifically, we define turnover as follows:

$$TURN_t = \ln\left(\frac{Traded\ Value_t}{Shares\ Traded_t}\right) - \frac{1}{6}\left[\sum_{i=1}^{6} ln\left(\frac{Traded\ Value_{t-i}}{Shares\ Traded_{t-i}}\right)\right] \qquad (1)$$

Where $TURN_t$ represents the monthly observation of the natural logarithm of the total traded value divided by the number of shares traded in month t, less this six-month simple moving average. The value is detrended using the six-month simple moving average due to the constant upward trend in turnover, also observed in Baker and Wurgler (2006) – who use a 5-year moving average. However, given that their data was quarterly and spanned over a significantly longer time relative to our study, an assessment of significant autocorrelations to the 99.9% revealed an adequate smoothing filter to be 6 lags. As such, this value reflects the amount above/below the smoothed mean. In periods of high sentiment, investors trade more freely, and we expect this value to be above 0.

Volatility Premium (VOLP)

Developed and defined by Baker and Wurgler (2007), VOLP has shown to be a powerful predictor of sentiment and reflects the difference in valuations on high versus low volatility stocks. Construction of this variable used Price-to-Book ratios of two value-weighted portfolios and was developed as follows:

$$VOLP_t = \ln\left(\frac{Price - to - Book_t{}^{\sigma=high_{t-1}}}{Price - to - Book_t{}^{\sigma=low_{t-1}}}\right) \quad (2)$$

Where $\sigma =$ high (low) are monthly rebalanced portfolios of the highest (lowest) price volatility decile of the month prior, with volatility being calculated as the annualized standard deviation in the last 30 days. As discussed in the review of literature, intuition behind this variable is that in periods of high sentiment, investors value volatility more favourably than periods of low sentiment and is the monthly adaptation of the variable developed Baker and Wurgler (2007).

Sentiment Index (INDEX)

As mentioned, the first principle component of the four discussed market variables was used in the construction of INDEX, with residual values comprising of $INDEX^r$. Eigenvalues for both INDEX and $INDEX^r$ were above 1 and accounted for 41.4% and 40.6% of the total common variation in all four variables respectively. (For complete Principle Component Analysis results, consult Appendix A1 & A2). With INDEX and $INDEX^r$ defined as follows:

$$INDEX_t = 0.6606NIPO_t + 0.5807RIPO_t + 0.3971VOLP_t + 0.2621TURN_t \quad (3)$$

$$INDEX_t^r = 0.668NIPO_t^r + 0.5945RIPO_t^r + 0.4008VOLP_t^r + 0.1992TURN_t^r \quad (4)$$

Figure 3 shows both $INDEX^r$ and INDEX, denoted by the solid and dashed lines respectively. All the component scores are positive, as expected, and the high values of NIPO and RIPO in comparison to values derived by Baker and Wurgler (2006) can be attributed to the relatively infrequent number of Initial Public Offerings on the JSE compared to that of the NYSE. Additionally, INDEX exhibits significant autocorrelations up to 5 lags, showing some form of monthly sentiment contagion.

In analysing the constituents of INDEX and its residual counterpart (consult Appendix A3), one can see positive correlation in all but VOLP and TURN variables. Indicating next to no correlation between liquidity of the market and the higher relative valuation of volatile stocks. Furthermore, positive correlations between CI and all INDEX constituents show sentiment moving in line with business cycle conditions and negative correlations between the REC provide similar insights of low sentiment during recessionary periods (See Appendix A4 for component graphics).

