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Risk Factors in the German Stock Market: Can Sentiment Improve the Performance of Traditional Multifactor Models?

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ABSTRACT

Capital market research usually focuses on the investment decision of a risk-averse investor, who determines the relationship between risky assets and risk-free investment. Furthermore, numerous capital market models assume normally distributed security returns and rational investors. In this framework, ex-ante investment decisions depend solely on the expected return, risk of investment opportunities, and investor risk affinity. For decades, empirical research findings have criticized this idealized framework. New risk factors were empirically confirmed and established. This study attempts to shed light on this issue. A comparative analysis considers the Fama-French and Carhart factors and a principal component analysis based sentiment-risk factor considering 76 sentiment indicators to examine the possible explanatory contribution to German stock market returns.

Introduction

This study focuses on the German stock market as an exemplary case, unlike other studies. The German stock market is very interesting for investigating the influence of classical risk factors, especially for analyses of investor sentiment. On the one hand, structural capital market characteristics have shown that classical risk factors in Germany differ from those in other stock markets in terms of their significance and strength of explanatory contributions (Hanauer et al., 2013; Ziegler et al., 2007). On the other hand, Germany, with the largest foreign trade surpluses in the EU (ranked second worldwide in 2020) and its strongly export-oriented economy, is particularly susceptible to global development and sentiment. The research gap to be investigated is whether and how traditional risk factors' explanatory contributions and significance have developed on a current sample compared to recent cross-sectional

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studies. In addition, we investigate the extent to which a sentiment-based risk factor can provide additional explanatory contributions.

Our empirical results based on a current dataset show that an arbitrage pricing theory (APT) model with Carhart's risk factors is substantially superior to a capital asset pricing model (CAPM) singlefactor model regarding the explanatory contributions of excess returns on the German stock market. Moreover, we show that a sentiment risk factor in an APT model provides further benefits. These are essential observations for portfolio theory research.

However, capital market research usually focuses on the investment decision of a risk-averse investor, who determines the relationship between risky securities and risk-free investment R_f. Furthermore, many capital market research models assume normally distributed security returns and rational investors (in the aggregate). As early as the 1970s, Fischer Black et al. (1972) observed that excess returns are not proportional to the risk taken, even for diversified portfolios. This observation forms the basis for considering that diversified portfolio returns are not solely determined by a single market risk factor, the beta factor of the CAPM. Ross (1976) formed the APT to address the CAPM's empirical weaknesses and suggests that stock-specific and macroeconomic factors can better explain stock market returns. Unlike CAPM, APT allows multiple factors as determinants of stock returns.

The observations of return anomalies stimulated the scientific discourse, which led to the insight that selecting factors in the APT model is often difficult. Risk factors are country-specific, not always known, and not stable over time. Therefore, research has not yet concluded the ideal factor selection for APT. However, the flexibility of APTs allows several factors to explain returns on the stock market. Despite the establishment of three and four factors by Fama and French (1992, 1993) and Carhart (1997) , respectively, in the 1990s, the ideal factor composition in APT models has not been pursued. More recently, newer factors such as "investor sentiment" have been investigated around the globe (e.g., Gutierrez and Perez-Liston (2021); Hadi and Shabbir (2021); Jiang et al. (2021)).

Theoretical Background

In addition to established risk factors, subjective information is crucial in the financial world, as opinions and speculation can influence investment decisions and asset prices. This important component may not yet be sufficiently considered in the currently prevailing multi-factor models, although empirical studies from other countries show a clear tendency in this direction.

It is often discovered that negative market phases follow the phases of positive sentiment and vice versa. In particular, retail investors tend to behave irrationally in that they buy (expensively) when sentiment is positive and the stock market is at the peak of the current cycle, and sell in phases of depression when prices are low. Investor sentiment is therefore considered a contra-indicator in various markets.

Although the precise behavioral economic relationships have not been fully elucidated, Baker and Wurgler (2006) could provide empirical evidence for these reversion patterns in the US market. The herd instinct could play a decisive role. An illustration of an exemplary sentiment cycle (yellow) in connection with the market cycle (blue) is shown in Figure 1.

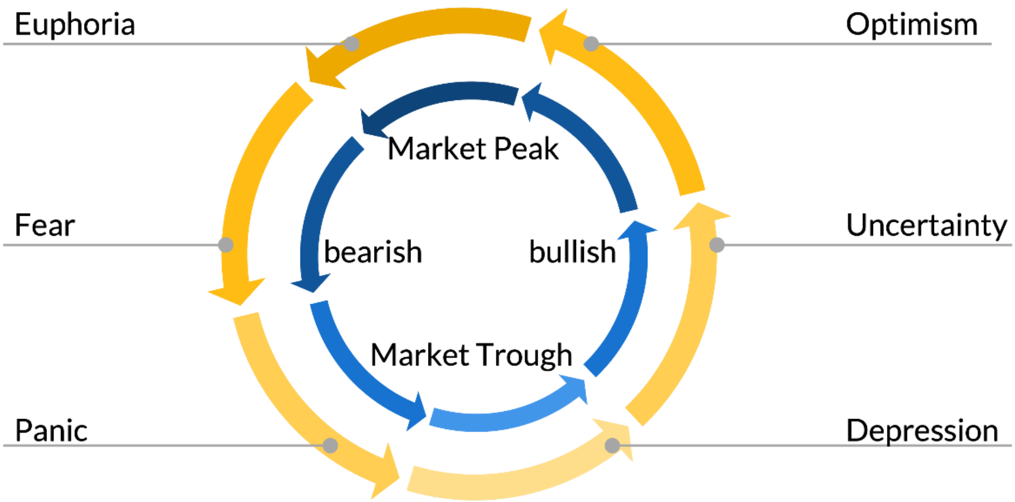

Figure 1. Sentiment Cycle (yellow) and Stock Market Cycle (blue). (Source: by the authors)

