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Francisca Beer, Mohamad Wat,
Mohamed Zouaoui

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Do Investors Care About Noise Trader Risk?

Francisca Beer – Professor of Finance, California State University of San Bernardino

Mohamad Watfa – Associate Professor of Finance ITIC, Paris

Mohamed Zouaoui – Associate Professor of Finance IAE, University of Franche-Comté and LEG-UMR 5118

Abstract

The link between investor sentiment and asset valuation is at the center of a long-running debate in behavioral finance. Using a new composite sentiment indicator, we show that the conventional risk does not explain the abnormal returns of portfolios most sensitive to the sentiment factor. Our result supports the existence of a sentiment risk valued by financial markets. We also find that the firms more impacted by the sentiment risk correspond to difficult-to-arbitrage and hard-to-value stocks, e.g. small stocks, growth stocks, young stocks, unprofitable stocks, lower dividend-paying stocks, intangible stocks and high volatility stocks.

Introduction

The standard risk-based asset pricing literature does not take into consideration the role of cognitive factors in financial markets. According to classical finance theory, investors are supposed to be Bayesian in forming fully rational expectations about future cash flows and investment risks. As a result the equilibrium asset price reflects the fundamental value, i.e. rationally-discounted value of expected cash flows. The classical theory further recognizes that some investors cannot be rational, arguing that their positions are offset by arbitrageurs bringing prices back to their fundamental value.

The succession of numerous stock market anomalies[1] has led to an alternative theory stating that asset prices are established through the dynamic interplay between noise traders and rational investors. Several theoretical studies have modeled the role of investor sentiment in asset pricing [Black (1986), De Long et al. (1990), Barberis et al. (1998)]. In these models, there are two types of investors that interact: rational investors and noise traders (i.e. individuals). Rational investors have rational expectations about asset returns. In contrast, noise traders' expectations about asset returns are subject to the influence of sentiment; they underestimate the expected returns (relative to the fundamental value) in some periods and overestimate them in others. Each period, rational investors and noise traders trade the assets based on their respective beliefs. The theoretical framework assumes that noise traders' sentiment is stochastic and cannot be perfectly forecasted by rational investors. Because assets are risky and all investors are risk averse, the equilibrium price reflects the opinions of both the rational investors and the noise traders. It follows that noise traders' sentiment influences asset prices. The theoretical studies point out that asset prices can significantly diverge from fundamental values. Moreover, because arbitrage has practical limits, rational investors fail to fully offset the effects of noise traders' sentiment. Thus, the "noise trader risk", also known as the "sentiment risk", becomes a priced factor by stock markets. As noted by De Long et al., (1990), "Noise traders can earn higher relative expected returns solely by bearing more of the risk they themselves create."

In financial markets, noise traders limit arbitrageurs' ability to bring prices to their fundamental value. Not knowing what the reaction of noise traders will be, arbitrageurs understand risk is involved and limit the funds committed. For example, suppose that in a given period, the noise traders' optimistic expectations result in asset prices inflation. Rational investors should theoretically react to this situation by using futures market to sell short these overvalued stocks. However, arbitrageurs could still experience a severe loss if prices increase instead of dropping because noise traders have continued to be too optimistic. Conversely, an investor who purchases these stocks thinking they are undervalued runs the risk that noise traders' pessimistic expectations result in lower prices. In this case, the risk of holding stocks comes from two sources: the traditional risk and additional risk introduced by noise traders.

While theoretical models early on incorporated the existence of noise traders into equilibrium asset pricing, few empirical tests have been undertaken to investigate the relationship between stock returns and sentiment risk. Furthermore, the studies often led to mitigated results. Some studies provide powerful and consistent empirical support for the hypothesis that stock prices are affected by sentiment risk [Lee et al. (1991), Lee et al. (2002), Kumar and Lee (2006)]. Other studies show that financial markets do not price cognitive factors [Elton et al. (1998), Sias et al. (2001), Glushkov (2006)].

