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ARTICLE INFO	Naeem Dalika and Yudhvir Seetharam (2015). Sentiment and returns: an analysis of investor sentiment in the South African market. *Investment Management and Financial Innovations*, *12*(1-2), 267-276
RELEASED ON	Thursday, 30 April 2015
JOURNAL	"Investment Management and Financial Innovations"
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
0	**0**	**0**

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Abstract

This study examines the relationship between investor sentiment and stock returns in the South African Market. Theory predicts that a broad wave of sentiment will disproportionately affect stocks whose valuations are highly subjective and are difficult to arbitrage. To test this prediction, the authors construct an aggregate measure of investor sentiment from several proxies and study the impact that it has on stock returns over the period from 1999 to 2009. The results indicate that investor sentiment has a strong impact on share returns in South Africa. When sentiment is low, subsequent returns are relatively high on smaller stocks, high volatility stocks, extreme growth stocks, and young stocks. When sentiment is high, on the other hand, these patterns fully reverse.

Keywords: sentiment, emerging markets, index construction, behavioral finance.
JEL Classification: G02, G14, G15.

Introduction

The relationship between sentiment and stock returns is at odds with classical financial theory that predicts that the stock price reflects the discounted present value of cash flows and there is no risk modification concerning investors' sentiment (Schmelling, 2009). Furthermore, classical financial theory contends that the influence of irrational investors on security prices is corrected by rational arbitrageurs who drive security prices back to their fundamental values (DeLong, Shleifer, Summers, Waldman, 1990). Thus, suboptimal trading behavior such as paying attention to signals unrelated to fundamental value will be quickly eliminated in competitive financial markets. However, the inability of traditional asset pricing models to explain some of the most striking events in the history of the stock market has led to the emergence of a body of research which argues that some of the anomalies observed in the stock market can be attributed to noise created through trades which are motivated by sentiment (Black, 1986; Baker & Wurgler, 2006). Ibbotson and Idzorek (2014) present a "theory of popularity" that relates excess returns to either market premiums or market anomalies. The authors explain that risk premiums, such as volatility, beta, size and value or growth firms, may be permanent and can provide excess returns after being discovered. Additional, transitory factors, such as trading volume or sentiment might be associated with mispricing. This concept illustrates that while sentiment may be an easily quantifiable concept, it is nonetheless important to consider in explaining asset pricing.

A number of studies have focused on the empirical relationship between investor sentiment and stock returns, however the results of these investigations have often been mixed. Fisher and Statman (2000) studied the sentiment of three groups of investors: Wall Street strategists, small investors and newsletter writers. The authors find that the sentiment of both small investors and Wall Street strategists were reliable contradictory indicators for future S&P 500 stock returns, but found no statistically significant relationship between the sentiment of newsletter writers and stock returns. Recently, Baker and Wurgler (2006) noted that investor sentiment has a significant impact on the cross-section of stock returns. The authors note that investor sentiment has larger effects on stocks which valuations are highly subjective and difficult to arbitrage. Motivated by these findings, we construct a sentiment index to analyze the role that investor sentiment plays in the South African stock market.

Research problem and hypothesis. Baker and Wurgler (2006) note that sentiment based mispricing is based on both an uninformed demand shock and a limit to arbitrage. Regarding the first element, uninformed demand shocks, Brown and Cliff (2005) argue that sentiment is most likely a persistent effect, such that demand shocks of uninformed noise traders may be correlated over time thus giving rise to strong and persistent mispricing. However, the second component, limits of arbitrage, deters informed investors from eliminating the mispricing (Black, 1986; Shleifer & Vishny, 1997). It is difficult to determine how long buying or selling pressure from overly optimistic or pessimistic noise traders will persist, however, every mispricing has to eventually be corrected such that one would observe low long run returns after periods of high investor optimism (Lemmon & Portniaguina, 2006). Empirical evidence does indeed indicate that there is a negative relationship between sentiment and stock returns (Brown & Cliff, 2005). We investigate this relation for the South African market, which leads to our first hypothesis:

Hypothesis 1: Investor sentiment predicts future aggregate market returns. The relation between sentiment and expected returns is significantly negative and robust to controlling for fundamental factors.

Researchers have recently shown that sentiment has a significant impact on the cross-section of stock returns. More specifically, sentiment disproportionately affects stocks which valuations are highly subjective and difficult to arbitrage. Baker and Wurgler (2006) extend the approach of Daniel and Titman (1997) and find that when sentiment is low, stocks that are smaller, more volatile, unprofitable, non-dividend paying, extreme growth and distressed have higher subsequent returns, whereas the patterns largely reverse when sentiment is high.