However, there are decisive differences in the observation of empirical reality compared to the more general theory of efficient markets, which states that investors act rationally on average and cannot achieve excess returns based on market information alone. Based on the prospect theory of Kahneman and Tversky (1979), Shiller (1999) proposed that human irrationality is responsible for empirical deviations from these theoretical constructs. The analysis of investor sentiment attempts to interpret the influence of human psychology on the development of markets or individual financial products. The discipline, which is located in behavioral finance, aims to directly or indirectly sound out the mood of market participants.

Thus, if this component is taken into account and considered as a risk (deviation from the expected value), standard pricing models such as the CAPM extended by a sentiment risk factor alongside the already established risk factors Carhart (1997) in an APT model should increase efficiency. This hypothesis and the question of whether traditional risk factors improve CAPM performance is empirically tested in the following chapters.

Literature Review

Investor sentiment can help make educated conjectures about future price developments, and these can then serve as the basis for short-term trading or long-term investment decisions. Baker and Wurgler (2007) define sentiment as expectations about future cash flows and investment risks that fundamental data cannot explain. Thus, airplane crashes and even lost soccer games can affect sentiment (Edmans et al., 2007; Kaplanski & Levy, 2010).

Current capital market research on the further development of multifactor models gives reason to believe that added potential for interpretation and improvement can be suspected in (still) unknown risk factors. Therefore, it is crucial to investigate whether, in addition to the known influencing factors of widely adapted multifactor models, factors that are difficult to quantify, such as investor sentiment, can also contribute to stock valuation.

As capturing individual investor behavior would be difficult, research tends toward models that make assumptions about investor behavior at the aggregate level. Baker and Wurgler (2007) show that sentiment contributes significantly to explain stock market returns based on aggregate investor behavior. Other substantial contributions come from Long et al. (1990) on the influence of irrational market actors (noise traders) and Barberis et al. (1998) on the psychological basis of investor sentiment.

The challenge of sentiment analysis is to quantify sentiment. One established method is the direct determination of sentiment with the help of investor surveys. However, the requirements of inferential statistics, such as the temporal, spatial, and factual ex-ante definition of the primary population or the randomization of the survey participants, are often not met in the survey and sample selection (panel). Furthermore, sentiment must be discriminated into short-, medium-, and long-term observations.

In addition to survey-based sentiment indicators, sentiment analysis focuses on market-implied sentiment derived indirectly from forward-looking market data.

Implied volatility and put-call ratios often reflect the future expectations of market participants and are frequently used as indirect indicators of market sentiment. Relatively new is news-based or social sentiment, which in a broader sense includes (online) media reports, where, apart from quality, the quantity of news is also essential. The social sentiment is currently becoming a much-discussed area in behavioral finance. What all sentiment indicators have in common, however, is that they attempt to depict a dichotomous picture of investor sentiment, namely optimism and pessimism.

Various studies on the relationship between sentiment and stock market returns are based on Pearson's correlation coefficient, linear regression, and nonlinear causality tests. Frequently, the threefactor model of Fama and French is chosen as the control model, and occasionally, the four-factor model of Carhart is also chosen.

While there are recent studies on this research worldwide (Al-Nasseri et al., 2021; Dunham & Garcia, 2021; Gao & Liu, 2020; Gutierrez & Perez-Liston, 2021; Hadi & Shabbir, 2021; Jiang et al., 2021; Jun Xiang Huang et al., 2020; Li et al., 2020; P.H. & Uchil, 2020; Steyn et al., 2020; Zaremba et al., 2020), these are mainly lacking for the German stock market, although the German stock market is an exciting object of study due to its peculiar capital market structure.

A study on German market data by Finter et al. (2012) based on a survey- and market-implicit sentiment sources shows that certain groups of stocks react more sensitively to sentiment without identifying any significant explanatory power for future stock returns. Krinitz et al. (2017) used a Granger causality test to show that news-based sentiment impacts German stock market returns.

In addition, several studies on risk factors in the German stock market have been conducted. From the current perspective, however, the underlying data samples no longer appear to be up to date, which is why the research question arises as to whether the corresponding explanatory contributions of classic risk factors for returns on the German stock market have changed.

In the context of such an analysis, this question can be extended to examine whether a sentimentrisk factor can further improve the model quality of established APT models. Three hypotheses arise from these questions, which we address in an empirical analysis.

H1: A multifactor model incorporating Carhart risk factors is a better explanatory model of the German stock market than a CAPM single-factor model.

H2: According to theoretical considerations of the cyclical behavior of market developments, a sentiment risk factor correlates negatively with expected future returns.

H3: A sentiment risk factor can improve the multifactor model's quality based on Fama-French respectively Carhart factors.