Figure 3: INDEX^r and INDEX from 2007 to 2019

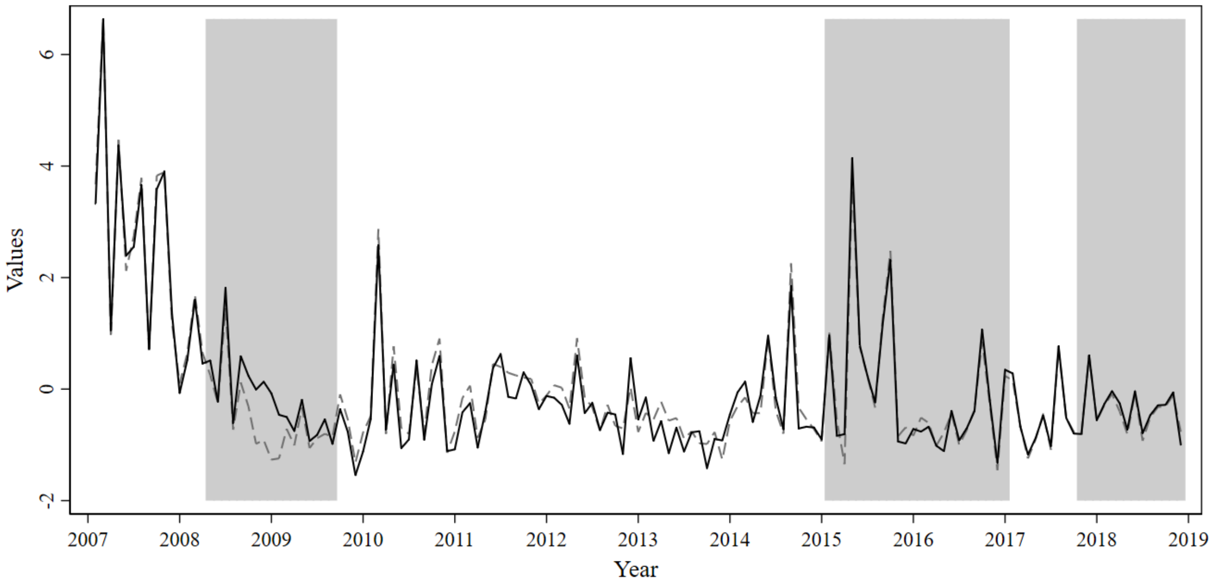

Figure 3 shows INDEX^r (Solid Line) and INDEX (Dashed Line) values, with grey areas denoting recessionary periods as defined by REC. INDEX^r is defined as the residuals of the regression of INDEX on CI.

3.3 Market Variables

As discussed in the review of literature, sentiment-based mispricing affects firms most susceptible to noise-traders. From such prior evidence, we have considered four different avenues of firm characteristics (Z) for investigation, namely: size, distributional capacity, volatility and profitability. In assessing returns of firms with characteristic (Z), we construct long-short holding period portfolios of assets long in characteristic (Z) and short in its complement (Z'). An example of such is the size premium (Fama & French, 1993); with Z symbolising market capitalization in the bottom 10th percentile and Z' symbolising market capitalization in the top 10th percentile. We then calculate equal-weighed return on the holding period basis as follows:

$$R_{Z,t} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{P_{Z,t} - P_{Z,t-1} + D_{Z,t}}{P_{Z,t-1}}\right) - \frac{1}{k}\sum_{j=1}^{k}\left(\frac{P_{Z\prime,t} - P_{Z\prime,t-1} + D_{Z\prime,t}}{P_{Z\prime,t-1}}\right) \qquad (5)$$

In a minor abuse of monthly notation, t reflects the end of the month, while $t-1$ reflects the start. Where $P_{Z,t-1}$ and $P_{Z,t}$ are the monthly closing price and opening prices of firm i of a total n firms with characteristics Z, and $D_{Z,t}$ denotes any distributions during and until (month end) t of firm i. Furthermore $P_{Z,t-1}$,$P_{Z',t}$, and $D_{Z',t}$ are the monthly opening prices, closing prices, and total distributions of firm j of a total k firms with characteristics Z', which is the complement of characteristic Z. Portfolios were rescreened for characteristics Z and Z' monthly and rebalanced respectively. The base equity screen consisted of an investable universe of all common stocks on with primary listings the Johannesburg Stock Exchange. Market Return (MKT) is value-weighted, following methodologies in line with Baker and Wurgler (2006) and Brown and Cliff (2005).

Evidently, this model of portfolio returns does not consider the limitations of short selling, nor transactions costs – in which such assumptions are considered. Table 1 summarizes all market variables used in this paper.

Table 1: Description of Portfolio's and Market Variables

Portfolio Variable Name	*Characteristics (Z & Z')*	*Weighting*	*Security Counts*
MKT	Market Return, return on the observable universe of common stocks listed on the JSE	Value	Max = 345 Min = 270
RF	Monthly Risk-Free Rate, South African 10 Year Government Bonds used as a proxy.	-	-
RMRF	Market Return, Less the Risk-Free Rate (RMKT-RF)	-	-
V101	Return on the portfolio of stocks short in the smallest, and long in the largest 10 percentiles of annualized volatility (measured in standard deviation) in the month prior	Equal	Max = 70 Min = 30
M110	Return on the portfolio of stocks long in the smallest, and short in the largest 10 percentiles of market capitalisation in the month prior	Equal	Max = 67 Min = 51
DIV	Return on the portfolio long on non-dividend paying stocks, and short on dividend paying stocks in the year prior to rebalancing.	Equal	Max = 345 Min = 270
NMP	Return on the portfolio long in firms with Net Income < 0, short firms with Net Income ≥ 0 in the last filing prior to rebalancing	Equal	Max = 345 Min = 270
SMB	Return on the portfolio of stocks short in the smallest, and long in the largest 3 deciles of annualized volatility (measured in standard deviation) in the month prior	Equal	Max = 201 Min = 151
HML	Return on the portfolio of stocks with Book-to-Market ratios short in the smallest, and long in the largest 3 deciles in the month prior	Equal	Max = 188 Min = 124