Barber, Odean and Zhu (2008) investigate the returns of stocks that are heavily traded by individuals in the U.S. The authors provide direct evidence that individuals are noise traders. The authors note that stocks that are heavily sold by individuals outperform stocks that are heavily bought by a substantial 13.5% the following year. The authors furthermore document strong herding behavior among individual investors. Correlated trading by irrational investors seems to be the likely cause for these return differentials (Schmelling, 2009).

We thus test for such cross-sectional effects in the South African market, which leads to our second hypothesis:

Hypothesis 2: The effect of sentiment on returns is stronger for stocks that are hard to value or hard to arbitrage.

A significant proportion of the body of research that analyzes the role of investor sentiment in asset pricing has focused on developed markets. In contrast to emerging markets, developed markets are believed to be more efficient when it comes to pricing assets. Emerging market investors may be highly influenced by social and cultural factors while their counterparts are more likely to base their investment decisions on the information available (Kang, Liu & Ni, 2002). Furthermore, developed market investors are believed to bear lower risk as a result of the information efficiency of these markets. For these reasons, the degree of influence of investor sentiment in emerging markets may differ from those of developed markets. This study intends to fill the gap by exploring the role of investor sentiment in emerging markets utilizing the framework employed by Baker and Wurgler (2006). There are no published studies that have a constructed a sentiment index solely utilizing the proxies mentioned in this paper. Additionally, prior research on investor sentiment did not take transaction costs into account.

1. Literature review

1.1. Defining investor sentiment. Researchers have broadly agreed that sentiment can be economically significant but the concept itself is still largely regarded as abstract. The crux of the problem is that, to date, there is no single commonly accepted definition of investor sentiment. Existing definitions of sentiment range from vague statements about investors' mistakes to specific psychological biases that are model-specific (Shefrin, 2007). Additionally, the term itself is subject to a wide spectrum of classifications and used in different ways by academic researchers, financial analysts and the media (Barberis, Shleifer & Vishny, 1998; Baker & Wurgler 2007).

Zweig (1973) contends that investor sentiment comes from investors' biased expectations on asset values. Black (1986) refers to investor sentiment as the noise in financial markets. Lee, Shleifer and Thaler (1991) define investor sentiment as the component of investors' expectations about asset returns that are not justified by fundamentals. Baker and Wurgler (2006) notes that investor sentiment generally refers to investors' propensity to speculate, or investors' optimism (pessimism) about stocks. Baker and Stein (2004) define investor sentiment as investors' misvaluation of an asset. Central to these definitions is that investor sentiment reflects the difference between what asset prices are and what asset prices should be. In a market with two groups of investors, assuming one holds rational expectations on an asset's value and the other makes biased valuations, investor sentiment reflects the valuation difference between the two groups of investors (Lee, Shleifer and Thaler, 1991). A common approach in the literature is to use a combined sentiment index consisting of several sentiment proxies. Baker and Wurgler (2006) argue that investor sentiment affects asset prices through two distinct channels: I) cross-sectional variation in sentiment, and II) variation in the difficulty of arbitrage. The authors construct a composite sentiment index based on the following proxies: The closed-end fund discount, the number of IPOs, turnover, the initial returns of IPOs, the equity shares in new issues and the dividend premium. The authors posit that the time-series relation between investor sentiment and expected stock returns is greater on stocks that are vulnerable to sentiment waves and are difficult to arbitrage. The authors hypothesize that stocks of low capitalization, unprofitable, non-dividend paying, young, distressed, high volatility or growth are likely to be disproportionately sensitive to broad waves of investor sentiment. These stocks are difficult value, and furthermore, are rarely monitored by arbitragers (Shleifer & Vishny, 1997; Baker & Wurgler, 2007). For this reason, such stocks are more likely to be influenced by changes in sentiment. Consistent with their predictions, the authors observe that these stocks earn high future returns when their beginning

of period proxies for investor sentiment are low, and the patterns attenuate when the beginning of period sentiment proxies are high. Utilizing such an index, Baker and Wurgler (2006) observe that investor sentiment has a significant effect on the cross-section of stock returns.

1.2. Sentiment proxies. Despite a growing body of literature on the influence of investor sentiment over the last two decades, there is still no consensus on the best method to measure investor sentiment. There are several proxies that researchers utilise to capture sentiment, but thus far there is no consensus about which one provides the best results (Baker and Wurgler, 2007). Investor sentiment measures employed generally fall into two categories: survey based and market based sentiment indices. Survey-based indices are obtained by directly polling the opinions or perceptions of investors through surveys and questionnaires. In contrast, market based indices seek to glean sentiment indirectly from financial proxies. Presented below is a review of several proxies that are utilized to measure sentiment.