Methodology

Data sources and sample

The data required to construct the multifactor models underlying the analyses were obtained from Thomson Reuters Eikon/Datastream (now: Refinitiv) and the publicly available Deutsche Bundesbank time-series database. We consider logarithmic returns in this study, corresponding to an empirically clean approach, but it reduces comparability with other studies that consider discrete returns in their respective studies. Furthermore, it should be emphasized that this analysis is based on a hand-curated database of the German Composite DAX (CDAX) index, whose returns are referred to as total returns; that is, they also consider dividend payments. Financial stocks are included, which is justifiable considering equallyweighted returns and not market-value adjusted returns. As a corollary, the influence is negligible.

It is noteworthy that the number of stocks listed on the CDAX is declining. Developments in the German stock market, such as voluntary delistings, mean that more companies belong to the unofficial regulated market, which is more favorable for companies as, among other factors, certain reporting obligations no longer apply. Overall, this leads to a relatively strong consolidation over time (see Table 1).

Table 1. Average number of stocks in the monthly CDAX data set

Year	**2001**	**2002**	**2003**	**2004**	**2005**
Stocks	787	771	727	703	679
Year	**2006**	**2007**	**2008**	**2009**	**2010**
Stocks	672	682	676	645	611
Year	**2011**	**2012**	**2013**	**2014**	**2015**
Stocks	582	554	509	481	441
Year	**2016**	**2017**	**2018**	**2019**	**2020**
Stocks	424	420	422	423	411

Note. This table shows the years from 2001 to 2020 and the respective average stocks considered in the CDAX each year.

The data for the return approximation of the risk-free investment opportunity is taken from the publicly available time-series database of the Deutsche Bundesbank. Book values and market-to-book valuebased ratios (PTBV), as well as market values (MV), were also taken from Thomson Reuters Eikon/Datastream and Worldscope, respectively. The limiting factors of the observation period are, in each case, the available data of the sentiment sources to be investigated. Consequently, the sample is based on monthly returns and covers January 15, 2001 to January 15, 2021 (T= 240 months). This ensures the comparability of the sentiment factors within the samples. The total return index (RI) is used to calculate returns because it considers dividends in contrast to the price index (P). All CDAX stocks are examined, which consider all stocks listed on the Frankfurt Stock Exchange in General Standard and Prime Standard and thus reflect the development of the entire German stock market.

Furthermore, although some of the sentiment factors examined refer specifically to the DAX, equally-weighted CDAX returns are examined. On the one hand, this is because the DAX 30 has too few values to construct 16 diversified Fama/French portfolios. On the other hand, the size risk factor, which is intrinsic to the multifactor models and which targets company size and acts as a control variable, would be incompatible and contradictory if applied to the DAX 30 as the DAX 30 only considers the companies with the largest market capitalization on the German stock market. It represents roughly two-thirds of the total German market capitalization.

In addition, DAX 30 and CDAX are highly correlated, which suggests that CDAX analysis is generally suitable. If the CDAX and the DAX move in tandem, there is reason to assume that the factors determining returns are almost homogeneous for both indices.

Although this study examines equally-weighted CDAX returns, there is good reason to suspect that sentiment has a tremendous impact on DAX 30 stocks because of its media presence (Fang & Peress, 2008). Smaller companies gain importance in this study compared to the capital-weighted index. The index performance of the CDAX, which serves as an approximated market portfolio for the study, was recalculated using the available equally weighted stocks. The Pearson's correlation coefficient of the approximated market portfolio with the original CDAX performance index is close to $\rho \approx 1$ for the sample in the respective periods under investigation. As a proxy for the risk-free asset r_f, the money market rate Euro Interbank Offered Rate (EURIBOR) on a monthly basis (BBK01.SU0310) is used for monthly data, following the usual procedure in the German market (Hanauer et al., 2013; Schrimpf et al., 2007; Ziegler et al., 2007).

Construction of the Carhart Risk Factors

In constructing the empirical multifactor models, this study follows the scheme of Fama and French (1992, 1993), Ziegler et al. (2007), and Hanauer et al. (2013). The market risk premium $RMRF$ is the difference between the approximated market portfolio (R_m) and the risk-free rate (R_f). The risk factor for size "Small Minus Big"(SMB) and the value risk factor "High Minus Low" (HML), which are based on monthly returns, are calculated analogously to Fama and French (1993). Hence, at the end of June (or beginning of July) of each year y, the median market capitalization and, independently, the 30 % and 70 % quotient quantiles of book and market value from December 31 of each year are calculated for all stocks considered.[1]

Fama and French (1993) initially used the balance sheet date rather than December 31. This approach is not followed in this study because, on the one hand, it is assumed that newly published book values are immediately

[1] The book value from December 31 of the year $y - 1$ is divided by the market capitalization of the same day.

reflected in stock prices. On the other hand, the vast majority of the companies observed have defined December 31 as their annual closing date according to the data available. Based on the median market capitalization, the shares with the largest market capitalization are assigned to Group B (Big) and the smallest market capitalization to Group S (Small). Similarly, stocks are divided into three groups based on the book-to-market value ratio of 30 % and 70 % quantiles. Public companies with a high book-to-market ratio are assigned to Group H (High), a medium bookto-market ratio to Group M (Medium), and a low book-to-market ratio to Group L (Low). This allocation forms the basis for the six equally-weighted stock portfolios, S/H, S/M, S/L, B/H, B/M, and B/L, representing the cross-product of the five groups.[2] Stocks in the monthly returns-based sample are assigned to one of the six portfolios in early July of year y and remain there until the end of June of year $y+1$. In July of year $y+1$, the portfolios were recalibrated using the updated data. Throughout the observation period, the equally weighted returns of the six portfolios $R_t^{S/H}$, $R_t^{S/M}$, $R_t^{S/L}$, $R_t^{B/H}$, $R_t^{B/M}$, and $R_t^{B/L}$ are calculated for each month t. Starting with the portfolios, SMB is the equally weighted average of small firm portfolio returns minus large firm portfolio returns (Equation 1).