All return data sourced from Bloomberg L.P

Table 2: Descriptive Statistics

Sentiment Variables	Mean	Std. Deviation	Min	Max
NIPO	0.27	0.51	0	2.56
RIPO	3.58	14.01	-29.48	116.11
TURN	0.02	0.15	-0.50	0.33
VOLP	-0.48	0.60	-1.68	1.61
INDEX	0	1.29	-1.46	6.63
BCI	-7.45	12.09	-25.00	31.00
CCI	2.67	10.62	-15.00	29.45
Economic Variables				
REC	0.38	0.49	0	1
CI	0.10	0.54	-2.10	1.10
Residual Variables				
$NIPO^r$	0	0.50	-0.42	2.28
$RIPO^r$	0	13.97	-33.43	112.16
$TURN^r$	0	0.15	-0.43	0.32
$VOLP^r$	0	0.60	-1.16	2.03
$INDEX^r$	0	1.27	-1.54	6.64
BCI^r	0	11.31	-19.09	37.66
CCI^r	0	10.28	-18.89	27.12
Market Variables (%)				
MKT	0.56	6.78	-26.90	21.20
RF	0.59	1.22	-5.37	6.27
RMRF	-0.02	6.90	-27.63	20.50
M110	3.80	8.25	-14.05	41.83
V101	-0.01	28.99	-334.75	23.78
DIV	-0.37	6.32	-43.20	19.26
NMP	-0.30	4.52	-13.65	16.84
SMB	0.76	4.19	-8.10	16.36
HML	-0.24	3.96	-12.97	17.66

n = 144 for all variables

3.4 Descriptive Statistics

Table 2 summarises all variables used in this paper. At a glance, the size premium (captured by both M110 and SMB portfolios) seems to be in effect and, besides market return itself, capture the only positive mean return in our sample. V101 portfolio aligns well with its defined characteristics, showing a significantly larger standard deviation of 28.99% and a maximum loss of -334.75% in one month.

3.5 Correlations of Market and Sentiment Variables

With respect to the Sentiment Variables, Appendix B shows the correlations of all variables of sentiment and the economic indicators included in this study. A commonality is the high correlation of all residual sentiment indices and their respective raw values, showing that residual sentiment does not differ too significantly from raw sentiment. Furthermore, all values are negatively correlated with REC, and all raw values are positively correlated with CI; showing that sentiment does seem to move in accordance to business cycle conditions. Between the variables, CCI and BCI seem to exhibit some form of correlation at around 50% while BCI and BCI^r are the most significantly correlated variable with INDEX and $INDEX^r$ respectively at around 62-66%.

Appendix C shows Correlations of all Market Variables. As expected, SMB exhibits high correlation with M110 at around 75% and both move against the market portfolio, which is to be intuitively expected as these portfolios are short on value, while MKT is value-weighted market return. NMP is also positively correlated with SMB and M110, showing potential for smaller firms having negative earnings. HML seems to be the least correlated with all other portfolios. High correlations between DIV and M110 and V101 show a potential link between returns on smaller, volatile and non-dividend paying firms. Overall, the positive correlations between our market variables show good potential for the firm characteristics explained earlier to be salient.

3.6 Brief Research Methodology

The methodology for this paper follows a synthesis of Baker and Wurgler (2006), Lemmon and Portniaguina (2006) and an adaptation of Brown and Cliff (2005). All discussed studies test for asset mispricing in a mean-reversion manner, with a simplified hypothesis that periods of high sentiment are expected to sway noise-traders to exhibit unjustifiable traits of bias and confidence towards certain assets. In turn, such demand forces prices up in periods of high-sentiment, causing such asset prices to revert to fundamentals in subsequent periods (Brown & Cliff, 2005).

In testing this, we look at all defined SENT and $SENT^r$ values in the prior month and explore their cross-sectional explanatory power in the subsequent returns of various long-short portfolio, as discussed.

4. DATA ANALYSIS AND RESULTS

4.1 Assessing the Explanatory Power of Sentiment on Asset Prices

Much Like Baker & Wurgler (2007), this section is more of an exploratory effort to identify characteristics of firms affected by sentiment, which in turn are the firms traded by noice-traders affected by sentiment. As predicted by prior studies and our assessed literature, firms most likely to be affected by noise-trader sentiment have characteristics of being small, more volatile, non-dividend paying, younger and potentially financially distressed. In assessing this, various long-short portfolios were constructed, and returns were estimated on a simple linear regression as follows:

$$R_{Z,t} = \alpha_t + \beta(SENT_{t-1}) + \varepsilon_t \qquad (6)$$

Where $R_{Z,t}$ is the monthly return at time t on various long-short portfolios of firms with characteristics Z. $SENT_{t-1}$ is the measure of sentiment for the month prior, and α and ε are the constant and error terms respectively, at time t.

Table 3 shows the results of the coefficient β and associated p-values in parenthesis for Equation 6. Included is a subsample from January 2009 to December 2019, to assess any differences in values post financial crisis. All coefficients are expected to be negative, in line with These results show that the absolute value of prior sentiment variables has little explanatory power in a simple linear format on almost all portfolios, in which CCI and CCI^r follow insignificant results in forecasting the size premium in fashion with Seetharam and Solanki (2014) as well as Lemmon and Portniaguina (2006). Notably, BCI and its residual counterpart show significantly positive

Table 3: Results from Regression Equation (6), with various Market Portfolios on various lagged SENT and SENT^r values

