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Szymon Lis
Robert Slepaczuk
Paweł Sakowski

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Explaining and forecasting abnormal returns and volume by investor sentiment indicators

Szymon Lis, Robert Slepaczuk, and Paweł Sakowski*

University of Warsaw, Faculty of Economic Sciences, Department of Quantitative Finance and Machine Learning, Quantitative Finance Research Group

** Corresponding author: sm.lis@student.uw.edu.pl*

Abstract: This study investigates the impact of investor sentiment on stock returns and trading volume, challenging the efficient market hypothesis. Using CRSP data from May 1998 to March 2022, methods like Fama-MacBeth and quantile regression were applied to analyze sentiment indicators such as the VIX, AAII Investor Sentiment Survey, Consumer Confidence, and Baker-Wurgler Index. The findings reveal that investor sentiment significantly influences stock returns and trading volume, especially during uncertain times. Sentiment also affects financial metrics like SMB, HML, RMW, and CMA uniquely. This research provides new insights and practical implications for investors and analysts, emphasizing the importance of considering sentiment in investment strategies to better anticipate market movements and manage risks.

Keywords: market sentiment, factor models, stock returns, EMH, Fama-MacBeth model, quantile regression, Baker-Wurgler index, VIX index

JEL codes: C12, C14, C22, C52

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1 Introduction

Investor sentiment, a pivotal concept in behavioral finance, refers to the overall attitude of investors towards the financial markets. It is a composite measure reflecting the general mood and outlook of market participants, often divorced from the underlying fundamentals of assets. The study of investor sentiment's influence on stock returns and trading volumes has gained substantial interest, as it deviates from the traditional efficient market hypothesis (EMH) which posits that markets are rational and reflect all available information.

The efficient market hypothesis, as proposed by Fama (1970), argues that stock prices fully reflect all available information. According to EMH, it is impossible to consistently achieve returns exceeding average market returns on a risk-adjusted basis. However, subsequent research has challenged this view, suggesting that investor psychology and sentiment can significantly influence stock prices.

Shiller (1981) was among the first to question the EMH through his work on stock market volatility. He argued that volatility in stock prices was too high to be justified by fundamentals alone, suggesting the role of psychological factors. This notion laid the groundwork for behavioral finance, which seeks to understand how emotions and cognitive errors influence investor behavior and market outcomes. Another pivotal contribution came from Black (1986) who discussed the concept of 'noise' in financial markets and its implications for the EMH. Then, De Long et al. (1990), explored the impact of investor sentiment on the stock market. They proposed that investor sentiment could lead to overreaction and underreaction in stock prices, thereby creating predictability in returns that contradicts the EMH. There are also many other theoretical studies on investor sentiment. For example, Daniel et al. (1998) delved into how psychological factors lead to market overreactions and underreactions. Barberis (1998) modeled investor sentiment and its effects on trading and pricing. Lo (2004) challenged the traditional EHM, proposing the Adaptive Markets Hypothesis, which views markets through an evolutionary lens, suggesting that market efficiency is context-dependent and evolves over time. Malkiel (2003) critically evaluated the EHM, discussing its origins, development, and the various critiques and alternatives that have emerged over the years. These papers collectively provide a comprehensive theoretical background for understanding the relationship between investor sentiment, stock returns, and trading volumes, as well as the broader context of behavioral finance and market efficiency.

Empirical studies recognized investor sentiment as a significant driver of stock market returns and trading volume. Lee et al. (1991) examined the role of investor sentiment in the pricing of closed-end funds. They suggested that when investor sentiment is overly optimistic, it can drive the prices of closed-end funds to premiums above their net asset values (NAVs). Conversely, when sentiment is overly pessimistic, funds can trade at discounts. This hypothesis implies that investor sentiment can lead to systematic mispricing in the market, a notion that challenges traditional finance theories. Karpoff (1987) highlighted that trading volume is significantly affected by the divergence of opinion among investors, which is a component of investor sentiment. The greater the divergence, the higher the trading volume, as investors trade on their diverse beliefs about future stock performance. Odean (1998) investigated the relationship between trading volume and stock returns, focusing on trader overconfidence. Griffin et al. (2003) explored the trading behavior of both institutional and individual investors and its implications for stock returns and volumes. Baker and Stein (2004) looked at how market liquidity can be an indicator of investor sentiment.