$$SMB_t = \frac{\left(R_t^{S/L} - R_t^{B/L}\right) + \left(R_t^{S/M} - R_t^{B/M}\right) + \left(R_t^{S/H} - R_t^{B/H}\right)}{3} \tag{1}$$

HML is defined analogously (Equation 2).

$$HML_t = \frac{\left(R_t^{S/H} - R_t^{S/L}\right) + \left(R_t^{B/H} - R_t^{B/L}\right)}{2} \tag{2}$$

Finally, the momentum risk factor “Winner Minus Losers” (WML) is calculated according to the procedure in Carhart (1997). For each month t from July of year y to June of year $y+1$, stocks are sorted by the performance from the beginning of month $t-12$ to the beginning of month $t-2$.[3] Using the ranked list of the previous year's performance stocks, the 30 % and 70 % quantiles were determined. The stocks with the best prior-year performance are assigned to the group W (winners), with the median prior-year performance to group N (neutral), and with the worst prior-year performance to group L (losers). As in the calculation for HML, the six portfolios S/W, S/N, S/L, B/W, B/N and B/L are again formed from the cross product with the market capitalization groups.[4] The associated returns are the equally weighted returns of the companies included in each portfolio. WML is the equally-weighted average of the returns of portfolios of companies with good prior-year performance minus the returns of portfolios of companies with poor prior-year performance (Equation 3).

$$WML_t = \frac{\left(R_t^{S/W} - R_t^{S/L}\right) + \left(R_t^{B/W} - R_t^{B/L}\right)}{2} \tag{3}$$

[2] S/H stands for "Small-High" and contains companies with small market capitalization and high book-to-market value ratios.

[3] For July of year y, this corresponds to the performance from the beginning of July of year $y-1$ to the beginning of June of year y. According to Ziegler et al. (2007), the last month is omitted. This is to avoid problems in the microstructure, such as the "bid-ask bounce" (Fama and French (1996)). These lead to a negative autocorrelation of one-month returns, which would contaminate the momentum effect and reduce its explanatory power (Asness (1995)).

[4] S/W stands for "Small-Winners" and contains stocks with a small market capitalization and good performance in the previous year.

This factor construction aims to ensure that $RMRF$, SMB, HML, and WML are largely uncorrelated. This assumption was confirmed for a monthly sample in the cross-section.

Construction of the Sentiment Factor

A principal component analysis (PCA) based sentiment factor was integrated into the multifactor models. For comparability, all sentiment factors are derived following the procedure of Fama and French (1993) and Hilliard et al. (2016). All stocks in the CDAX are first ranked according to their Pearson correlation with the first principal component from a PCA with 76 sentiment factors from the areas of market-implied and survey-based sentiment. An equally weighted portfolio is formed for each observation, reflecting the return differential of the 10 % strongest or positively and weakest or negatively correlated stocks with the principal component.

Three portfolios are defined based on the 10 % and 90 % quantiles to do so. HS stands for "High-Sentiment" and corresponds to an equally weighted portfolio of stocks with a high or positive correlation to the principal component. LS stands for "Low-Sentiment" and corresponds to an equally weighted portfolio of stocks with a low or negative correlation to the principal component. The third portfolio NS "Neutral-Sentiment", corresponds to stocks that are not or neutrally correlated to the sentiment source. For each observation time t, the sentiment factor is determined as the return difference between the HS and LS portfolios.

Construction of the Fama/French Portfolios

First, we construct portfolios based on market capitalization and the book-to-market value ratio, whose excess returns are then explained by linear regressions. In the present study, in line with Ziegler et al. (2007) and Hanauer et al. (2013), 16 (= 4 × 4) Fama/French portfolios are constructed instead of 25, as in the method of Fama and French (1993). The quartiles of market capitalization and book and market value quotient form the basis for constructing the groups. This ensures that each portfolio has a sufficient number of stocks. Consequently, multifactor models are more comparable to other studies on the German stock market.

The 16 Fama/French portfolios follow the sorting according to their market value as well as their quotient of book and market value with 1-1 ("Small-Low"), ... , 1-4 ("Small-High"), ... , 4-1 ("Big-Low"), ... , 4-4 ("Big-High"). The factor weights of the single-factor model shown in Equation (4) were estimated for the 16 portfolios using OLS regression based on the CAPM.

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot RMRF_t + \varepsilon_{it} \quad (4)$$

Then, the single-factor model is extended by the two factors SMB and HML to form the Fama-French three-factor model, which is described in Equation (5) in the empirically testable version.

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + \varepsilon_{it} \quad (5)$$

Equation (6) describes the Carhart four-factor model presented in an empirical form.