1.2.1. Closed end fund discount. Zweig (1973) and Delong et al. (1990) contend that if closed-end funds are partly held by individual investors, the average discounts of closed-end funds (measured as the average difference between the Net Asset Value (NAV) and the trading price of the fund) can effectively measure the degree of investor sentiment. When investors are optimistic about the fund's future, they will sell the fund with a premium or smaller discount, as they believe their holdings may be worth more in the future. However, if fund holders are pessimistic, they will sell their funds with a large discount as compensation for the buyers. For these reasons, large discounts observed in a given period suggest that investors are bearish and small discounts indicate that investors are bullish. Consistent with this argument, Lee et al. (1991) indicate that fluctuations in these discounts are driven by changes in individuals' investor sentiments.

1.2.2. Trading volume. Jones (2001) and Baker and Stein (2004) suggest that turnover may reflect the sentiment of investors if short selling is constrained. Trading volume or market liquidity, measures the amount of funds available on the market. Unsophisticated traders are willing to add additional liquidity to markets only when they are optimistic about the future performance of the market. Thus irrational traders are more likely to trade when investor sentiment is high. Higher trading volume increases market liquidity and may induce overvaluation, which results in abnormally low subsequent returns. Hence, high turnover may have a negative influence on market returns.

1.2.3. Dividend premium. Baker and Wurgler (2006) define dividend premium as the difference between the average market-to-book ratios of dividend payers and non-dividend payers. Generally, dividend-paying stocks are perceived as less risky with more predictable future cash flows, as they are associated with larger and more profitable firms. As a result, demand for stocks with these characteristics is inversely related to the prevailing sentiment (Zaharieva, 2012).

1.2.4. Initial public offerings, first day returns and volume. The IPO market is often regarded as a reflection of the expectations and beliefs of investors with high first day returns reflecting investors' enthusiasm (Loughran and Ritter, 1997). Baker and Wurgler (2006, 2007) contend that firms are more likely to offer an IPO when investor sentiment is high. In such periods, investors are generally over-optimistic on the newly issued shares which may induce greater first day returns and provide additional benefit for newly listed firms. Hence, the underlying demand for IPOs is perceived to be extremely sensitive to the prevailing sentiment in the stock market.

1.2.5. Equity issue over total new issues. Baker and Wurgler (2000) argue that the share of equity issues in total equity and debt issues could be utilized to capture investor sentiment. The authors contend that this measure indicates that rational managers take advantage of temporary mispricing in the stock market by issuing equity when stocks are overpriced. In their empirical study, the authors observe that high values of the equity share predict low market returns.

1.3. Sentiment in the financial market. De Long, Shleifer, Summers and Waldman (1990) contends that there are two types of investors: rational arbitrageurs who are sentiment free and irrational (noise) traders who are prone to exogenous sentiment. The trading of irrational investors creates risk (noise trader risk), and is a deterrent to the arbitrage activities of rational investors. As a result, stock prices can diverge significantly from fundamental values even in the absence of fundamental risk. Moreover, noise traders, bearing a disproportionate amount of risk that they themselves create earn higher expected returns than rational investors. Lee, Shleifer and Thaler (1991) examine the proposition that fluctuations in discounts of closed-end funds are driven by changes in an individual investor's sentiment. The theory implies that discounts are high when investors are pessimistic about future returns and low when investors are optimistic. Average discounts exist because the unpredictability of investor sentiment creates a risk to holding a closed end fund in addition to the risk inherent in the fund's portfolio

(Lee, Shleifer & Thaler, 1991). The authors employ monthly discount data in the period from July 1956 to December 1985, and construct a value-weighted index of discounts based on 20 closed-end funds. The authors observe that discounts on closed end funds are indeed a proxy for changes in individual investor sentiment and that the same sentiment affects returns on smaller capatilization stocks that are traded by individual investors.

Neal and Wheatley (1998) examine the forecasting power of three popular measures of individual investor sentiment: the level of discounts on closed-end funds, the ratio of odd-lot sales to purchases and net mutual fund redemptions. The authors confirm the results obtained by Lee, Shleifer and Thaler (1991) as they observe a positive relation between fund discounts and small firm expected returns, but no relation between discounts and large firm expected returns. This is consistent with the investor sentiment hypothesis as small firm stocks are generally held by individuals, while large firm stocks are mostly held by institutions (Lee, Shleifer & Thaler, 1991). Additionally the authors find reliable evidence that net redemptions predict the size premium whereas there is no indication that the odd-lot ratio predicts either small or large firm returns.