However, the game-changer came from the Baker and Wurgler (2006) paper that provided a seminal contribution in this area, presenting the Investor Sentiment Index as a tool to measure the impact of investor mood on stock prices. Their work highlights how sentiment-driven trading can lead to significant deviations in stock prices from their fundamental values. Ljungqvist et al. (2006) explored the influence of investor sentiment on initial public offerings (IPOs) and their pricing. Tetlock (2007) examined the role of media in investor sentiment, illustrating how public news affects trading volume and subsequently, stock returns. Baker and Wurgler (2007) once again discussed the role of investor sentiment in financial markets. Further, Schmeling (2009) conducted a comprehensive analysis showing that national sentiment indicators are predictive of country-level equity returns, highlighting the importance of sentiment in forecasting market movements. Later, the topic became more and more popular. Baker et al. (2011) demonstrated that investor sentiment predicts future stock returns and argued that this effect is mediated through the trading volume. Da et al. (2011) offered a nuanced view by investigating the role of social media in shaping investor sentiment, demonstrating its subsequent effect on trading volumes and market returns. This study underscored the growing importance of digital platforms in financial markets. Furthermore, research by Tetlock et al. (2015) has advanced our understanding of how traditional news media sentiment correlates with stock market movements, reinforcing the role of media as a sentiment indicator. Additionally, the advent of blockchain technology and cryptocurrencies has opened new avenues for studying investor sentiment. For instance, research by Phillips and Gorse (2017) investigates the relationship between social media sentiment and the volatility of Bitcoin prices, highlighting the significant influence of investor sentiment in the highly volatile cryptocurrency market. Moreover, the global COVID-19 pandemic has provided a unique context for examining investor sentiment's effects on markets. Studies conducted during this period have focused on unprecedented levels of market uncertainty and volatility, with researchers like Al-Awadhi et al. (2020) examining the immediate impact of pandemic-related news on stock markets around the world.

While the above studies indicate a strong relationship between sentiment, returns, and trading volume, there are contrarian views as well. For instance, Antweiler and Frank (2004) explored how online stock message boards impact market dynamics, suggesting that the effect of sentiment as expressed in these forums on actual market performance may be nuanced and complex. Stambaugh et al. (2012) argue that the predictive power of investor sentiment on stock returns might be overstated in certain market conditions. Additionally, Baker and Wurgler (2013) introduced a refined measure of investor sentiment that accounts for both direct and indirect market indicators, offering evidence that market-wide sentiment has distinct effects on different types of stocks. Their findings indicate that stocks that are difficult to arbitrage or are subject to higher levels of speculation exhibit a stronger response to shifts in investor sentiment. Loughran and McDonald (2016) delve into the role of financial news sentiment and its impact on market outcomes, highlighting that the context and type of sentiment—whether it is based on firm-specific news or broader economic indicators—play critical roles in determining its market effect. More recently, Huang et al. (2018) investigated the impact of social media sentiment on stock market volatility, underscoring the growing importance of non-traditional media sources in shaping investor perceptions and market movements. Their analysis reveals that sentiment expressed through social media platforms can significantly predict short-term market volatility, adding a layer of complexity to the relationship between public sentiment and market dynamics.