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + w_i \cdot WML_t + \varepsilon_{it} \quad (6)$$

Operationalization

The examined sentiment indicators in the monthly sample are based on market expectations. We examine the extent to which market expectations can explain future returns with a time horizon of one month (see Figure 2). Here, a sentiment publication is considered to be released on the 15th of month t_{-1} even if it is published in the first half of the month t_0 under consideration. The time of the sentiment survey is considered more important than the time of publication in this study

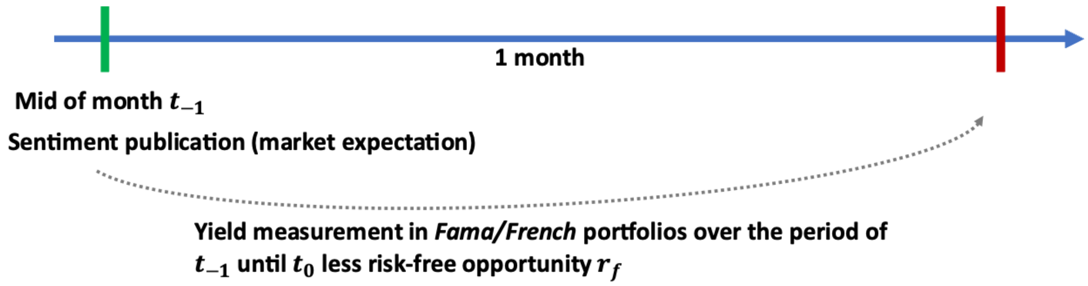

Figure 2. Regressive sentiment analysis on a monthly basis (Source: by the authors)

All risk factors are integrated into the empirical CAPM model to test the hypothesis that risk factors can explain stock returns. The following linear multivariate regression models emerge for the integration of sentiment into the empirical three- and four-factor models:

To integrate the PCA sentiment factor based on 76 sentiment sources, Equations 7 and 8 were formulated.

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + \psi_i \cdot SENT_{PCA_t} + \varepsilon_{it} \quad (7)$$

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + w_i \cdot WML_t + \psi_i \cdot SENT_{PCA_t} + \varepsilon_{it} \quad (8)$$

Empirical Results

Descriptive Statistics of the Fama-French-Portfolios

The empirical CAPM is determined by bivariate linear regression of the 16 Fama/French portfolios, while the multifactor models based on the empirical CAPM are determined by multivariate linear regression. For estimation and evaluation of the regression results, we used R version 4.1.1, (2021) in combination with the packages lm-test (Zeileis and Hothorn (2002)) in version 0.9-38, and zoo (Zeileis and Grothendieck (2005)) in version 1.8-9. The coefficients and their significance were analyzed. Furthermore, the adjusted coefficient of determination $\bar{R}^2$ was considered. The α-constant is considered separately in the context of regression diagnostics. Breusch-Pagan and Durbin-Watson's tests show heteroskedasticity and autocorrelation in several cases. Therefore, we corrected the standard errors in addition to the results presented in this study. To estimate the standard errors, we use the Newey and West (1987) estimator of order p, which corrects for autocorrelation and heteroskedasticity. Further, following Hanauer et al. (2013) and Liew and Vassalou (2000), we chose three periods for the parameter p. Again, to ensure comparability of findings, results are considered significant if they are different from zero according to the two-sided t-test at a significance level of 10 %.

Table 2 illustrates the monthly excess returns of the 16 Fama-French portfolios for the German stock market from January 15, 2002 to January 15, 2021, showing a substantial range for the average monthly excess returns from -3.508 % (Portfolio 1-1) to 0.768 % (Portfolio 4-4) in the cross-section. The ranges in Ziegler et al. (2007) are from 0.002 % to 0.668 % and in Schrimpf et al. (2007) from -0.329 % to 0.472 %, and in Hanauer et al. (2013) from -0.656 % to 1.094 %. The excess returns of Fama and French (1993) range from 0.32 % to 1.02 %. Remarkably, the excess returns of the Fama/French portfolios are significantly different from zero in all 16 portfolios (Hanauer et al. (2013) three of 16). A negative correlation can be detected between the standard deviations of the returns and returns expressed by Pearson's correlation coefficient of -0.658. In Hanauer et al. (2013), no relationship can be detected. According to μ-σ theory, the correlation should be positive.

Table 2. Monthly excess returns of i = 1,...,16 Fama-French portfolios

Variables to be explained, i.e., excess returns $R_{it} - R_{ft}$ of the $i = 1, \ldots, 16$ portfolios				
	Ratios of book value to market value			
Market Value	1 (Low)	2	3	4 (High)
	Arithmetic mean (standard deviation)			
1 (Small)	-3.742 %	-1.378 %	-0.618 %	-3.137 %
	(8.986 %)	(9.115 %)	(8.171 %)	(9.435 %)
2	-2.756 %	-0.572 %	-0.101 %	-0.413 %
	(6.933 %)	(6.173 %)	(5.692 %)	(6.736 %)
3	-1.081 %	-0.187 %	0.164 %	0.592 %
	(6.053 %)	(6.104 %)	(5.559 %)	(6.881 %)
4 (Big)	0.023 %	0.373 %	0.603 %	0.872 %
	(5.653 %)	(5.441 %)	(6.017 %)	(7.636 %)

Note. This table shows the excess returns of the 16 Fama-French portfolios for the German market and the corresponding standard deviations. At the beginning of July each year, the shares are independently assigned to four groups based on their market capitalization at the end of June. They are independently assigned to four groups based on the book-to-market ratio at the end of the previous year. The intersection of the four groups results in 16 portfolios. All calculations were based on monthly returns from 2001 to 2020.