Baker and Stein (2004) contend that in a world with short sales constraints, market liquidity can be utilized as a sentiment indicator. The authors contend that an unusually liquid market is one in which pricing is being dominated by irrational investors, who underreact to information contained in equity issues. Thus high liquidity is an indication that the sentiment of these irrational investors is positive, and that expected returns are therefore abnormally low. Since there are short sales constraints on the market, rational investors cannot counteract the overconfident investors' transactions. This is of particular interest to our study as the JSE does not allow short selling to occur. Therefore, it is possible that if sentiment is found to exist in the South African market, it cannot be counteracted by rational investors' actions.

Baker, Wurgler and Yuan (2009) apply the methodology developed by Baker and Wurgler (2006) to a study of global markets. The authors include both global and local factors to determine the impact that sentiment has across various countries, and to measure the contribution of the global component of sentiment on the stock pricing mechanism of highly integrated markets. Consistent with previous research, the study supports the theory that stocks that are difficult to value and arbitrage tend to be more influenced by the fluctuation of sentiment.

Utilizing survey data, Brown and Cliff (2005) examined the forecasting power of several investor sentiment proxies proposed in prior research. In contrast with previous studies, the authors constructed a single sentiment index, employing principle component analysis to abstract the correlated among several sentiment proxies. Moreover, the authors employ vector auto regression (VAR) methods to investigate the casual relationship between expected returns and a sentiment index. The authors find that many commonly cited indirect measures of sentiment are related to direct measures (surveys) of investor sentiment. Furthermore, the authors note that even though changes of sentiment levels are strongly correlated with contemporaneous market returns, the predictive power in a sentiment index for near-term future stock returns is relatively weak. The evidence presented in this study does not support the conventional wisdom that sentiment primarily affects individual investors and small stocks.

Zouaoui, Nouyrigat and Beer (2011) examine the influence of investor sentiment on the probability of a stock market crisis over the period from 1995 to 2009. The empirical analysis reveals that investor sentiment increases the probability of occurrence of a stock market crisis within a one-year horizon. The impact of investor sentiment on stock markets is found to be more pronounced in countries that are culturally more prone to herd like behavior and overreaction or in countries with low institutional involvement.

2. Data and methodology

2.1. Basic approach. To analyze the impact that sentiment has on stock returns, this study utilizes the following empirical design. We develop an aggregate measure of investor sentiment by employing a number of sentiment proxies that we hypothesize contain some component of investor sentiment and some component of non-sentiment related idiosyncratic variation. To isolate the sentiment component of the proxies from business cycle components, we orthogonalize each proxy with respect to several macroeconomic variables. The residuals from the regressions are taken as a cleaner proxy that is independent of major business cycle effects. The sentiment series is then estimated as the first principle component of the orthogonalized sentiment proxies. We organize our empirical work around the following model:

$$E_{t\text{-}1}[R_{it}] = \alpha + b_1 'X_{it\text{-}1} + b_2 'T_{t\text{-}1} X_{it\text{-}1}, \quad (1)$$

where i indexes firms or securities, t is time, X is a vector of firm or security characteristics and T is a time series conditioning variable that proxies for investor sentiment. The null hypothesis is that b_2 is zero or, more precisely, that any non-zero effect is due to rational compensation for bearing systematic

risk. The alternative is that b_2 is non-zero and reflects the correction of mispricing's. We use Eq. (1) as an organizing framework to test for conditional characteristic effects, not as a structural model.

2.2. Share price data. Share price data is obtained from I-Net Bridge and McGregor BFA. The data consisted of closing monthly prices of all firms listed and subsequently delisted on the Johannesburg Securities Exchange (JSE) for the period December 1999 to July 2009. It is important to note that the inclusion of delisted firms is done to prevent any look ahead bias. Furthermore, the closing prices of the JSE All Share Index (ALSI) over the same 10 year period is obtained from McGregor BFA. The ALSI will be compared with the aggregate sentiment index. This index is specifically chosen as it is likely to be representative of the entire South African securities market.

2.3. Firm data. McGregor BFA as well as the Findata@Wits (a database compiled and owned by the University of the Witwatersrand, South Africa) is utilized to obtain data on the characteristics of all companies listed as well as delisted on the JSE over the analysis period. The age of a company, volatility, book equity (BE), market equity (ME) and size are the firm characteristics that are assessed in the study. This data are used to observe the impact that sentiment has on shares with these varying characteristics.