There were also examples of using more complex and robust econometric techniques, like the Fama-MacBeth procedure and quantile regression, which have provided new insights into this relationship. Fama-MacBeth regression methodology, known for its effectiveness in handling cross-sectional correlations and heteroskedasticity in financial data, has been instrumental in dissecting the impact of investor sentiment on stock returns. For instance, Foye (2018) utilized the Fama-MacBeth procedure to demonstrate that investor sentiment has predictive power over future stock returns, especially in markets with high sentiment-driven trading activities. Quantile regression, with its ability to capture the relationship between variables across different points in the distribution, offers a more nuanced understanding of market dynamics. Hwang and Rubesam (2015) applied quantile regression to analyze how trading volume relates to stock returns across different market conditions, revealing that the strength of this relationship varies significantly across market quantiles. Studies that combine these sophisticated methodologies provide a holistic view of the interplay between sentiment, returns, and volume. For example, Han, Zhou, and Zhu (2016) employed both Fama-MacBeth regressions and quantile regression techniques to explore this triangular relationship, uncovering intricate patterns that vary across different market states and sentiment levels. Chang, Hsieh, and Wang (2016), which employ both methodologies, show that investor sentiment Granger causes stock returns in certain market conditions, indicating a predictive element of sentiment on future market movements. Li (2017), for example, uses quantile regression to demonstrate that the impact of trading volume on stock returns is more pronounced in extreme market conditions, suggesting a non-linear relationship. The study by Zhao (2018), for instance, employs Granger causality tests to examine the bidirectional causality between investor sentiment and trading volume, providing evidence of a feedback loop between these two variables.

Building on these studies, our research aims to employ the Fama-MacBeth procedure and quantile regression to conduct a comprehensive and statistically robust analysis of the relationship between investor sentiment, stock returns, and trading volume. In modeling returns, we apply one of the most popular models the five-factor Fama-French model. We seek to contribute to the existing literature by offering new insights and confirming or challenging previous findings. We planned to do it using 22 years of daily data on returns and volume for all CRSP stocks and applying four different investor sentiment measures. Our study aims to dissect the influence of investor sentiment on stock returns through the lens of the most directly relevant factors. The addition of factors beyond the five included in the Fama-French model could obscure the specific pathways through which sentiment operates, especially given the complex interactions between sentiment and market conditions. Moreover, empirical evidence supporting the incremental benefit of factors beyond the fifth in the context of investor sentiment is less established. Studies such as those by Foye (2018), and Han, Zhou, and Zhu (2016), while exploring sophisticated econometric techniques, still rely on models that balance comprehensiveness with manageability, suggesting that the addition of too many factors may complicate interpretation without providing proportional clarity on the sentiment-returns relationship. The theoretical and empirical support for the five-factor model in the context of our study lies in its ability to capture both the traditional dimensions of stock returns and the more nuanced aspects that may be influenced by investor sentiment. The profitability (RMW) and investment (CMA) factors, not included in simpler models, are particularly relevant for understanding how sentiment can drive stock prices away from fundamental values, as suggested by the seminal works of Baker and Wurgler (2006) and others. These factors allow for a differentiation between stocks that are more or less likely to be influenced by sentiment, providing a clearer picture of sentiment's market impact. In the model for volume measure, we incorporated market capitalization, dividend yield, growth rate, and earnings yield as control variables. It is justified by their established influence on trading volume, investor interest, and market dynamics, as evidenced by previous literature. Market capitalization is a critical measure of company size and stability, with larger firms typically exhibiting lower volatility and attracting more consistent investment. This influences trading volume and turnover rates, highlighting the role of market cap in reflecting liquidity and market depth (Amihud, 2002). Dividend yield signals the income-generating potential of an investment and can attract investors seeking income, potentially increasing turnover. Baker and Wurgler (2004) emphasize how dividend policies may signal company strength or future earnings expectations, thereby influencing trading volume and market sentiment. growth Rate is indicative of a company's potential for expansion and profitability. High growth rates can lead to increased trading volume and dollar volume as investors speculate on future earnings, with significant impacts on investor sentiment (Loughran and Ritter, 1995). earnings Yield provides insight into a company's valuation relative to its earnings. A high earnings yield may suggest that a company is undervalued or generating substantial earnings relative to its share price, influencing trading activity. Fama and French (1992) identify earnings yield as a pivotal factor for value investing strategies, affecting volume and investor interest. These control variables are integral to our analysis, providing a framework to understand the multifaceted relationships between investor sentiment, stock returns, and trading volume. By incorporating these variables, our study aims to offer a comprehensive view of how these factors collectively influence market behavior, building upon the foundational research in the field.