Empirical (multi-)factor models

The formal CAPM (Equation 9)

$$E[r_i] - r_f = \beta_{CAPM,i} \cdot \left(E[r_m] - r_f\right) \tag{9}$$

is transformed into the empirical form according to Hanauer et al. (2013) (Equation 10).

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot RMRF_t + \varepsilon_{it} \tag{10}$$

For the monthly sample, the coefficient β_i averages 1.036 and is significant at the 1 % level in all 16 portfolios, while $\bar{R}^{2}$- averages 0.685.

The formal (cf. Lübbering et al. (2018, p. 10)) Fama-French three-factor model (Equation 11)

$$E[r_i] - r_f = \beta_{FF,i} \cdot E[RMRF] + s_i \cdot E[SMB] + h_i \cdot E[HML] \quad (11)$$

is transformed into the empirical form according to Hanauer et al. (2013) (Equation 12).

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + \varepsilon_{it} \quad (12)$$

In the Fama-French three-factor model sample, the CAPM coefficient β_i averages 1.033 and is significant at the 1 % level in all 16 portfolios. According to the theory, the CAPM coefficient should be $\beta_i = 1$. The empirical value of the Fama/French coefficient deviates only slightly from this but shrank marginally compared to the single-factor model. The coefficient of the size factor SMB averages -0.040 and is significant at the 1 % (5 %, 10 %) level in 11 (4) of 16 portfolios, while the coefficient of the value factor HML averages -0.041 and is significantly different from zero in only eight of the 16 portfolios. $\bar{R}^2$ (Jong et al., 2017) averages 0.765, which is, as expected, higher than that of the single-factor model.

The formal (cf. Lübbering et al. (2018, p. 12)) four-factor model, according to Carhart (1997) is described in Equation 13.

$$E[r_i] - r_f = \beta_{Carhart,i} \cdot E[RMRF] + s_i \cdot E[SMB] + h_i \cdot E[HML] + w_i \cdot E[WML] \quad (13)$$

After transforming Equation 13 into the empirical form, according to Hanauer et al. (2013), we can form Equation 14.

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + w_i \cdot WML_t + \varepsilon_{it} \quad (14)$$

For the empirical Carhart model, the CAPM beta factor β_i averages 1.050 and is again significant at the 1 % level in all 16 portfolios. Compared to the CAPM and the three-factor model, the market risk coefficient moved further away from the ideal of 1. The coefficient of the size factor SMB averages -0.029 and is significant in 14 of 16 portfolios. In comparison, the coefficient of the value factor HML averages -0.010 and is significantly different from zero in only 10 of the 16 portfolios. The coefficient of the momentum factor WML averages 0.041 and is significant in 11 of the 16 portfolios. $\bar{R}^2$ averages 0.774 which is slightly higher than that of the three-factor model.

Sentiment-Factor integration

After integrating the non-lagged PCA-derived sentiment factor into the empirical three-factor model of Fama/French, the CAPM beta factor β_i averages 1.028. It is significant in all 16 portfolios, with the closest value to 1 compared to the other models. The coefficient of the size factor s_i averages -0.038, which is slightly higher than that in the three-factor model. As in the three-factor model, s_i is significant in the 14 portfolios. The coefficient of the value factor h_i is -0.041, which is unchanged compared to the three-factor model. The factor coefficient is significantly different from zero in nine of the 16 portfolios, in line with the three-factor model. The sentiment factor coefficient ψ_i averages $-2.67 \cdot 10^{-4}$ and is significantly different from zero in the seven portfolios. $\bar{R}^2$ averages 0.767, marginally higher than in the original three-factor model (0.765). Nevertheless, it remains lower than that in a comparable Carhart four-factor model (0.774).

Overall, the results suggest that integrating the sentiment factor into the three-factor model leads to a marginal model improvement compared to the Fama/French model, which remains below the model quality of a four-factor model, according to Carhart. After integrating the sentiment factor into the empirical four-factor model, according to Carhart, the CAPM beta factor β_i averages 1.045, which is significant at the 1 % level in all 16 portfolios. Thus, the CAPM beta factor value is marginally lower than that in the original four-factor model (1.050). The coefficient of the size factor $s_.$ averages -0.026 and is closer to zero than in the original model (-0.029). As in the Carhart four-factor model, the coefficient of SMB is significant in the 14 portfolios. The coefficient of the value factor $h_.$ is -0.050 which is equal to the Carhart model value.

The factor coefficient is significantly different from zero in 10 of the 16 portfolios. The coefficient of the momentum factor w_i is 0.044, which is slightly higher than that in the Carhart model (0.041). The coefficient of the sentiment factor averages $-3.15 \cdot 10^{-4}$. It is significant in nine portfolios, corresponding to a rise in significance compared to the extended three-factor model. $\bar{R}^2$is also marginally higher (0.777) than that in the original Carhart model (0.774). Overall, the results suggest that incorporating the sentiment factor into the four-factor model contributes to a marginal increase in model goodness of fit. An investigation with a lagged sentiment integration of one period yields considerable significance in six of the 16 portfolios in the Fama/French model and five of the 16 portfolios in the Carhart model.

This gives rise to the assumption that sentiment can also help explain future returns. Nevertheless, the results suggest that integrating the sentiment factor is not appropriate because of its minimal impact on the model performance. It can be concluded that the risk factors of Fama/French and Carhart explain a large part of the return differences in the German stock market.