This paper investigates two important questions. Is sentiment risk valued by the stock market? If so, what are the characteristics of the firms most concerned by the sentiment risk? Our main contributions, consistent with the predictions of models based on noise-trader sentiment, can be summarized along three dimensions. First, we develop a new composite sentiment indicator by combining several well-known direct and indirect sentiment indicators. The eyeball test reveals that our composite sentiment index produces a faithful reproduction of the bubbles and crashes during our study period, i.e. July 1981 to December 2008. For instance, our composite index records a significant decline when the speculative bubble of October 1987 burst. Between 1998 and 2003, it peaks in March 2000 at the beginning of the internet bubble. Significant decreases are also recorded during the market collapse following the subprime crises.

Second, we implement a trading strategy that consists of buying stocks most impacted by the sentiment factor and selling stocks less impacted by the sentiment factor in the past 36 months. We find that such a strategy can lead to a significant raw profit unexplained by traditional risk factors. Thus, the existence of a sentiment risk valued by financial markets is likely.

Third, we find that the impact of sentiment risk on stock returns is not uniform across all stocks and is more associated with certain types of stock. We show that the effect of sentiment risk is more prominent for hard-to-value and difficult-to-arbitrage stocks, e.g. small stocks, growth stocks, young stocks, unprofitable stocks, lower dividend-paying stocks, intangible stocks and high volatility stocks.

The remainder of this paper is organized as follows. The first section describes the sentiment measure employed in the study. The second section exposes the methodology used to test the existence of sentiment risk priced by stock market. The third section presents the characteristics of the firms most affected by the sentiment risk. The fourth section includes our concluding remarks.

1 For a detailed presentation about these anomalies see Schwert (2003).

Measuring investor sentiment

The first step of our study is to measure the unobserved sentiment variable. Investor sentiment can be defined as the degree of optimism or pessimism about future cash flows and investment risks that are not justified by the facts at hand. Several empirical studies have attempted to quantify investor sentiment. These studies employ two distinct approaches. The first approach uses several survey-based measures that directly ask individuals how they feel about current or future economic and stock market conditions. De Bondt (1993) uses the ratio of bullish to bearish responses surveyed by the American Association of Individual Investors. Clarke and Statman (1998) employ the Investors' Intelligence survey data of bulls minus bears. Qiu and Welch (2006) recommend the use of the UBS/Gallup surveys. Zouaoui et al. (2011) focus on the indexes of consumer confidence. The second approach draws on economic and market variables susceptible to capture the overall investors' state of mind, such as closed end fund discount, number of IPOs, average first-day returns on IPOs, mutual fund flows, aggregate trading volume and put/call ratio, among other.[2]

It is important to note that there are no uncontroversial and universally accepted sentiment measures. Each individual measure has advantages and limitations. Surveys provide information about investors' state of mind even without sophisticated financial theory to validate them. Notice, however, that survey responses are weighted equally regardless of the magnitude of funds managed by respondents and no distinction is made between the different degrees of optimism or pessimism expressed by respondents. On the other hand, indirect measures offer an excellent indication of the power of market participants and the strength of their bullishness or bearishness. Yet, using economic and market data makes indirect measures very endogenous to the market and economic activity, so they may not measure exclusively investor sentiment.

To sum up, it is difficult to use a unique indicator to measure investor sentiment. Each individual indicator could measure sentiment at a specific point in the market cycle, not necessarily during the sample period. The closed-end fund discount, for instance, will not be a worthwhile proxy if a large number of investors have come to prefer open-end funds. During some months, the number of IPOs might be equal to zero although the market is not necessarily at the lower level during the period studied. These considerations induce us to consider that the best empirical approach is to condense several imperfect indicators into an aggregate index. As a result, we build a new measure of sentiment by combining several well-known direct and indirect sentiment indicators.

In this study, we focus on two direct sentiment indicators and four indirect sentiment indicators. Similar to Baker and Wurgler (2006, 2007), we use principal component analysis to construct a composite sentiment index based on the common variation in six underlying proxies of investor sentiment identified in previous studies: the University of Michigan consumer confidence index (UMI), the Investors Intelligence spread Bull-Bear (II), the number of IPOs in a given month (NIPO), the average monthly first-day returns on IPOs (RIPO), the net new cash flows of U.S. equity mutual funds (FLOW) and finally the closed-end fund discount (CEFD). All proxies are measured monthly over the period from June 1981 to December 2008. Table 1 provides more details on the list of variables used for the construction of the composite sentiment index.

