Can Sentiment be predicted to have Cross-Sectional Effects?

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This version: August 2007

Abstract

Previous research suggests that sentiment has incremental explanatory power for returns and conditional volatility of stocks. When sentiment-based demands vary across stocks, to what extent then is sentiment responsible for the observed cross sectional patterns in stock returns? Assuming that sentiment correlates with contemporaneous returns of particular categories of stocks, subsequent cross-sectional variation in stock returns is assumed to represent corrections of the initial mispricing. Therefore, this paper investigates if sentiment can be predicted to have cross-sectional effects. We find that when investors are bullish, next periods returns are relatively high for growth stocks, small cap stocks, highly leveraged firms, low volatility stocks and profitable stocks. Results are consistent with economic intuition and in line with most of the empirical literature.

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Motivation

In this paper investor sentiment will refer to the expectations and beliefs investors have about the future developments of the stock market. The main question to be examined here is how the cross-section of subsequent stock returns varies with the proxy for beginning-of-period investor sentiment. Investor sentiment can be defined as the common judgement errors made by a group of investors (noise traders) rather than a series of uncorrelated mistakes (Black, 1986). It is assumed that sentiment will disproportionately affect stocks with certain characteristics. Several firm characteristics will be taken into account in order to determine what 'kind of stocks' are more sensitive to sentiment than others. Classification will be made according to age, firm size, book-to-market, earnings per share, dividends per share, external finance and the riskyness of the firm. Depending upon the overall investor sentiment in the market, it is expected that some stocks will be more affected by the changes in the beliefs and expectations of investors than others (Barberis et al. (1998)). The differences in response or reaction of stock prices to the bullishness or bearishness of the market leads to a relative mispricing of particular categories of stocks. Firms with specific characteristics are being mispriced, because those are more exposed to noise trader sentiment. However, this mispricing is corrected in the subsequent period. Therefore, if we assume a contemporaneous relationship of sentiment with particular categories of stocks (Frijns et al (2006), Lee et al. (2002)), sentiment can be predicted to have effects for the cross-section of stock return, which motivates particular trading strategies (Barberis and Thaler (2003) and Busse et al. (1998)).

According to Baker and Wurgler (2006), a mispricing can be defined as an uninformed demand shock and limited arbitrage. Investor sentiment can firstly be defined as the propensity to speculate. In this view, the demand for speculative investments is driven by sentiment and causes cross sectional effects even if arbitrage restrictions are equal across stocks. Speculation is certainly a highly subjective process. However, the more information that is available from a certain stock, the smaller the chances for the stock to be influenced by changes in the propensity to speculate. Secondly, investor sentiment can be seen as optimism or pessimism about stocks in general. In this particular view, sentiment affects stocks when arbitrage forces are relatively weak. Arbitrage is more risky and costly for some firms such as like young, small, unprofitable extreme growth or distressed stocks. Selling short such stocks would be more risky and the lower liquidity of these securities would expose the arbitrageurs to predatory attacks. According to Baker and Wurgler (2006), one can conclude that generally, stocks that are the hardest to arbitrage are also most vulnerable to sentiment.

Empirical Tests

In the empirical part of the paper, we focus on large-, medium- and small-cap stocks traded in the German market over the period December 1991 until April 2005. The historical share prices and firm specific data are obtained from DataStream. As a proxy for the level of sentiment in the German stock market, the German Market Indicator (G-Mind) from the Centre for European Economic Research (ZEW) is used (see e.g. Anders et al. (1997)). The G-Mind provides an indication of the level of bearish- or bullishness among a selected sample of German investors (see Figure 1). Since 1991, the ZEW conducts a monthly survey among 350 financial analysts and institutional investors. This ZEW financial market survey is the basis for the indicators used. The sentiment index can take a value between minus ten and plus ten, the latter representing optimism or bullishness and the former representing pessimism or bearishness. All firm specific data is converted into monthly observations in order to match the monthly data points of the sentiment index.