	$SENT_{t-1}$			$SENT^r_{t-1}$		
From: Jan 2007 to Dec 2019	INDEX	BCI	CCI	INDEX^r	BCI^r	CCI^r
V101	0.84 (0.66)	0.01 (0.96)	0.068 (0.77)	1.16 (0.55)	0.02 (0.93)	0.09 (0.69)
M110	0.34 (0.53)	0.12 (0.03)**	-0.03 (0.64)	0.39 (0.47)	0.14 (0.02)**	-0.03 (0.68)
DIV	0.58 (0.16)	0.08 (0.06)*	0.02 (0.66)	0.64 (0.13)	0.08 (0.08)*	0.02 (0.73)
NMP	0.01 (0.96)	0.03 (0.27)	-0.02 (0.57)	0.09 (0.75)	0.05 (0.14)	-0.01 (0.74)
From: Jan 2009 to Dec 2019						
V101	-0.01 (0.99)	-0.39 (0.38)	0.00 (0.99)	0.71 (0.84)	-0.31 (0.50)	0.04 (0.90)
M110	-0.80 (0.37)	0.16 (0.14)	-0.11 (0.16)	-0.80 (0.38)	0.17 (0.14)	-0.11 (0.16)
DIV	0.30 (0.68)	0.07 (0.41)	-0.05 (0.42)	0.42 (0.56)	0.09 (0.34)	-0.05 (0.45)
NMP	-0.80 (0.07)*	-0.016 (0.77)	-0.08 (0.038)	-0.055 (0.22)	0.02 (0.67)	-0.06 (0.09)*

Results of coefficient β (and associated p-values in parenthesis) from Model (1) on various market portfolios using OLS linear regression. *,**,*** denote significance to the 10%, 5% and 1% level respectively. INDEX, BCI and CCI are variables for the constructed Sentiment Index, Business Confidence Index and Consumer Confidence Index respectively, lagged by 1 month. V101, M110, DIV, NMP are long-short market portfolios of Volatility, Size, Dividend Paying and Profitable characteristics.

effects on size and dividend portfolios in the whole sample set, which falls insignificant in the subsample.

This indicates that high levels business confidence has some significant relationship with high returns in smaller and non-dividend paying firms the month later. Many of the coefficients seem to turn negative in the subsample, particularly those relating to INDEX and $INDEX^r$, potentially indicating that the market turns to a more predictable environment, as such negative coefficients fall in line with values from Baker and Wurgler (2006). The NMP portfolio, long firms with negative earnings in the prior filing and short firms with positive earnings in the prior filing, is an example of this – turning significantly negative in the subsample for INDEX and CCI^r. Indicating a statistically significant relationship between high sentiment and low subsequent returns for unprofitable firms, though this could be due to the nature of such distressed firms' operations and have nothing to do with noise trader sentiment as mentioned. (Baker & Wurgler, 2006). Unlike prior literature, V101 exhibits no significance across all variables, and only in a post-crisis setting do some of the coefficients turn the expected sign. R-Squared values for all regressions ranged from 0.01 to 0.07, concluding that while this section serves as an exploratory effort in identifying firm characteristics susceptible to the values of sentiment, in no way does it account for significant explained variance in all portfolio returns.

4.2 Assessing Changes in Sentiment on Asset Prices, controlling for known explanatory variables

In this section we continue to look at sentiment and the discussed portfolios, though switch our view from sentiment in the absolute sense, to changes in sentiment which has shown further explanatory power of asset prices . We consider on residual values, ensuring robustness, and define changes in sentiment ($\Delta SENT_t$) as follows:

$$\Delta INDEX_t^r = INDEX_t^r - INDEX_{t-1}^r \quad (7)$$

$$\Delta BCI_t^r = BCI_t^r - \Delta BCI_{t-3}^r \quad (8)$$

$$\Delta CCI_t^r = CCI_t^r - \Delta CCI_{t-3}^r \quad (9)$$

The reason for the differences in our definitions for ΔINDEX and ΔCCI/ΔBCI arises from the quarterly nature of the survey data, thus a 1-month inspection of the change would not hold significant interpretation, as the values have been interpolated. Furthermore, Brown and Cliff (2004) find higher significance in assessing changes in sentiment values as predictors for samples of higher frequencies (they use weekly data), rather than their absolute values. As pertinent literature uses quarterly data (Baker & Wurlger, 2006; Lemmon & Portniaguina, 2006) we consider a model with lags equivalent to the first, using changes in $SENT^r$ as an explanatory variable in the monthly return on our market portfolios, rather than its absolute value. For further robustness, we control for known explanatory variables from Fama and French (1993) and only include residual values of sentiment. The models are as follows:

$$R_{Z,t} = \alpha_t + \beta(\Delta SENT_{t-1}^{r}) + \varepsilon_t \tag{10}$$

$$R_{Z,t} = \alpha_t + \beta_1(\Delta SENT_{t-1}^{r}) + \beta_2(RMRF_t) + \beta_3(HML_t) + \beta_4(SMB_t) + \varepsilon_t \tag{11}$$

Table 4 shows the results of both Model 2 and 3. Firstly, in both models the sentiment index ($\Delta INDEX^r$) is the only significant explanatory variable in asset prices. With a significantly negative coefficient on the size portfolio (M110) in Model 2, it can be interpreted that positive changes in $\Delta INDEX^r$ correlate to low subsequent returns in small stocks relative to large ones which corresponds with Baker & Wurgler (2007). However, this significance falls away when controlling for known market explanatory variables, though it remains negative (along with all coefficients of $\Delta INDEX^r$ on both models). The only significant value of the coefficient of $\Delta INDEX^r$ in Model 3 is when explaining for the Profitability portfolio, with the interpretation being that increases in sentiment through $\Delta INDEX^r$ explain for significantly lower subsequent return in portfolios long on firms with negative earnings, and short on those with positive earnings in their last filing. SMB has been left as an explanatory variable in the M110 portfolio regressions due to the high correlation (by nature) with each other.