The raw sentiment indicators encompass a psychological component related to sentiment and a rational component related to economic fundamentals. The bullishness or the bearishness of an investor can reflect rational future expectations or irrational enthusiasm or both. To isolate one aspect from the other, all sentiment measures are orthogonalized with respect to several contemporaneous economics variables. Similar to previous studies, we use data on growth of industrial production (IP), inflation (INF), term spread (TS), default spread (DS) and growth in durable (DC), nondurable (NDC) and services consumption (SC). The composite sentiment index (CSI) is as follows:

$$CSI_t = 0.213\ UMI^{\perp}_{t} + 0.197\ II^{\perp}_{t-1} + 0.201\ NIPO^{\perp}_{t} + 0.189\ RIPO^{\perp}_{t-1} + 0.238\ FLOW^{\perp}_{t-1} - 0.206\ CEFD^{\perp}_{t-1} \quad (1)$$

Figure 1 shows the development of the composite sentiment index during the period from July 1981 to December 2008. Our indicator produces a faithful reproduction of the bubbles and crashes during our study period. For instance, our composite index records a significant decline when the speculative bubble of October 1987 burst. Significant decreases are also seen during the collapse of the bonds market in 1994 and during the collapse of LTCM in 1998. Between 1998 and 2003, the composite index peaks in March 2000 at the beginning of the internet bubble. The index also decreases in 2008 during the so-called subprime crisis. This alignment is encouraging because it shows that our composite index captures major fluctuations in sentiment.

The sentiment risk: myth or reality?

To empirically test the hypothesis that the risk sentiment is priced by financial markets, we calculate the raw profit of a strategy consisting of buying portfolios of stocks with greater exposure to sentiment and selling portfolios of stocks with the lower exposure to sentiment. Stock returns and firm's characteristics are collected from the merged CRSP-Compustat database. To implement this strategy, each month we regress the monthly returns of each stock on the variations of composite sentiment indicator over the window [t-1, t-36], i.e.:

2 See Brown and Cliff (2004) and Baker and Wurgler (2007) for a detailed description of the various sentiment indicators.

Code	Variables	Measures	Sources
Investor sentiment indicators			
UMI	Consumer sentiment index	Five questions making up the consumer sentiment index	University of Michigan Survey Research Center
II	Investors Intelligence index	Bull minus bear spread	Investors Intelligence
NIPO	Number of IPOs	Number of IPOs in a given month	http://bear.cba.ufl.edu/ritter
RIPO	First-day returns on IPOs	Average monthly first-day returns on IPOs	http://bear.cba.ufl.edu/ritter
FLOW	Net new cash flows of U.S. equity mutual funds	(Inflows-outflows)/Total asset	Investment Company Institute http://www.ici.org/index.html
CEFD	Closed-end fund discount	Equal-weighted average difference between the NAV of closed-end fund and the stock price of fund	Wall Street Journal
CSI	Composite sentiment index	First component from the principal component analysis of six measures of sentiment	
Macroeconomic variables			
IP	Growth of industrial production	Change in the natural logarithm of industrial production index	Federal Reserve system
INF	Inflation	Change in the natural logarithm of the consumer price Index	Federal Reserve system
TS	Term spread	Difference between the yields on 10-year U.S. government bonds and 3-month Treasury bills	Federal Reserve system
DS	Default spread	Moody's Baa-rated corporate bond yield less the Aaa-rated corporate bond yield	Datastream
DC, NDC and SC	Growth of durable goods, non-durable goods and services consumption expenditures	Change in the natural logarithm of durable goods, non-durable and services consumption expenditures	Federal Reserve system

Table 1 – Description of the variables used for the construction of sentiment index

$$R_{i,\tau} = \alpha_i + \beta_{i,t}\Delta CSI_\tau + \varepsilon_i \quad (2)$$
$$\tau = t\text{-}36,...t\text{-}1$$

We then use the absolute value of the estimated sentiment betas to classify the stocks each month into ten portfolios. Portfolio 1 includes the stocks least impacted by sentiment factor, and Portfolio 10 the stocks most impacted by sentiment factor. Finally, as the sentiment betas are estimated on a rolling basis of one month over the period August 1984 to December 2008, we investigate the sentiment portfolio returns on a holding horizon of a month. The monthly portfolio returns are calculated as a value-weighted average of all stocks in the portfolio.