[Figure 1]

In the analysis, a two-stage regression is performed. In a first step, a cross-sectional regression is conducted on a monthly basis to test for the influence of preceding period firm characteristics on the return of the firm in the current period:

$$\begin{aligned} R_{it} = a_t + b_t Age_{it-1} + c_t \log(MV)_{it-1} + d_t div/share_{it-1} + e_t EPS_{it-1} \\ + f_t \log(BV/MV)_{it-1} + g_t EF/A_{it-1} + h_t RISK_{it-1} + e_t \end{aligned},$$

where R_{it} represents the return of firm i in period t an e_t is the error term. The variable Age_{it-1} is the age of the firm i . The size of the firm will be measured in terms of market value (MV). Dividend per share is measures how much dividends are paid out per share. DataStream uses a rolling 12-month dividend per share measure to account for this. Earnings per share (EPS) is the latest annualized rate that may reflect the last financial year or be derived from an aggregation of interim period. The variable book-to-market-ratio (BV/MV) is the result of dividing book value over market value. Book value represents the proportioned common equity divided by outstanding shares at a company's fiscal year end. Market value is defined as the share price multiplied by the number of ordinary shares in issue. External finance consists of company's financing from outside sources, including the issuance and retirement of stock and debt. Together with the total assets the measure EF/A, external finance over assets, can be constructed to provide a measurement of the financing structure. Finally, a measure of risk is needed to be able to distinguish more risky from less risky firms. The measure RISK is taken as the standard deviation of the monthly returns over the period of one year starting exactly one year before t.

In the second step, a time series regression is performed. The estimated coefficients from the cross-sectional regression are regressed (as a time series) on the previous period sentiment proxy, the G-Mind, e.g.:

$$\hat{b}_t = \gamma_0 + \gamma_1 Sentiment_{t-1} + u_t$$

Regarding the cross-sectional regression, it can be assumed that there is some time variation in the importance of various characteristics to explain the cross-section of returns. As a result, for the time series regression, we have to deal with the heteroskedasticity in the time series of coefficients. One of the underlying assumptions of standard linear regressions is that the variable of interest has constant standard deviation. Under this assumption, all observations are assumed to be of equal quality, also referred to homoscedasticity. Heteroscedasticity is a common problem in cross-sectional data analysis, it does not imply invalidation of the analysis but it does however weaken the analysis as a consequence. Contrary to Ordinary Least Squares (OLS), the assumption of constant standard deviation of the random errors is not implicit to the Weighted Least Squares (WLS) analysis. Therefore, WLS is functional when determining the values of model parameters whilst the observed values have differing degrees of variability over the combinations of estimated values. However, the distinctiveness of WLS is that each term in the weighted least squares includes an additional weight that determines how much each observation in the data set will influence the final parameter estimates. Rather than using equal weights in the regression (OLS), the reciprocal of the square of the standard error of the coefficient is used as a weight. For example, if a coefficient has proven to have a low significance in one month, it will have a respectively low weight in the regression to follow. Conversely, if a coefficient has shown a high significance in one month, it will have a respectively high weight in the successive regression. In order to control for autocorrelation in the time series of coefficients, a Durbin-Watson test is performed before the second stage of the regression. For our data, we find strong evidence that the time series observations are independent of each other (all values are close to 2) and hence the problem of serial correlation does not influence the results.

The result of the first stage regression, the cross sectional regression, are presented in Table 1. The table presents the average coefficients and their corresponding standard errors in brackets. The standard errors are computed as the time series standard deviation of the coefficient divided by the square root of the number of months. The table clearly shows nearly all coefficients are time-varying, as the resulting t-values are rather low. At the same time, the monthly cross-sectional regressions have sufficient explanatory power, with R^2's of up to 85%. However, this does not impede the conclusion of the research. The second stage of the regression deals with the time series regressions in which the effect of a (previous period) sentiment indicator on the estimated coefficients from the first regression is tested. Some stocks are expected to respond more to the level of investor sentiment than others. This reaction to the level of sentiment among investors can lead to a mispricing, indicative of an over- or under reaction. The correction of this mispricing (in the subsequent period) is the effect that is picked up in the second part of the regression.

[Table 1]

From the seven firm characteristics that were considered, five of the resulting coefficients showed a significant relation with the previous period sentiment indicator. Hence, the five variables that will be discussed are: BV/MV as an indication of growth or value stocks, MV as a measure of the size of the firm, EF/A providing information about the level of leverage that is used in the company, the risk measure RISK enabling a distinction between risky and less risky firms and finally EPS as an indicator for profitability.

The results of the 2-step regression are presented in Table 2. The coefficients should be interpreted in the following way: A negative coefficient for the 'book-to-market-ratio coefficient' means that if investors are bullish in period t, a trading strategy that is long in value stocks and short in growth stocks on average earns a relatively low (or even negative) return in period t. Therefore, the appropriate strategy in a bullish market should be to be long in growth stocks and short in value stocks. Equivalently, if investors are bearish in period t, a trading strategy that is long in value stocks and short in growth stocks on average earns a relatively high return in period t. Value stocks typically experienced low earnings growth and are therefore undervalued by the market. It is argued that this undervaluation increases the risk of financial distress. Since theses distressed firms perform poorly just when the economy is weakening, the investors demand a higher return for holding such a stock and bearing the extra risk. The higher return generated by the value stocks can therefore be warranted as compensation for the risk borne by the investors, since the value stocks are most risky in periods of recession. The weakening economy or recession that is mentioned here is likely to have similar traits as an environment with decreasing sentiment or growing pessimism (see e.g. Petkova and Zhang (2005) or Zhang (2005)).