2.4. Transaction costs. Transaction costs consist of two components – explicit costs, such as brokerage fees and taxes; and implicit costs, such as bid-ask spreads and the price impact of the trade. As implicit costs are difficult to quantify, many studies instead deduct a fixed percentage of the value of each trade to account for trading costs. This value is referred to as unconditional trading costs. Studies that have utilized unconditional trading costs range from 0.5% (Jegadeesh & Titman, 1993) to 1.5% (Grundy and Martin, 2001). However, there are no published studies of investor sentiment that take transaction costs into account. This study uses an amount of 1% per share per month for transaction costs. While the amount is particularly high for trading, it serves as a "worst case" scenario for our results.

2.5. Sentiment proxies: motivation. The first proxy we employ to construct our sentiment index is volatility premium. This simply identifies times when valuations on high idiosyncratic volatility stocks are high or low relative to valuations on low idiosyncratic stocks. The motivation for this variable derives from the theoretical prediction that sentiment has its strongest effects on hard to value and hard to arbitrage stocks. Volatile stocks are inherently riskier to trade – volatility brings with it fundamental risk as well as arbitrage risk (Wurgler & Zhuravskaya, 2002). Furthermore, volatile stocks are particularly unattractive to arbitrageurs, which in turn increase the potential for such stocks to be affected by noise trader sentiment.

The volatility premium is the year end log ratio of the value-weighted average market-to-book ratio of high volatility stocks to that of low volatility stocks. High (low) volatility denotes one of the top (bottom) three deciles of the variance of the previous year's monthly returns. Total volatility is defined as the standard deviation of the 12 trailing months of monthly returns.

The second and third proxies employed are derived from initial public offering (IPO) data. They are the total volume of IPOs and their initial first day returns. The theoretical motivation for using the volume of IPOs is simply that insiders and long run shareholders have strong incentives to time the equity market for when valuations are greatest, which presumably is when sentiment is highest. Low long-run returns to IPOs have been noted by Ritter (1991) and Loughran, Ritter, and Rydkvist (1994), which is ex post evidence of successful market timing relative to a market index. Additionally, researchers have widely noted that the initial returns on IPOs increase in hot markets, and that the worst future returns occur for IPOs and equity issues from hot market cohorts with high total issuance volume.

The number of IPOs (NIPO) is the log of the total number of IPOs that year. The initial returns on IPOs (RIPO) are the average initial return on that year's offering. The returns are equally weighted across firms. Data will be obtained from the Johannesburg Securities Exchange and McGregor BFA.

The final sentiment proxy employed is market turnover. Researchers such as Bagehot (1873) have noted that high trading volume in the overpriced asset is a pattern that goes back to the tulip bubble. Cochrane (2002) asserts that the association of volume and price is a generic feature of historical bubbles while Smith, Suchanek and Williams (1988) indicate that bubbles are associated with high turnover. Furthermore, there is ample evidence in financial literature to connect sentiment with trading volume. Baker and Stein (2004) observe that when shorting is relatively costly, sentimental investors are more likely to trade when they are optimistic, and overall volume will increase. Barber, Odean and Zhu (2009) argue that abnormal trading volume can be considered as a signal of irrational investor sentiment. Scheinkman and Xiong (2003) provide a complimentary argument based on overconfidence for using turnover as a proxy for sentiment. As with

the other three measures, we expect a positive relationship between the observed proxy and the underlying sentiment. Market turnover (TURN) is the log of total market turnover – total rand volume over the year divided by total capitalization at the end of the prior year. To my knowledge, there are no published studies of investor sentiment that utilize the above stated proxies to construct an aggregate sentiment index.

Finally, to remove information about expected returns that may be contained in our sentiment proxies that is not related to sentiment, we adopt the methodology noted by Baker and Wurgler (2006) and orthogonalize each proxy to three macro-economic series. These are: inflation (Fama & Schwert, 1977), employment growth (Santos & Veronesi, 2006) and industrial production growth (Chen, Roll & Ross, 1986). This data is obtained from the Johannesburg Securities Exchange, Statistics South Africa (Stats SA) and the International Monetary Fund (IMF) database.

3. Results

3.1. Principal component analysis. The principal axis method was used to extract the components and this was followed by a varimax (orthogonal) rotation[1]. Principal component analyzis (PCA) is a multivariate technique that analyses a data table in which observations are described by several inter-correlated quantitative dependent variables. The goal of PCA is to extract the important information from the table and to express this information as a set of new orthogonal variables called principal components. A varimax solution means that each component has a small number of large loadings and a large number of zero (or small) loadings. This simplifies the interpretation because, after a varimax rotation, each original variable tends to be associated with one (or a small) number of components, and each component represents only a small number of variables. Each of the components were cleaned of macroeconomic factors and standardized.