The explanatory control variables do well at accounting for large significance in the portfolios, while all indices show weak predictive power for the Volatility portfolio (V101). Both the BCI and CCI indices explanatory power fall away when considering changes, this could be due to our statistical interpolation or due to the far smoother nature of these survey indices, thus accounting

Table 4: Results from Regression Models (10) & (11), with various Market portfolios regress on changes in SENT^r

	ΔSENT^r	ΔSENT^r, Controlling for Fama & French Factors (RMRF, SMB, HML)				
	(Month Prior)	*(Month Prior)*				
Changes in the Sentiment Index	ΔINDEX^r	ΔINDEX^r	RMRF	HML	SMB	Adj-r^2
V101	-0.37 (0.85)	-0.41 (0.825)	0.73 (0.07)*	-0.53 (0.4)	1.67 (0.01)**	0.03
M110	-0.88 (0.098)*	-0.70 (0.17)	-0.27 (0.01)***	-0.37 (0.03)**	-	0.09
DIV	-0.29 (0.47)	-0.24 (0.49)	0.18 (0.01)**	0.20 (0.09)*	0.93 (0.00)***	0.28
NMP	-0.74 (0.01)**	-0.65 (0.01)**	0.08 (0.13)	-0.17 (0.04)**	-0.63 (0.00)***	0.38
Changes in Business Confidence	ΔBCI^r	ΔBCI^r	RMRF	HML	SMB	
V101	0.00 (0.99)	0.02 (0.96)	0.72 (0.07)*	-0.53 (0.40)	1.67 (0.02)**	0.03
M110	-0.1 (0.2)	-0.08 (0.29)	-0.29 (0.00)***	-0.40 (0.02)**	-	0.10
DIV	-0.01 (0.86)	0.02 (0.73)	0.17 (0.02)**	0.20 (0.09)*	0.93 (0.00)***	0.27
NMP	-0.04 (0.28)	-0.025 (0.48)	0.05 (0.3)	-0.18 (0.02)**	0.6 (0.00)***	0.34
Changes in Consumer Confidence	ΔCCI^r	ΔCCI^r	RMRF	HML	SMB	
V101	-0.03 (0.93)	0.01 (0.97)	0.72 (0.07)*	-0.54 (0.40)	1.66 (0.02)**	0.03
M110	-0.12 (0.18)	-0.10 (0.27)	-0.30 (0.00)***	-0.39 (0.02)**	-	0.10
DIV	0.36 (0.61)	0.01 (0.92)	0.18 (0.02)**	0.20 (0.10)*	0.93 (0.00)***	0.27
NMP	-0.05 (0.34)	-0.01 (0.73)	0.05 (0.31)	-0.18 (0.03)**	0.61 (0.00)***	0.34

Results of coefficients (and associated p-values in parenthesis) from Model (10) and Model (11) on various market portfolios using OLS linear regression. *,**,*** denote significance to the 10%, 5% and 1% level respectively. INDEX, BCI and CCI are variables for the constructed Sentiment Index, Business Confidence Index and Consumer Confidence Index, lagged by 1 month. V101, M110, DIV, NMP are long-short market portfolios of Volatility, Size, Dividend Paying and Profitable characteristics.

for little variation in asset prices. Though almost all coefficients from the survey indices are of the expected sign, none show significant explanatory power.

3.4 Historical effects of sentiment the current size premium

While some findings have found significance, it could be that a 1-month lagged measure is not enough time for sentiment to have explanatory power on asset returns. In this section we consider an endogenous environment in which the current size premium is explained only by its prior values and prior sentiment, analogous to the model used in Brown and Cliff (2004). In capturing a broader sense of the size, we use the SMB portfolio and consider only INDEX^r due to the autocorrelation embedded in CCI^r and BCI^r, from interpolation. To estimate such an environment, a Vector Autoregressive Model (VAR) is used as follows:

$$SMB_t = \alpha_t + \sum_{i=1}^{p} \theta_i SMB_{t-i} + \sum_{i=1}^{p} \beta_i INDEX_{t-i}^{r} + \varepsilon_t \qquad (12)$$

Where SMB_t is monthly return on the portfolio long in firms in the smallest third decile and short in firms in the largest third decile of market cap at time t, with its autocorrelations denoted by θ at lag i. $INDEX_t$ is the monthly sentiment index value at time while β_i its coefficient at lag i. Furthermore, α and ε are the constant and error terms respectively, at time t. The number of lags used, p, is six, as suggested by Akaike's information criterion and final prediction error selection statistics. Both variables are stationary, with significance to the 1% in Dicky-Fuller tests for unit roots.