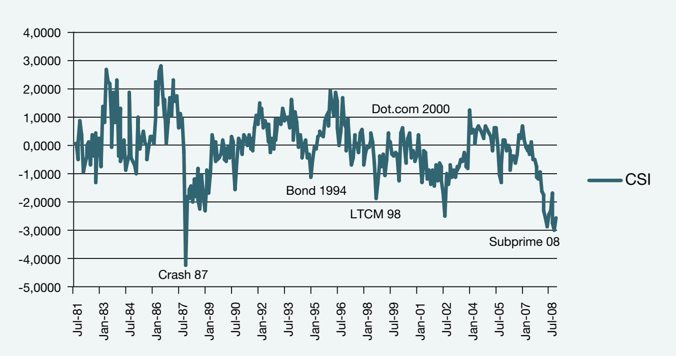

Figure 1 – The composite sentiment index

Findings are presented in Table 2. The portfolios of stocks the most sensitive to sentiment have an average sentiment beta of 1.110, those including the stocks the least sensitive to sentiment factor have an average sentiment beta of 0.017. With the exception of portfolio 5, the portfolio returns increase with the stock exposure to sentiment factor. Portfolio 1 earns an average return of 0.95% and Portfolio 10 an average return of 1.96%. Using Portfolio 1 as a benchmark, we continue our test of the significance of the strategy sentiment.[3] Specifically, we estimate the mean difference between the returns of Portfolio 10 and Portfolio 1, Portfolio 9 and Portfolio 1, and so on.

Results depicted in Table 2 show that the difference in mean returns between Portfolio 10 and Portfolio 1 is significant at the 5% level. It reaches 1% per month, for annual raw profit of 12%. Results also show that the difference in mean returns between Portfolios 9 and 1 is significant at 10%. The differences in mean returns for the other portfolios are not significant at conventional levels.

To sum up, the stocks that have higher exposure to sentiment factor earn greater returns than stocks with lower exposure to sentiment. Notice however, that these portfolios also have the highest traditional risk

3 In the remainder of this paper, the strategy consisting of buying the stocks most influenced by the sentiment factor and selling the stocks least influenced by the sentiment factor will be referred to as the strategy sentiment.

Portfolios	Mean Sentiment Beta	Mean Market Beta	Mean Returns	The raw profits of sentiment strategies			
				Strategies	Mean	t-stat	P-value
Portfolio 1: low exposition	0.017	0.903	0.0095	**Portfolio 10 - Portfolio 1**	0.010	**1.803****	**0.035**
2	0.056	0.902	0.0102	**Portfolio 9 - Portfolio 1**	0.009	**1.606***	**0.054**
3	0.097	0.934	0.0103	**Portfolio 8 - Portfolio 1**	0.006	0.892	0.186
4	0.142	0.897	0.0114	**Portfolio 7 - Portfolio 1**	0.005	0.823	0.205
5	0.193	0.943	0.0104	**Portfolio 6 - Portfolio 1**	0.002	0.817	0.207
6	0.254	0.949	0.0116	**Portfolio 5 - Portfolio 1**	0.000	0.754	0.225
7	0.322	1.002	0.0152	**Portfolio 4 - Portfolio 1**	0.001	0.664	0.253
8	0.435	1.112	0.0159	**Portfolio 3 - Portfolio 1**	0.000	0.400	0.344
9	0.601	1.379	0.0189	**Portfolio 2 - Portfolio 1**	0.000	0.264	0.395
Portfolio 10: high exposition	1.110	1.366	0.0196				

This table reports some summary statistics of the sentiment portfolios and the raw profit of the sentiment strategy. The column titled Mean Sentiment (market) Beta represents the time series average of the cross-section of the mean of sentiment (traditional) beta coefficient of each portfolio. The average monthly return of each portfolio is presented in the column titled Mean Returns. Portfolio 1 contains the stocks least impacted by investor sentiment and Portfolio 10 the stocks the most impacted. This table also presents the raw profits for sentiment strategies, which consist of buying a portfolio exposed to the sentiment factor and selling the portfolio the least exposed to this factor. Portfolio 1 is used as a benchmark for the significance tests.
The symbols ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 2 – Sentiment betas and the sentiment strategy

(market beta). This last observation makes us wonder. What can explain these high returns? A compensation for traditional risk bearing or a compensation for the risk sentiment?