Regression diagnostics

Risk Premia

Table 3 shows the means and standard deviations of the four Carhart and sentiment factors to be analyzed and Pearson's correlation coefficients. Furthermore, the table includes the returns on the stock market portfolio R_m and risk-free investment R_f.

Table 3. Descriptive statistics of the variables in the monthly sample

Variable	Mean	SD	Pearson's correlation coefficient ρ				
			$RMRF$	SMB	HML	WML	$SENT$
R_m	-0.505 %	5.195 %					
R_f	0.096 %	0.129 %					
$RMRF$	-0.601 %	5.223 %	1				
SMB	-1.431 %	3.476 %	0.090	1			
HML	1.357 %	2.960 %	-0.197	-0.122	1		
WML	2.056 %	4.711 %	-0.519	-0.257	0.251	1	
$SENT$	-0.433 %	356.050 %	-0.271	0.043	0.041	0.206	1

Note. This table presents descriptive statistics for the risk premiums in the German stock market of the Carhart factors $RMRF$ ($R_m - R_f$, excess return of the equity market portfolio), SMB ("Small minus Big", differential return based on market capitalization), HML ("High minus Low", differential return based on book-to-market ratio), WML ("Winners minus Losers", differential return based on prior year performance), and $SENT$ ("Sentiment", differential return based on stock-correlation to the principal sentiment component). In addition, the returns and associated standard deviations of the equity market portfolio R_m and risk-free investment R_f are also shown. All calculations were based on monthly returns from 2001 to 2020.

For the observation period between January 2002 and January 2021, the average monthly return of the stock market portfolio (excess return) is -0.505 % (-0.601 %). The return of the stock market portfolio and the average monthly excess return is significantly different from zero at the 1 % level. The average monthly risk-free rate of 0.096 % is significant at the 1 % level. Of the three factors, SMB, HML, and WML, the momentum effect premium is the most substantial, with an average value of 2.056% per month. The size effect premium was -1.431 %, and the value effect premium was 1.357 %. Apart from $SENT$, all the risk factors were significant. The sentiment factor has a negative premium of -0.433 %, which is insignificant. Furthermore, a high standard deviation indicates a high volatility in sentiment.

Analysis of the α-constant and GRS test

The estimates for the constants α_i and the associated significance levels were analyzed subsequently. The more the return components α_i that cannot be explained by the factors are not significantly different from zero, the more compatible the empirical models are with the CAPM and the three- and four-factor models of Fama and French (1993) and Carhart (1997), respectively. The α_i values were tested both individually and jointly against this hypothesis. The joint test uses the F-test proposed by Gibbons et al. (1989) (GRS statistics), which tests all α_i within a set of portfolios against the hypothesis that all α_i equals zero. It is interesting to determine whether the α-constants are significantly different from 0. The estimates of α_i for the single-factor model compatible with the CAPM range from -2.896 % to 1.510 % (Hanauer et al. (2013): -1.050 % to 0.562 %). Eleven (Hanauer et al. (2013): three) constants are significantly different from zero. This result suggests that extension of the CAPM may be beneficial. For the three-factor model, the range of α_i decreases further (-1.687 % to 0.832 %) (Hanauer et al. (2013): -0.513 % to 0.537 %). The GRS test rejects the null hypothesis $\alpha_i = 0 \; \forall i$ for all models, indicating further potential for explanatory power in the unapplied risk factors. Nonetheless, the T-test indicates six and seven significant alphas at the portfolio level in the three- and four-factor models, respectively. This seems to indicate that there is room for additional risk factors.

Furthermore, we find that the null hypothesis of the GRS statistic, that $\alpha_i = 0\, \forall i$, can be rejected in all the extended three- and four-factor models. The smallest α_i range among the extended three-factor models is the extended Fama/French model with around $SENT$, which ranges from -1.680 % to 0.831 %. No deterioration was observed in any of the portfolios relative to the original model. The number of significant alphas at the portfolio level is six compared to seven in the Carhart model. Overall, the results indicate that the factors do not explain all return components, and there is room for improvement even after integrating sentiment.

VIF diagnostics for multicollinearity

Variance inflation factor analysis was used to check whether the correlation between the explanatory variables led to multicollinearity in the models. Thus, for the monthly sample, the focus is primarily on the observed correlation of $\rho_{RMRF,WML}$, which has a Pearson's correlation coefficient of -0.519. The results of the VIF analysis rejected the multicollinearity hypothesis in all models under consideration. As a heuristic, multicollinearity must be assumed if the VIF values are > 4. However, this is not the case for any of the models considered.

RESET test for misspecification

All models examined were tested with RESET tests for fitted values and the second to the fourth power. The null hypothesis H_1 : no specification error. If the test statistic F becomes large, H_0 is rejected, and the alternative hypothesis H_1: specification error holds. In Table 4, the assumption of H_1 rejection was made for $p < 0.1$.

Table 4. Results of the reset test for the monthly sample

Model	Regression models with suspected specification errors
1F-Model	11/16
3F-Model	9/16
3F+SENT	9/16
4F-Model	5/16
4F+SENT	4/16

Note. This table shows the models examined and how often the RESET test suspects misspecification errors in each of the 16 regression analyses. A clear trend of decreasing presumed misspecification is drawn, and more risk factors are used to explain the respective excess returns.

In the multifactor models extended by the risk factor SENT, the misspecification rate decreased compared to the Carhart model. Due to the generally high level of misspecification, the conjecture arises that correlations may not be linear. This is consistent with the observations in Tiwari et al. (2018). Still, the sentiment risk factor can lower the misspecification rate in the four-factor model.