Table 5 shows the results from this model. Firstly, and most discerning is the chi-squared test against the null hypothesis that all values θ_i and β_i are zero cannot be rejected to the 5% level. This could be due to the insignificant autocorrelation seen in SMB, at only the third lag do we see significance to the 10% level. However, when considering the model to be significant (Which it is at the 10% level), INDEX^r coefficients paint a profound picture of the historical effects of sentiment has the relative return between small and large stocks. Significance can be found in the first, second, fifth and sixth lags.

We find that values of sentiment five and six months prior have a significantly negative effect on the returns of small firms relative to large ones, while sentiment values in the two most recent months prior have significantly positive effects on return respectively.

Table 5: Results from VAR Model (12), with SMB as the dependant variable

Independent Variables				
SMB		$INDEX_r$		Constant
Lag	Coefficient	Lag	Coefficient	Coefficient
1	-0.14 (0.10)	1	0.81 (0.05)**	0.79 (0.03)**
2	-0.10 (0.22)	2	0.83 (0.03)**	
3	0.16 (0.05)*	3	0.29 (0.45)	
4	0.09 (0.31)	4	-0.19 (0.59)	
5	0.01 (0.85)	5	-0.57 (0.09)*	
6	-0.03 (0.68)	6	-0.82 (0.02)**	
Model Parameters				13
R-Squared				0.13
Chi-Squared Test Statistic				19.9634
P > Chi-Squared				0.07
				n = 138

Given the endogenous and over-simplistic nature of this model, this value should be considered in a hypothetical setting, though results still pose significant statistical and intuitive interpretation. Brown and Cliff (2004) find a similar positive to negative shift in coefficient values of lagged sentiment measures on similar size portfolios, though no significance. Furthermore, Baker & Wurgler (2007) use mutual fund flows to show, intuitively the same effect of sentiment effects through momentum and mean-reversal. In which they observe short-run sentiment values having positive relationships with returns (showing momentum effects) and negative relationships long-run sentiment values (showing mean-reversion effects) on size premium portfolios. Furthermore, Jiang and Zhou (2015) find similarly negative long-run relationships at lags from 6 months to 1 year, though coupled with neutral (and statistically insignificant) short-run effects.

In our model, short-run levels of sentiment (3 months prior or less) have significantly positive causal effects on the size premium while in long-run, (3 to 6 months prior) levels of sentiment have significantly negative effects on the size premium. Figure 4 shows this in a graphical representation, and further demonstrates time-based effects of sentiment in this simple environment, showing the negatively linear trend in sentiment coefficients as lags increase. Lags of 3 and 4 months seem to have an ambiguous effect on the size premium, showing statistical insignificance.

Figure 4: Coefficients of Lagged $INDEX^r$ explanatory variables in VAR Model (12)

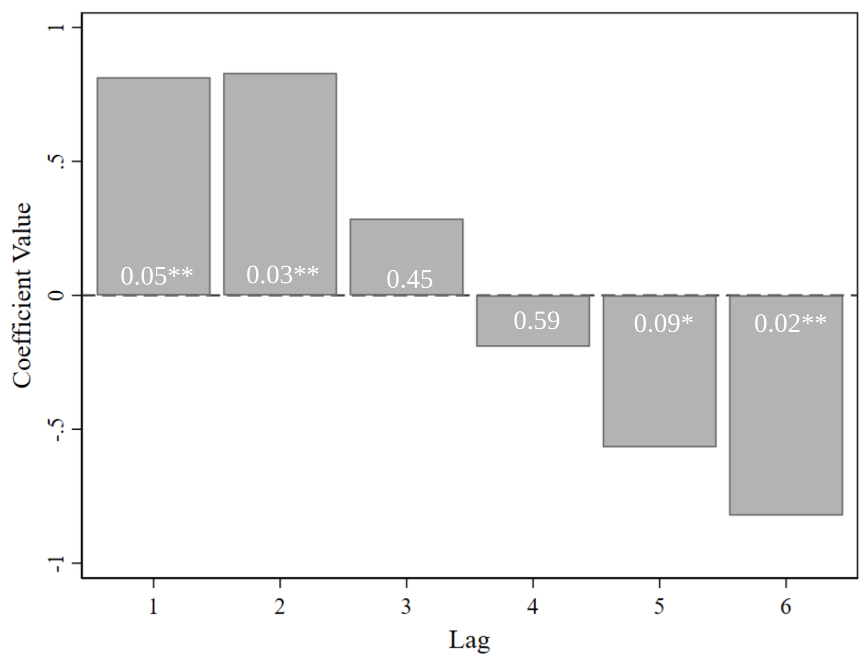

Figure 4 Shows Coefficient Values of $INDEX^r$ at different time lags up to p = 6, included in each bar are each coefficient's respective p-values; with *,**,*** denoting statistical significance to the 10%,5% and 1% respectively

Additionally, this result could pose insight to the insignificance found in our earlier results, as negative trend in lagged coefficient values was consistent (though unreported due to redundancy) in the M110 portfolio. Given that our earlier models investigate a relationship between the various portfolios on either one lagged sentiment measure or two (given the change in sentiment measures), these results stand to show that sentiment and asset prices exhibit relationships in a more systemic way than previously examined in this paper.