This procedure led to the following index:

$$\text{SENTIMENT} = 0.623\text{NIPO} + 0.420\text{TURN} + \\ + 0.451\text{RIPO} + 0.482\text{PREMIUM}. \quad (2)$$

All, but one of the proxies (PREMIUM) enter the equation with the expected signs. The correlation matrix, given in Table 1 below, indicates that RIPO and NIPO have the highest correlation closely followed by TURN and NIPO. TURN and RIPO are negatively correlated; either of the two variables could have been removed without impacting on the quality of the results.

[1] An oblimin (Kaiser normalization) rotation is additionally conducted and the results are available upon request.

Table 1. Pearson correlation matrix

Variables	Premium	NIPO	TURN	RIPO
Premium	**1**			
NIPO	0.154	**1**		
TURN	0.151	**0.189**	**1**	
RIPO	0.101	**0.247**	-0.026	**1**

Note: Values in bold are different from 0 with a significance level alpha = 0.05.

Table 2 below shows the output for the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. The KMO measure of sampling adequacy is used to compare the magnitudes of the observed correlation coefficients in relation to the magnitudes of the partial correlation coefficients. The KMO statistic varies between 0 and 1. A value of 0 indicates that some partial correlations are large relative to the sum of correlations, indicating diffusion in the pattern of correlations (hence, factor analysis is likely to be appropriate). A value of close to 1 indicates that patterns of correlations are relatively compact, thus factor analysis should yield distinct and reliable factors. Kaiser (1974) recommends accepting values greater than 0.5 as reliable (values below you either collect more data or rethink which variables to include). The KMO sampling adequacy test provides a value of 0.530, indicating that factor analysis is likely to be appropriate.

Table 2. Kaiser-Meyer-Olkin measure of sampling adequacy

Premium	0.623
NIPO	0.532
TURN	0.502
RIPO	0.494
KMO	0.530

Table 3 below displays the output for Bartlett's sphericity test. Bartlett's test of sphericity is used to test the hypothesis that the original correlation matrix is an identity matrix (all diagonal terms are one and off diagonal terms are zero). We are looking for significance (a significance level of less than 0.05), as we want the variables to be uncorrelated. The computed p-value of 0.010 is less than the significance level, thus we accept the alternate hypothesis that at least one of the correlations between the variables is significantly different from zero.

Table 3. Barltett's sphericity test

Chi-square (Observed value)	16.887
Chi-square (Critical value)	12.592
DF	6
p-value	0.010
alpha	0.05

Test interpretation:

H0: There is no correlation significantly different from 0 between the variables.

Ha: At least one of the correlations between the variables is significantly different from 0.

Figure 1 below indicates that the sentiment index constructed lines up well with anecdotal accounts of sentiment over the analysis period. In particular the sentiment proxies clearly capture the decline in sentiment at the turn of the century due to the Internet bubble and the subsequent rise in investor sentiment as market conditions improved. The sharp decline in sentiment in the year 2008 coincides with the collapse of the investment bank Lehman Brothers, during financial market crises. Sentiment is generally low through this period reflecting the uncertainty and pessimism that existed in the market at the time.