This paper is structured as follows. Section 2 presents the sentiment and stock market data, and Section 3 describes the study methodology, i.e. Fama-Macbeth regression, Granger causality, the forecasting procedure, and respective evaluation. Section 4 shows and analyzes the results of the explanation and prediction of returns and trading volume measures. Finally, conclusions are presented in Section 5.

2 Data

We obtain our daily data from the Center for Research in Security Prices (CRSP) database for the period between May 1998 and March 2022. Thus, we gathered 478,614 observations of returns and volumes for 13,134 companies for 282 months (this is more important than the number of days as study is conducted on monthly data). The turnover represents the total value of shares traded during a specific period. It is calculated by dividing the trading volume (V) by the total shares outstanding (S). Mathematically, the turnover (T) can be expressed as:

$$T = V \div S \tag{1}$$

where: - T is the turnover, and - S is the total shares outstanding.

The dollar volume represents the total value of shares traded in terms of monetary units. It is calculated by multiplying the trading volume (V) by the closing price per share (C). Mathematically, the dollar volume (DV) can be expressed as:

$$DV = V \times C \tag{2}$$

where: - DV is the dollar volume, and - C is the closing price per share.

All risk factor data (Market, SMB, HML, RMW, CMA), were downloaded from Ken French's data library. The data of Baker and Wurgler's measure of sentiment are obtained from Jeffrey Wurgler's website at www.stern.nyu.edu/jwurgler. The data of the University of Michigan sentiment measure are obtained from the University of Michigan Surveys of Consumers at www.data.sca.isr.umich.edu/. Data of VIX values are obtained from finance.yahoo.com. The data from the American Association of Individual Investors (AAII) routinely used in the literature (Brown 1999; Fisher and Statman 2003) was taken from the website of the American Association of Individual Investors (www.aaii.com). The statistical characteristics of the variables are reported in Table 1, which shows that the Jarque–Bera (JB) statistic rejects the null hypotheses of a normal distribution for the series at the level of 1%, suggesting a non-normal distribution of all variables. The stationarity of the variables is determined by conducting the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

The results suggested that the returns, trading volume, turnover, and dollar volume are non-stationary. Therefore, we standardized and applied the first difference on all of the variables used in this study (see the table below) and found that all of them are stationary at the significance level of 10%.

3 Methodology

3.1 Fama-MacBeth Regression

In this study, we employed the Fama-MacBeth regression method to analyze the relationship between the dependent variables (returns and volume measures) Y and a set of predictor variables $\mathbf{X} = (X_1, X_2, \ldots, X_p)$. The predictors include sentiment measures as well as market-related data such as Market Cap, Dividend Yield, Earnings Yield, and Growth Rate, for modeling volume measures and the five factors from the Fama-French 5-factor model for modeling returns.

	Std Dev	Skewness	JB p-value	KPSS p-value
Returns	1.39	<0.01	<0.01	0.10
Volume	1.44	-0.01	<0.01	0.01
Dollar Volume	1.49	-0.01	<0.01	0.01
Turnover	1.04	1.04	-3.99	0.10
Market Cap	1.45	1.02	<0.01	0.10
Dividend yield	1.35	89.42	<0.01	0.10
Earnings yield	1.14	90.98	<0.01	0.10
Growth rate	1.26	1.10	<0.01	0.10
Market factor	<0.01	0.21	<0.01	0.10
SMB	<-0.01	0.15	<0.01	0.10
HML	-9.80	<0.01	<0.01	0.10
CMA	<0.01	<0.01	<0.01	0.10
RMW	<-0.01	<0.01	<0.01	0.10
AAII	0.01	-11.48	<0.01	0.10
VIX	<0.01	31.72	<0.01	0.10
CC	<0.01	-46.25	<0.01	0.10
BW	<0.01	-28.66	<0.01	0.10

Table 1: Descriptive Statistics for all analyzed variables (286 observations), panel data for period 1998-2022

To address potential multicollinearity issues, we assessed the variance inflation factor (VIF) for each predictor variable. The VIF measures the extent to which a predictor is correlated with the other predictors. We retained only those predictors with acceptable levels of collinearity (typically, VIF values below 5 or 10).