To address this question, we use the multifactor asset-pricing model of Pastor and Stambaugh (2003). In addition to liquidity, the model allows for the control of the market risk and the risks associated with firm size, the book-to-market ratio (B/M) and momentum. The model is presented in equation (3):

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + m_p UMD_t + l_p LIQ_t + \varepsilon_p \quad (3)$$

R_p is the portfolio rate of return, R_f is the risk-free rate of return. R_m-R_f is the market return in excess of the risk-free rate (one-month bill rate). SMB is the difference between the value-weighted return of a portfolio of small stocks and the value-weighted return of a portfolio of large stocks. HML is the difference between the value-weighted return of a portfolio of high B/M stocks and the value-weighted return of a portfolio of low B/M stocks. UMD is the difference between the value-weighted return of a portfolio of stocks with high returns during months t-12 to t+2 and the value-weighted return of a portfolio of stocks with low returns during months t-12 to t+2. LIQ is the difference between the value-weighted return on the high liquidity sensitive portfolios and the value-weighted return on the low liquidity sensitive. The intercept, α_P, measures the average monthly abnormal return. The monthly time series of theses factors are obtained from Ken French's data library, with the exception of the liquidity factor which is obtained from Pastor and Stambaugh.

Findings in Table 3 show high-adjusted R^2 and a significant F-statistic of Gibbons et al. (1989). Findings also show that Portfolios 9 and 10 have the largest alpha coefficients and exhibit significant excess returns. The null hypothesis that the 10 constants are equal to zero is rejected at the threshold of 1%, allowing us to conclude that the risk premium for the stocks most exposed to sentiment is not justified by the traditional risk. Indeed, the abnormal returns of portfolios most sensitive to the sentiment factor cannot be explained by the three risk factors of Fama and French (1993), the momentum factor and the liquidity factor.

Overall, we conclude that the traditional risk does not explain the abnormal returns of portfolios most sensitive to the sentiment factor. Thus, a risk premium for the stocks most exposed to sentiment appears justified.

The characteristics of firms exposed to risk sentiment

Which stocks are most affected by risk sentiment? Previous studies find that investor sentiment mainly affects the small capitalizations. The studies justify this result by the fact that individual investors concentrate their holding in small-capitalization stocks. Recently, Baker and Wurgler (2006, 2007) assert the effect of investor sentiment on stock returns is more prominent for certain categories of stocks. The authors consider that there are two conduits through which investor sentiment shapes the cross-section of stock prices. Under the first conduit, sentiment demand shocks vary across stocks while arbitrage is equally difficult across them. Defining investor sentiment as an appetite for speculation, investor sentiment will create higher demands resulting in higher returns for hard-to-value stocks. The second conduit interprets sentiment as the degree of

Portfolios	Alpha	Rm-Rf	SMB	HML	UMD	LIQ	Adjusted R²
1 Low exposition	-0.003	0.979	-0.098	0.021	-0.081	-0.087	0.886
	(-0.942)	(29.601)***	(-2.428)***	(0.544)	(-3.123)***	(1.897)*	
2	-0.003	0.943	-0.082	0.293	-0.038	-0.062	0.853
	(-0.828)	(31.928)***	(-2.415)***	(6.653)***	(-1.720)*	(1.564)	
3	-0.000	0.992	-0.062	0.131	-0.062	0.058	0.843
	(-0.982)	(31.772)***	(-1.402)	(2.552)***	(-1.418)	(1.237)	
4	-0.000	0.996	-0.082	0.162	0.017	0.056	0.813
	(-0.291)	(28.005)***	(-1.998)**	(3.304)***	(0.501)	(1.134)	
5	-0.000	0.994	-0.121	0.301	-0.088	0.044	0.899
	(-0.423)	(34.347)***	(-3.345)***	(4.456) ***	(-1.345)	(1.145)	
6	0.000	0.916	-0.153	0.062	-0.015	0.028	0.867
	(0.872)	(32.089)***	(-3.934)***	(0.939)	(-0.934)	(1.092)	
7	0.002	1.064	-0.184	-0.047	-0.122	-0.022	0.869
	(1.412)	(33.234)***	(-5.073)***	(-0.103)	(-3.963)***	(-0.937)	
8	0.003	1.063	0.012	-0.182	0.005	-0.066	0.859
	(1.425)	(30.637)***	(0.234)	(-3.735)***	(1.658)*	(-1.864)*	
9	0.006	1.244	0.316	-0.284	-0.023	-0.089	0.789
	(2.494)***	(20.564)***	(5.093)***	(-3.112)***	(-0.645)	(-1.897)*	
10 High exposition	0.007	1.198	0.184	-0.321	0.012	-0.949	0.802
	(3.156)**	(21.738)***	(1.982)**	(-4.222) ***	(0.319)	(-2.012)**	