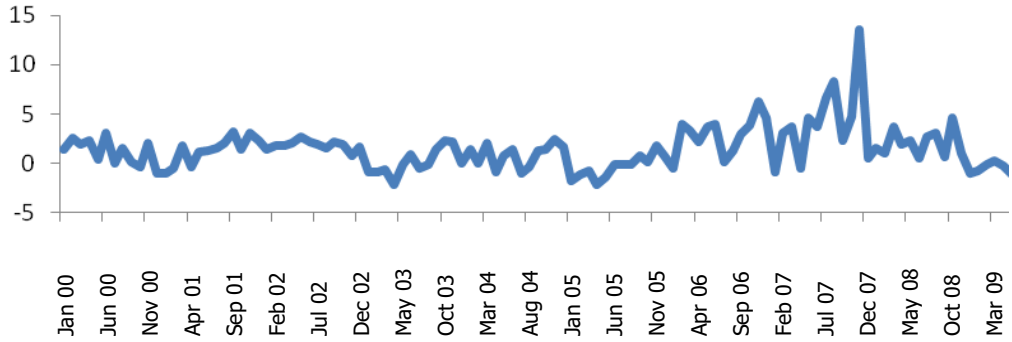

Fig. 1. Graphical representation of the sentiment index

3.2. Portfolio sorts. Table 4 analyzes the conditional characteristics effects. Each monthly return observation is placed into a bin according to their portfolio rank that a characteristic takes at the beginning of that month, and then according to the level of a sentiment proxy from the end of the previous calendar year. Portfolios are constituted according to the methodology advocated by Fama and French (1993). Portfolio 1 represents the first three deciles, portfolio 3 is composed of the top three deciles and portfolio 2 is the intermediate portfolio. We compute the average monthly return for that bin and analyze the results. We report sorts on TURN in Table 4 and SENTIMENT in Table 5. For brevity we omit sorts on the three other sentiment proxies as they provide similar results.

The first rows of Table 4 illustrate the effect of size conditional on TURN. Specifically, the cross-sectional effect of size exists when TURN is positive. When TURN is positive, portfolio 1 provides a return of greater than 5% while portfolio 3 provides an average return of 4.28% per month. This implies that a higher trading volume of smaller firms appears to generate a higher portfolio return after costs.

Similarly, the conditional cross-sectional effect of Age reveals that investors tend to demand young stocks when TURN is positive and older stocks when TURN is negative. When TURN is positive, the top Age firms achieve a return of 0.94% lower than the bottom Age firms. In other words, younger firms that are traded more tend to generate higher portfolio returns after costs.

However, when examining the Volatility and TURN variables, or the BE/ME and TURN variables, this pattern is reversed. In other words, for these two variables (volatility and BE/ME), we observe that portfolio 1 has the lowest return compared to portfolio 3 when TURN is positive. When volatility is high (or when firms are considered to have high BE/ME ratios), then the average returns of these firms are also higher compared to low volatility or low BE/ME firms. This is in contrast to Ibbotson and Idzorek (2014) who found that less popular stocks (proxied by turnover) with low volatility performed better than their counterparts. Reasons for the contrasting results could stem from the market examined (emerging or developed) as well as the sample period (ten years compared to 41 years).

Table 4. Two-way sorts: TURN and firm characteristics

$TURN_{t-1}$		Portfolio			Overall			
		1	2	3	3-1	3-2	2-1	T-Stat
ME	Positive	5.97	5.65	4.28	-1.69	-1.37	-0.32	0.00*
	Negative	1.12	1.38	1.80	0.62	0.42	0.26	
	Difference	4.85	4.27	2.48	-2.31	-1.79	-0.58	
Age	Positive	6.00	5.95	5.06	-0.94	-0.89	-0.05	0.01*
	Negative	2.88	2.93	1.96	-0.92	-0.97	0.05	
	Difference	3.12	3.02	3.1	-0.02	0.08	-0.1	

Table 4 (cont.). Two-way sorts: TURN and firm characteristics

$TURN_{t-1}$		Portfolio			Overall			
		1	2	3	3-1	3-2	2-1	T-Stat
Volatility	Positive	4.28	4.89	5.92	1.64	1.03	0.61	0.07*
	Negative	2.42	1.89	0.93	-1.49	-0.96	4.97	
	Difference	1.86	3.01	4.99	0.15	0.07	-4.36	
BE/ME	Positive	4.87	5.42	6.01	1.14	0.59	0.55	0.02*
	Negative	-0.18	1.52	2.46	2.64	0.94	1.7	
	Difference	5.05	3.90	3.55	-1.50	-0.35	-1.15	

Notes: *Denotes p-values that are statistically significant at the 5% level of significance. **Transaction costs of 1% are employed.

The first rows of Table 5 illustrate the effect of size conditional on sentiment. Specifically, the cross-sectional effect of size exists when SENTIMENT is negative. When sentiment is negative, portfolio 1 provides a return of greater than 5% while portfolio 3 provides an average return of 3.17% per month.

The conditional cross-sectional effect of Age reveals that investors tend to demand young stocks when SENTIMENT is positive and older stocks when SENTIMENT is negative. When SENTIMENT is pessimistic, the top Age firms achieve a return of 1.32% lower than the bottom Age firms, but return an average of 0.89% more when SENTIMENT is optimistic.

Table 5 indicates that high volatility stocks are out of favor when SENTIMENT is positive. High volatility firms achieve a return of 2.42% as opposed to an average return of 3.61% for low volatility firms. However, similar to Age, the cross sectional effect of volatility fully reverses in low sentiment conditions.

The last row displays the effect of BE/ME conditional on SENTIMENT. Table 5 illustrates that when SENTIMENT is positive, average returns of portfolios sorted on BE/ME increase and similarly average returns broadly decrease when SENTIMENT is negative. This simply implies that average returns are generally greater for securities with high BE/ME values.