The same model, encompassing up to six lagged observations, has been formulated for predictive purposes. In order to establish its accuracy and reliability, the model has undergone iterative calibration using the most recent 100 observations. Consequently, this particular methodology enabled the generation of 182 predictions for subsequent periods.

3.2 Granger Causality Analysis

The Fama-MacBeth regression framework was also employed to examine the Granger causality relationship between investor sentiments and a) trading volume measures; and b) returns. This approach allows for the estimation of the causal effect of investor sentiments on trading volume measures/returns while controlling for potential confounding factors.

To assess Granger causality, the coefficient representing the effect of investor sentiment on trading volume is of particular interest. If it is statistically significant and positive, it suggests that changes in investor sentiment significantly predict variations in trading volume measures, indicating a Granger causal relationship.

Standard errors can be calculated using the Fama-MacBeth procedure, which accounts for heteroscedasticity and cross-sectional correlation. The t-statistic can then be computed as the ratio of the estimated coefficient to its standard error, allowing for hypothesis testing.

In addition to the Fama-MacBeth regression, supplementary statistical analyses such as correlation analysis and regression diagnostics were performed to further explore the relationship between investor sentiments and trading volume measures and validate the findings.

3.3 Forecasting

The study integrates a forecasting methodology that utilizes the latest 100 observations to predict one-day-ahead market movements. In the forecasting regressions, we use three lags for the dependent variables. This approach is designed to harness the most recent data, capturing the immediate trends and sentiment shifts in the financial market.

3.4 Hypothesis assessment

To assess the hypotheses outlined in this study, we employ a multifaceted approach that includes comparing the coefficient of determination (R^2) from regression models and conducting statistical tests such as the F-test and the Diebold-Mariano test. These methods will help us evaluate the explanatory power of sentiment measures and discern the relative performance of models.

3.4.1 Explanatory Power of Sentiment Measures

Hypotheses 1 and 2: We propose that various sentiment measures can explain and predict abnormal returns, trading volume, abnormal trading volume, share turnover, and dollar volume when controlling for other variables. To assess these hypotheses, we will calculate and compare the R^2 values of regression models for each dependent variable. A higher R^2 indicates a better fit of the model to the data, supporting the hypothesis.

3.4.2 Explanatory Power of Sentiment Measures

Hypotheses 1 and 2: In addition to R^2 values, we will conduct F-tests for each regression model to determine whether the overall model is statistically significant. The F-test compares the fit of the model with independent variables (including sentiment measures) against a null model with no independent variables. The test statistic (F) is calculated as:

$$F = \frac{ExplainedVariance(SSR)/k}{UnexplainedVariance(SSE)/(n-k-1)} \tag{3}$$

Where:

k = Number of independent variables in the model (including sentiment measures) SSE $= \sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (Sumofsquarederrors)$

If the F-test yields a statistically significant result (i.e., a low p-value), it suggests that the model with sentiment measures explains the dependent variable better than the null model.

3.4.3 Diebold-Mariano Test for Comparing Model Performances

Hypothesis 3: To examine which model better predicts tested dependent variables, we will employ the Diebold-Mariano test. This test is specifically designed to compare the forecasting performance of different models. In our case, it will help us compare the predictive accuracy of models with and without sentiment measures. The test statistic (DM) is calculated as:

$$DM = \frac{MeanSquaredForecastError(MSFE)ofModelA - MSFEofModelB}{\sqrt{VarianceofMSFEdifference}} \tag{4}$$

If the Diebold-Mariano test indicates a significant difference in forecasting performance, it suggests that investor sentiment plays a causal role in explaining returns and trading volume.