5. SUMMARY AND CONCLUSIONS

In the past, little to no emphasis was placed on investor sentiment and its relation to traditional finance theory. However, many recent studies have found that traditional finance theory may not be capturing the basic intuition of people, and the incorporation of sentiment may prove to be beneficial, specifically when analysing its relationship in asset pricing models. Our review of literature assesses all pertinent and significant measures of sentiment, which then further investigates assets most susceptible to such sentiment-based mispricing and theoretic reasoning behind such.

Whilst most prior studies on this topic employ a bottom-up approach, this study makes use of a top-down approach to investigate the relationship between investor sentiment and asset pricing on the JSE, using both survey and market proxies. In South Africa, survey metrics such as the Consumer Confidence Index (CCI) and Business Confidence Index (BCI) are the closest thing to such a proxy and their usability as such is doubtful (Solanki & Seetharam, 2014). These indices are susceptible to changes in economic outlook and the structure of the underlying questions in the surveys do not necessarily pertain to investor sentiment but are rather skewed towards consumption and general economic perspectives. To complement further analysis, we make develop market constructed sentiment index, analogous to the work of Baker and Wurgler (2006) using the first principle component of four market derived proxies of sentiment. We then regress all measures against a business cycle variable, using the residuals as evidence of sentiment unrelated to business cycle conditions. Firstly, we assess correlation with survey traditional measures of sentiment (BCI and CCI), and subsequently analyse the relationship between sentiment and return on portfolios with characteristics most attractive to noise-traders, and most susceptible to sentiment-based miss-pricing.

We test for miss pricing in a mean-reversion manner, looking for low returns on certain portfolios following periods of high sentiment. Initially, simple regression tests show Business Confidence exhibits positive relationships with said portfolio returns, and that the market constructed index shows a relationship with distress and unprofitable firms in line with the literature.

Furthermore, we consider changes in sentiment over the absolute sense, and additionally control for known explanatory pricing factors from Fama and French (1993). Finding similar results as initial our simple regression tests, indicating a significantly negative effect between high positive change in sentiment and subsequently low relative returns in unprofitable firms. While survey indices exhibit the correct signs of coefficients, when controlling for know asset pricing factors, we find no significance on all assessed portfolios.

Finally, we create an environment in which sentiment and the return on small stocks relative to large one act in an endogenous system using a VAR model with 6-lags. We develop a scenario in which we assess the time-lagged effect of sentiment on said return. Significant results pose support in the short-term momentum hypothesis and long-term mean-reversion hypothesis, potentially suggesting that insignificance found in our prior models could be justified due to not accounting for the systemic, time-based, interaction of sentiment on asset prices.

Although measures were taken to ensure that this study is as robust as possible, limitations are present. Predominant limitations in INDEX and INDEX^{r} and its usefulness arise from the nature of its adaptation from the NYSE, as in Baker and Wurgler (2006) to a far smaller market such as the JSE; resulting in several sample size issues ranging from the inability to incorporate certain proxies (for example, there is only one publicly traded Closed-End Fund on the JSE) to the significantly fewer number of IPO’s per year relative to other global exchanges. As discussed, historical portfolio analysis limits from Bloomberg L.P posed further limitations in sample size and frequency.Using interpolation for datasets is a further limitation. The problem with this approach is that the interpolated values are not realistic as they are not readily available to investors. This approach solves a statistical problem, though has limited interpretability given its nature.

Interesting areas of future research would an examination of sentiment levels in a predictive context. Allowing foresight for significant financial anomalies, such asbubbles and crashes. Given the severity of the financial crises that have previously occurred and the many spill-over effects that these have had, it may be beneficial to investigate whether investor sentiment provides any indication as to when market events may occur, and what salient features are present. Further avenues for research lie in modelling the systemic interaction of fundamental and behavioural variables in asset pricing, particularly in a South African context

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APPENDICES

Appendix A1: Principle Component Analysis Results for INDEX

Principle Components for INDEX

Component	Eigenvalue	Difference	Proportion	Cumulative
#1	1.658	0.630	0.414	0.414
#2	1.028	0.200	0.257	0.671
#3	0.827	0.340	0.207	0.878
#4	0.487		0.122	1.000

Component Scores (Eigen Vectors)

Variable	#1	#2	#3	#4
NIPO	0.661	-0.022	-0.071	-0.747
RIPO	0.581	0.086	-0.579	0.566
VOLP	0.397	-0.610	0.611	0.311
TURN	0.262	0.787	0.535	0.158

Unrotated principle component eigenvalues and eigenvectors for n = 144.

Appendix A2: Principle Component Analysis Results for INDEX^r

Principle Components for INDEX$_r$

Component	Eigenvalue	Difference	Proportion	Cumulative
#1	1.623	0.564	0.406	0.406
#2	1.059	0.236	0.265	0.670
#3	0.823	0.326	0.206	0.876
#4	0.496		0.124	1.000

Component Scores (Eigen Vectors)

Variable	#1	#2	#3	#4
NIPO^r	0.668	0.001	-0.058	-0.742
RIPO^r	0.595	0.123	-0.546	0.578
TURN^r	0.401	-0.584	0.634	0.311
VOLP^r	0.199	0.803	0.545	0.139

Unrotated principle component eigenvalues and eigenvectors for n = 144.