A closer look at the conditional pattern in the BE/ME variable reveals a U-shaped configuration in the conditional difference of average returns. When SENTIMENT is high there is a U-shaped pattern across BE/ME portfolios, which is illustrated in the 3-1 and 2-1 portfolio contrasts. When SENTIMENT is negative however, this becomes an inverted U configuration. This pattern is only present in the BE/ME variable. Baker and Wurgler (2006) comment that BE/ME may identify extreme growth opportunities and distress stocks. However, Baker and Wurgler (2006) further note that BE/ME may simply just serve as a generic valuation indicator.

The U-shaped conditional difference pattern observed in the BE/ME variable, suggests that investors demand both high growth and distressed firms when they are optimistic, or when their propensity to speculate is high. Furthermore, investors avoid these extreme stocks when their propensity to speculate is low, or when they are pessimistic.

Table 5. Two-way sorts: SENTIMENT and firm

$SENTIMENT_{t-1}$		Portfolio			Overall			
		1	2	3	3-1	3-2	2-1	T-Stat
ME	Positive	1.79	2.05	2.68	0.69	0.37	0.26	0.01*
	Negative	5.46	4.38	3.17	-2.29	-1.21	-1.08	
	Difference	-3.67	-2.33	-0.49	2.98	1.58	1.34	
Age	Positive	2.40	3.61	3.29	0.89	-0.32	1.21	0.02*
	Negative	5.34	4.88	4.02	-1.32	-0.87	-0.46	
	Difference	-2.94	-1.27	-0.73	2.21	0.55	1.67	
Volatility	Positive	3.61	3.27	2.42	-1.19	-0.85	-0.34	0.04*
	Negative	3.68	4.89	5.33	1.65	0.44	1.21	
	Difference	-0.07	-1.62	-2.91	-2.84	-1.29	-1.55	
BE/ME	Positive	2.07	3.19	3.71	1.64	0.52	1.12	0.01*
	Negative	4.18	3.88	3.76	-0.42	-0.13	-0.3	
	Difference	-2.11	-0.69	-0.05	2.06	0.65	1.42	

Note: *Denotes p-values that are statistically significant at the 5% level of significance. **Transaction costs of 1% are employed.

The implication that sentiment has a greater impact on distressed firms is consistent with theoretical predictions that both rapidly growing firms and firms that are extremely distressed are difficult to value and

have high idiosyncratic risk (Baker & Wurgler, 2004). Theory predicts that such securities, which are more subjective to value and harder to arbitrage, tend to be more sensitive to swings in sentiment.

Conclusion

In classical financial theory there is typically no room for investor sentiment. The standard argument is that in highly competitive financial markets, suboptimal trading behavior such as paying attention to sentiment signals unrelated to fundamental value will be quickly eliminated by aggressive rational arbitrageurs. However the rise in non-traditional financial concepts, such as investor sentiment, demonstrates that classical financial theories may not be capturing the basic intuition of what people know all along − that individuals are imperfect, they believe things that seem objectively irrational, and may not make decisions in a rational manner.

This study explored two fundamental questions regarding investor sentiment: does investor sentiment have an impact on the South African market and is the influence of sentiment greater on securities that are hard to value and arbitrage. To test the hypothesis, we construct a composite sentiment index as the linear combination of four indirect measures, namely, volatility premium, total volume of IPOs, average initial first day returns of IPOs and market turnover. The main empirical finding is that sentiment has a rich and broad cross-sectional impact on securities in the South African market. More specifically, when investor sentiment is relatively high, young stocks, small firm stocks, highly volatile stocks, and extreme growth experience low future returns relative to other securities. These securities are likely to be attractive to speculators and optimists and at the same time they are unattractive to arbitrageurs. On the other hand, conditional on low sentiment, these cross-sectional patterns in returns attenuates or reverses. This result gives credence to the argument by financial researchers, that often-neglected behavioral aspects, such as sentiment, should be incorporated into classical financial theories to improve traditional asset pricing and risk models.

An interesting area of future research would be to examine if investor sentiment could be utilized to predict stock market crashes. Given the difficulty caused by the global financial crises it would be appealing to analyze if investor sentiment provides an indication as to when a financial market crash may occur.

A further avenue of future research relates to incorporating investor sentiment into portfolio selection. MPT is dominated by rational investors and arbitrageurs who select stocks based on their fundamental values. It would be interesting if investor sentiment could be incorporated into an asset allocation model to construct portfolios that generate superior returns.

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