[Table 2]

Regarding the size of the firm, results suggest that small-cap stocks perform well in a bullish market and poorly in a bearish market. Equivalently, the appropriate strategy in a bearish market should be to be long in large-cap stocks and short in small-cap stocks. Small firms tend to perform well in good economic conditions, because the majority of small firms have a lower productivity and a higher financial leverage than larger firms.

These specifics make them more vulnerable to changes in the economic cycle (Chan et al. (1985)), and thus any abnormal returns are much more likely to be earned in an expansionary state of the economy. In good economic conditions small firms lead to a higher growth rate compared to larger, more mature firms. The presented hypotheses are completely in line with the results from the empirical tests and thus function as a sound explanation for the results.

Equivalent logic applies to the variable leverage measured by the amount of external finance with respect to total assets. Highly leveraged stocks perform well in a bull market and perform poorly in a bearish environment. The appropriate strategy in a bearish market should be to be long in firms with low leverage and short in highly leveraged firms. The results do coincide with the empirical literature. Usually small firms also exhibit a larger portion of leverage in their capital structure than larger firms. Therefore the same conclusions as were made for small firms also apply for firms that are highly levered. One can logically reason that the best performance for highly levered firms is made in periods of optimism. Consequently, in periods of pessimism, low levered firms perform poorly. Therefore, one can conclude that the results are in line with expectations.

The next variable of interest is risk. Risk is measured by the standard deviation of the monthly returns over a period of one year, starting exactly one year prior to *t*. From the empirical test, we can conclude that risky stocks perform poorly in a bullish market and perform well in a bearish environment. The appropriate strategy in a bearish market should be to be long in risky stocks and short in less risky stocks. As was discussed previously, the more information that is available from a certain stock, the smaller the chances for the stock to be influenced by changes in the propensity to speculate, or sentiment. Thus, non-risky stocks are influenced less by sentiment and therefore perform well in periods of optimism and poorly in periods of pessimism. The opposite is true for risky stocks, which are more likely prone to be influenced by sentiment. This argumentation confirms the results found and thus validates the significance of the variable risk.

The final variable that has shown to be significant is profitability. Profitability is measured by means of EPS and represents the latest annualised rate that may reflect the last financial year or be derived from an aggregation of interim period. The results show that profitable stocks perform well in a bullish environment and perform poorly in a bearish one. Alternatively, the appropriate strategy in a bearish market should be to be long in profitable firms and short in unprofitable firms. Unprofitable firms perform poorly in a period of optimism compared to their profitable competitors. However, in a period of pessimism they outperform the more profitable firms, in terms of productivity. Consequently, the results found are in line with the reasoning that the overconfident firms need to adjust for their overconfidence over time and this is precisely the pattern that is observed in the subsequent period, just as the concept of correction of mispricing would suggest.

Conclusion

In this paper, we find evidence that investor sentiment has predictive power for the cross-section of stock returns. It is assumed that sentiment correlates with contemporaneous returns of particular categories of stocks and that as a result, subsequent cross-sectional variation in stock returns represents corrections of the initial mispricing. Using a two-step regression approach, we find strong evidence that the beginning of period level of sentiment can be used to predict pattern in the cross-section of stock returns. Specifically, when investors are bullish, growth stocks, small-cap stocks, highly leveraged, non-risky and profitable stocks are experiencing significantly higher subsequent returns. The empirical results presented here are in line with most of the empirical literature.

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Figure 1. Values of the G-Mind sentiment index over the period December 1991 until April 2005. The G-Mind provides an indication of the level of bearish- or bullishness among a selected sample of German investors. The index can take a value between minus ten and plus ten, the latter extreme representing optimism or bullishness and the former representing pessimism or bearishness. The index is based on the results of the ZEW financial market survey and is constructed on a monthly basis.