Appendix A3: Correlations of INDEX and $INDEX^r$

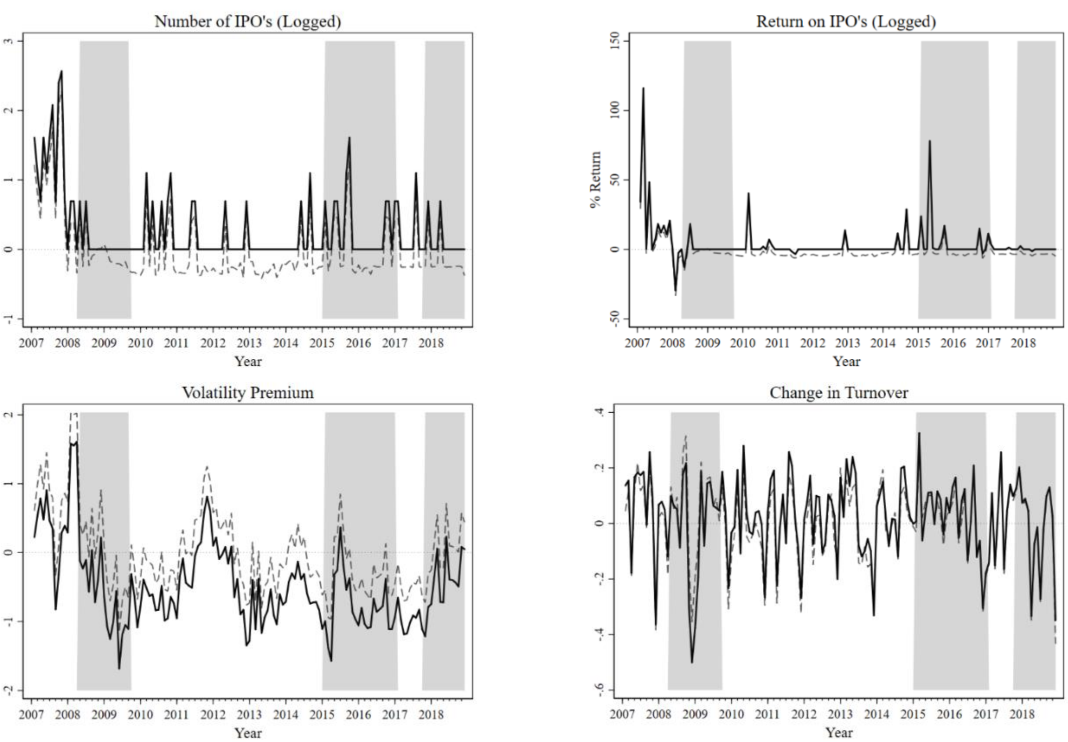
Correlations for components of INDEX

	NIPO	RIPO	TURN	VOLP
NIPO	1			
RIPO	0.462	1		
TURN	0.1806	0.1095	1	
VOLP	0.2994	0.1212	-0.0265	1

Correlations for components of $INDEX^r$

	$NIPO^r$	$RIPO^r$	$TURN^r$	$VOLP^r$
$NIPO^r$	1			
$RIPO^r$	0.462	1		
$TURN^r$	0.1806	0.1095	1	
$VOLP^r$	0.2994	0.1212	-0.0265	1

Appendix A4: Figures of INDEX and $INDEX^r$ components over the sample



Appendix C: Correlations of Sentiment Indices and Economic Variables

	INDEX	$INDEX^r$	CCI	CCI^r	BCI	BCI^r	CI	REC
INDEX	1							
$INDEX^r$	0.9765	1						
CCI	0.3989	0.3671	1					
CCI^r	0.3588	0.3779	0.9714	1				
BCI	0.6603	0.6300	0.5317	0.4898	1			
BCI^r	0.6220	0.6481	0.4856	0.5069	0.9649	1		
CI	0.2063	0	0.2224	0	0.2276	0	1	
REC	-0.1793	-0.0991	-0.279	-0.1885	-0.4074	-0.31	-0.4005	1

Appendix B: Correlations of Market Portfolios on the JSE

	MKT	RF	RMRF	M110	V101	DIV	SMB	HML	NMP
MKT	1								
RF	-0.0077	1							
RMRF	0.9843	-0.1842	1						
M110	-0.2771	-0.0576	-0.2622	1					
V101	0.059	0.0108	0.0561	0.1766	1				
DIV	-0.0747	-0.0929	-0.057	0.5097	0.6359	1			
SMB	-0.4254	0.1874	-0.4512	0.7476	0.181	0.485	1		
HML	0.1154	0.0339	0.1075	-0.2055	-0.1141	-0.006	-0.2419	1	
NMP	-0.1646	0.0617	-0.1727	0.5131	0.2023	0.4452	0.5599	-0.2791	1

Plagiarism Declaration

FTX4051H / FTX4052H project (2016)
Department of Finance & Tax
University of Cape Town

STUDENT NAME	***STUDENT NUMBER***
1. Cameron Singh	*SNGCAM001*
2. Jonathan Doyle	*DYLJON001*

Project Title

Investor sentiment and asset returns on the Johannesburg Securities Exchange

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