F_{GRS} = 2.763   P-value $_{GRS}$ = 0.0028

This table reports the factor model estimates for the 10 sentiment portfolios. The multi-factor model is as follows:

$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + m_p UMD_t + l_p LIQ_t + \varepsilon_p$

R_p is the portfolio rate of return. R_f is the risk-free rate of return. R_m-R_f is the market return in excess of the risk-free rate (one-month bill rate). SMB is the difference between the value-weighted return of a portfolio of small stocks and the value-weighted return of a portfolio of large stocks. HML is the difference between the value-weighted return of a portfolio of high B/M stocks and the value-weighted return of a portfolio of low B/M stocks. UMD is the difference between the value-weighted return of a portfolio of stocks with high returns during months t-12 to t+2 and the value-weighted return of a portfolio of stocks with low returns during months t-12 to t+2. And ε_p is the residual return on the portfolio. LIQ is the difference between the value-weighted return on the high liquidity sensitive portfolios and the value-weighted return on the low liquidity sensitive portfolios. The Newey-West adjusted t-values of the coefficient estimates are reported in the parentheses.
The FGRS is the F-statistic of Gibbons, Ross and Shanken (1989) testing the null hypothesis that the intercepts are jointly zero.
The symbols ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3 – Regression of monthly excess returns on portfolio risk factors of Pastor and Stambaugh (2003)

optimism or pessimism about stocks in general. Sentiment is uniform but the difficulty of arbitrage differs among stocks. In this case, sentiment will have a stronger effect on stocks that tend to be riskier and more costly to arbitrage. Note that the same stocks that are difficult to arbitrage also tend to be hard to value.

Following Baker and Wurgler (2006), we consider the following firm characteristics: size, growth potential and distress, age, profitability, dividend policy, tangibility and arbitrage costs. Size is the market capitalization measured as price times shares outstanding from CRSP. The firm's growth potential and distress characteristics include the book-to-market computed as the book value reported anytime during the fiscal year t divided by market value at the end of the calendar year. Age is the number of months since the firm's first appearance on the CRSP tapes. Profitability is captured by the return on assets defined as the earnings divided by total assets. Asset tangibility is captured by property, plant and equipment over total assets. Dividend policy is dividends per share at the ex date, multiplied by Compustat shares outstanding, divided by book equity. Arbitrage costs are measured by idiosyncratic volatility measured by the standard deviation of residuals (over 60 months preceding month t) in the regression of individual stock returns on Fama and French (1993) risk factors.

Our methodology helps us to answer this question. In December of each year t, we rank all stocks by the ascending absolute value of the sentiment betas and group them into 10 portfolios. Companies for which data are missing in any year t are excluded from the ranking for that specific year. We calculate the cross-section mean of each characteristic in every portfolio. The portfolios are then rebalanced every year in December and we form time series of the cross-section mean of each characteristic for the 10 portfolios over the period December 1984 to December 2008.