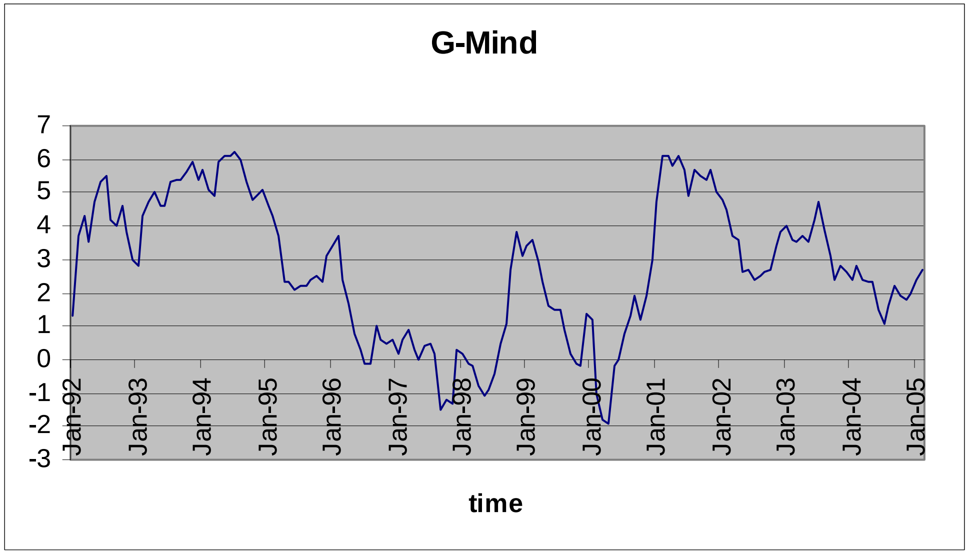

Table 1. The table presents the average monthly coefficients and the corresponding standard errors in brackets. The standard errors are computed as the time series standard deviation of the coefficient divided by the square root of the number of months. The coefficients are the result of the first part of a two-stage regression. The model reads:

$$R_{it} = a_t + b_t Age_{it-1} + c_t \log(MV)_{it-1} + d_t div/share_{it-1} + e_t EPS_{it-1} + f_t \log(BV/MV)_{i\,t-1} + g_t EF/A_{i\,t-1} + h_t RISK_{i\,t-1} + e_{it}$$

Age_{it-1} is the age of the firm i . The size of the firm will be measured in terms of market value (MV). Dividend per share is measures how much dividends are payed out per share. DataStream uses a rolling 12-month dividend per share measure to account for this. Earnings per share (EPS) is the latest annualized rate that may reflect the last financial year or be derived from an aggregation of interim period. The variable book-to-market-ratio (BV/MV) is the result of dividing book value over market value. Book value represents the proportioned common equity divided by outstanding shares at a company's fiscal year end. Market value is defined as the share price multiplied by the number of ordinary shares in issue. External finance consists of company's financing from outside sources, including the issuance and retirement of stock and debt. Together with the total assets the measure EF/A, external finance over assets, can be constructed to provide a measurement of the financing structure. Finally, a measure of risk is needed to be able to distinguish more risky from less risky firms. The measure RISK is taken as the standard deviation of the monthly returns over the period of one year starting exactly one year before *t*. (***, **, * Coefficient is significant at the 1%, 5%, 10% level, respectively)

	Mean	Standard Error	Min	Max
Age	-0.0008	0.0007	-0.0323	0.0341
Log((MV)	0.0133	0.0082	-0.2077	0.5114
Div/Share	-0.0163	0.0060***	-0.2084	0.1554
EPS	-0.0041	0.0023*	-0.1430	0.0911
Log(BV/MV)	0.0109	0.0077	-0.1885	0.4657
EF/A	0.0022	0.0156	-1.1842	09090
Risk	0.0005	0.0008	-0.0360	0.0452

Table 2. The coefficients resulting from the second regression are reported below. The model reads, e.g.:

$$\hat{b}_t = \gamma_0 + \gamma_1 Sentiment_{t-1} + u_t$$

The coefficients are the result of the second part of a two-stage regression, where the different regressors from the first stage of the regression are re-gressed on previous period sentiment. Sentiment stands for the level of the G-Mind, the ZEW indicator of investor sentiment. The level of significance corresponding to the coefficient is displayed by means of an asterisk. The practical implication that can be concluded with respect to the coefficient of the variable and its significance can be found next to the respective variable.

(***, **, * Coefficient is significant at the 1%, 5%, 10% level, respectively)

	Mean		When investors are bullish, expected returns tend to…
Age	0.0003		
Log((MV)	-0.0149	***	Decrease for large firms
Div/Share	-0.0013		
EPS	0.0054	***	Increase for profitable firms
Log(BV/MV)	-0.0127	**	Decrease for value stocks or increase for growth stocks
EF/A	0.2797	***	Increase for highly leveraged firms
Risk	-0.0031	***	Decrease for risky firms