Discussion and concluding remarks

The classical theory states that competition among rational investors who diversify their portfolios leads to a market equilibrium in which the price of each stock equals the discounted rationally expected cash flows. Here, the cross-section of expected returns depends solely on the cross-section of systematic risks (Gomes et al., 2003). Because of its robustness to other risk factors, the CAPM still serves as a blueprint for multifactor models and is used to estimate the cost of equity under uncertainty (Ziemer, 2018, p. 2).

However, the existence of factor-specific risk premia in equity markets, in addition to general equity risk premia, is now widely recognized (Henne & Teloeken, 2016). Recent studies suggest that sentiment can be transferred into risk factors and explain return variances. The observations of this study also confirm this to a certain extent for the German stock market. An overview of the key findings is provided in Table 5.

Table 5. Overview of key results.

Model	$\bar{R}^2$	α -Range	Sig. α	Sig. ψ	∅ ψ
1F-Model	0.685	0.044	11/16	./.	./.
3F-Model	0.765	0.025	6/16	./.	./.
3F+SENT	0.767	0.025	7/16	7/16	−0.027 %
4F-Model	0.774	0.024	7/16	./.	./.
4F+SENT	0.777	0.024	7/16	9/16	−0.032 %

Note. This table provides an overview of the key results of this empirical study. The average model goodness of fit is shown for each model investigated based on the adjusted coefficient of determination $\bar{R}^2$ and the range of the respective alpha values. The table also shows the proportion of Fama/French portfolios with significant alpha in each case. In the models extended by a sentiment risk factor, the frequency of significance and average values are indicated accordingly.

Linear regression analyses show that sentiment can contribute as an additional risk factor in explaining stock market returns. The sentiment sources examined also suggest that sentiment influences large caps. The research results of this study show that an abstract concept such as the transformation of aggregated sentiment into measurable factors is possible and appears to be useful because it contributes explanatory power to returns and is capable of increasing model goodness of fit. However, the $\bar{R}^2$ gain achieved by the sentiment factors was small. This is due to the high empirical relevance of the Fama/French and Carhart risk factors.

The Fama/French three-factor model explains the return difference better ($\bar{R}^2 = 0.765$) than the CAPM ($\bar{R}^2 = 0.685$). The explanatory contribution of Carhart's (1997) four-factor model increased marginally by adding the momentum factor ($\bar{R}^2 = 0.774$). Integrating the sentiment factor into the Carhart model can further increase the model's goodness of fit ($\bar{R}^2 = 0.777$).

This evidence supports hypothesis H1 and shows that the examined APT models with Fama/French and Carhart factors are superior to the CAPM in the German stock market. Regarding the practical relevance of the study results, direct use of the findings on the significance of sentiment factors in the German stock market may only be possible after further studies with different sample sizes and time frames. It is also essential to determine the ideal time lag between sentiment detection and investment decisions (Sul et al., 2017).

However, caution should be exercised when using multiple risk factors in the same model. Even if they are mainly uncorrelated, there is a risk of a sudden increase in the correlation in extreme market phases. The desired diversification effects would then be diminished. For further evaluation, back testing methods can validate the trading strategies. In conclusion, this study demonstrates that integrating sentiment factors into multifactor models is possible and reasonable. The PCA-derived sentiment risk factor meets the criteria for rational integration into multifactor models.

This evidence supports hypothesis H2, because a negative correlation between the sentiment risk factor and future returns was observed in the cross-section. However, the goodness of fit of the model remains lower than that of a comparable Carhart model. The observed premia of the sentiment risk factor are negative, in line with the literature, which strengthens the existing conjecture of sentiment as a contra-indicator (Du & Hu, 2018, p. 207). VIF diagnostics showed no evidence of multicollinearity. The RESET test also showed no evidence of increased misspecification compared to the three- and four-factor models.

Hypothesis H3 is weakly supported because the actual quality improvements in model quality are small or marginal. However, the fundamental influence of sentiment on excess returns on the German stock market can be confirmed, as in other recent studies around the globe (Al-Nasseri et al., 2021; Gutierrez & Perez-Liston, 2021; Zaremba et al., 2020).

The approach taken in this study to integrate sentiment factors into multifactor models offers an added value compared to the classical portfolio theory. Regardless of this and subsequent studies on the German stock market, only a broad cross-national significance will permanently establish sentiment factors. However, the high relevance of the Fama/French and Carhart factors was empirically demonstrated in the German stock market. They still represent a substantial improvement in model quality compared to the CAPM.

Compared to previous studies, this study makes a significant contribution to academic research using individual indicators to measure investor sentiment in the German stock market by developing a general PCA-based investor sentiment risk factor considering survey-based and market-implied investor sentiment.

Second, it shows the impact of the general sentiment indicator on stock returns even when known risk factors such as size, value, and momentum are included as control variables.

Third, investor sentiment makes a valuable explanatory contribution to returns in the German stock market. However, when considering these results in the context of a larger theory, the efficient-market hypothesis cannot be fully supported by this empirical evidence because, based on available market information, return developments of the subsequent period can be systematically explained to some extent.

Finally, the research results provide valuable information for those involved in the German stock market. Investors can select criteria for investment stocks based on the statistical significance of the variables in the research models. Portfolio managers can anticipate that positive investor sentiment is likely to negatively influence future stock market returns.

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