Table 4 reports the time series average of the cross-section mean of each characteristic. We find a negative correlation between exposure to the sentiment factor and market capitalization. The stocks most exposed to sentiment have a small market capitalization. Those stocks evidence an

Portfolios	Size (millions $)	Book-to-market	Age (months)	Profitability	Tangibility	Dividend policy	Arbitrage costs
1 Low exposition	2058.995	1.403	160.573	0.085	0.331	0.228	0.0136
2	2047.35	1.438	160.510	0.063	0.326	0.198	0.0136
3	2026.715	1.427	161.360	0.039	0.322	0.132	0.0147
4	2010.865	1.460	160.194	0.031	0.321	0.131	0.0154
5	1927.19	1.440	159.165	0.022	0.319	0.090	0.0167
6	1924.33	1.421	157.249	0.026	0.306	0.077	0.019
7	1902.92	1.402	155.172	0.023	0.299	0.036	0.021
8	1703.18	1.378	151.287	0.0218	0.287	0.039	0.025
9	1213.695	1.432	146.817	0.020	0.261	0.022	0.032
10 High exposition	475.5	1.269	137.857	0.018	0.251	0.019	0.058
Portfolio 10 - Portfolio 1	-1583.5	-0.134	-22.716	-0.067	-0.08	-0.209	0.044
t-stat	**-7.978*****	**-1.333***	**-2.286****	**-2.098****	**-5.345*****	**-2.811*****	**6.043*****

This table reports the time series average of the cross-section mean of each sentiment portfolio characteristic. Size is the market capitalization measured as price times shares outstanding from CRSP. The firm's growth potential and distress characteristic are included. The book-to-market is computed as the book value reported anytime during the fiscal year t divided by market value at the end of the calendar year. Age is the number of months since the firm's first appearance on the CRSP tapes. Profitability is captured by the return on assets defined as the earnings divided by total assets. Asset tangibility is captured by property, plant and equipment over total assets. Dividend policy is dividends per share at the ex date multiplied by Compustat shares outstanding, divided by book equity. Arbitrage costs are measured by idiosyncratic volatility measured by the standard deviation of residuals (over 60 months preceding month t) in the regression of individual stock returns on Fama and French (1993) risk factors. The last line depicts the Student t-test of mean differences.
The symbols ***, **, * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 4 – The characteristics of firms exposed to sentiment risk

average size four times smaller than the stocks least exposed to sentiment. This difference in size is statistically significant at the 1% level. This result is consistent with that of most empirical studies showing that investor sentiment impacts principally the performance of stocks mainly held by individuals.

Note also that the stocks most exposed to sentiment are growth stocks, young stocks, less profitable stocks, less tangible stocks, and low-paying dividend stocks. These stocks also exhibit high idiosyncratic volatility. On average stocks in Portfolio 10 have a book-to-market ratio 10% smaller than the stocks in Portfolio 1. These stocks are about two years younger, approximately four times less profitable, 24% less tangible and pay four times less dividends than stocks in Portfolio 1. These stocks also display three times more idiosyncratic volatility than the stocks in Portfolio 1. All tests of difference in average characteristics between Portfolio 10 and Portfolio 1 are statistically significant at least at the 10% level.

Overall, our main finding supports the hypothesis that stocks that are hard to value and difficult to arbitrage are more vulnerable to the risk sentiment. Similar to the literature, we find that the stocks most vulnerable to sentiment factor are small stocks, growth stocks, young stocks, unprofitable stocks, intangible stocks, lower dividend-paying stocks and high idiosyncratic volatility stocks.

Conclusion

Testing if the sentiment risk is priced by the stock market is an empirical challenge. This study tests the hypothesis that the risk introduced by noise traders in the financial markets may not be diversifiable, because their views are correlated and affect many assets. We first develop a new measure of sentiment by combining six traditional measures of sentiment using principal component analysis. An eyeball test shows that our composite sentiment index produces a faithful reproduction of the bubbles and crashes during our study period. We then implement a strategy that consists of buying stocks with the higher exposure to sentiment and selling stocks with the lower exposure to sentiment. Findings show that the stocks that have higher exposure to the sentiment factor earn greater returns than stocks with lower exposure to sentiment. Exploring the sources of profit, we show that traditional risk does not explain the high returns of portfolios most affected by the sentiment factor. We finish our study by re-identifying the characteristics of firms exposed to risk sentiment. Consistent with the predictions of models based on noise-trader sentiment, our results show that the stocks that are hard to value and difficult to arbitrage are more vulnerable to the risk sentiment. Future research should focus on developing a model that includes a risk premium linked to investor's psychology.

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