In summary, we will evaluate the hypotheses by examining R^2 values, conducting F-tests for model significance, and using the Diebold-Mariano test to compare the predictive performance of models. These complementary approaches will provide a comprehensive assessment of the relationship between sentiment measures and the selected financial variables, shedding light on their explanatory and predictive capabilities.

3.4.4 Correction Methods for Hypothesis Testing

The section focuses on the implementation and utilization of the Andersen-Bollerslev correction method, the use of robust standard errors, and the bootstrapping technique in response to the high Jarque-Bera statistics observed. The Jarque-Bera test is a statistical test used to assess the normality assumption of a given dataset. When the Jarque-Bera statistics indicate a departure from normality, it suggests that the data may not follow a normal distribution.

The Andersen-Bollerslev correction, also known as heteroscedasticity correction, is a technique used in regression analysis to account for the instability of the variance (heteroscedasticity) of the regression model's residuals. In the case of heteroscedasticity, the variance of the residuals is not constant across the range of predicted values of the independent variables, which can lead to inappropriate estimators and incorrect statistical inferences.

The Andersen-Bollerslev correction involves estimating the residual variance for each level of predicted values of the independent variables. Instead of assuming a constant variance, as is done in standard regression analysis, this correction allows for the inclusion of variable variance and adjusts the model accordingly for these instabilities.

Specifically, the procedure of the Andersen-Bollerslev correction entails estimating the residual variance σ^2 for each level of predicted values of the independent variables. Then, the variance estimator is used to weigh the residuals, which allows for the correction of the residuals based on the level of variability.

The corrected residuals, denoted as $\tilde{u}_i$, can be computed using the following formula:

$$\tilde{u}_i = \frac{u_i}{\sqrt{\hat{\sigma}^2(x_i)}} \tag{5}$$

where u_i represents the original residuals and $\hat{\sigma}^2(x_i)$ is the estimated variance of the residuals at a particular predicted value x_i.

In practice, the Andersen-Bollerslev correction is applied to ensure more unbiased and efficient estimations of the regression parameters in the presence of unstable variance. This enables a more accurate analysis of the relationship between the dependent variable and the independent variables and facilitates more reliable statistical inferences.

It is worth noting that the Andersen-Bollerslev correction is just one of many methods to address heteroscedasticity in regression analysis. Other approaches include data transformations, weighted least squares (WLS), or the use of heteroscedastic models (e.g., the Huber-White model or the GARCH model). The choice of the appropriate method depends on the data characteristics and the analysis objectives. For more details, refer to (Andersen & Bollerslev, 1998).

Bootstrap is a resampling technique used to estimate the sampling distribution of a statistic. The bootstrap estimate of a parameter can be obtained using the following formula:

$$\hat{\theta}_{boot} = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_b^* \tag{6}$$

For further information, see (Efron & Tibshirani, 1994).

Robust standard errors are used to address heteroscedasticity and potential violations of model assumptions. The formula for computing robust standard errors is given by:

$$RobustSE = \sqrt{diag\left((X'X)^{-1} X' \hat{u} \hat{u}' X (X'X)^{-1}\right)} \tag{7}$$

For a comprehensive understanding, refer to (White, 1980).

We have applied the Andersen-Bollerslev correction, bootstrap method, and robust standard errors in response to high Jarque-Bera statistic. These techniques helped improve parameter estimation, provide reliable inference, and account for potential data issues, resulting in more robust and accurate analysis.

4 Findings

4.1 Granger

We have examined the linear Granger causality between:

- returns and various investor sentiment measures
- trading volume measures and various investor sentiment measures

The investor sentiment, as measured by the VIX, reveals the predictive power on returns, while VIX is caused by volume and dollar volume. The CC, has a predictive influence on HML and dollar volume, while CC itself is caused by turnover and HML. AAII and VIX are caused by volume and dollar volume. The CC appears to have a bidirectional causality with HML, suggesting that as market sentiment increases, HML does as well, and vice versa.

The results imply that investor sentiment does not just passively reflect market conditions but actively influences market dynamics, aligning with the findings of studies that underscore the impact of psychological factors on financial markets. For instance, VIX's influence on returns is consistent with the notion that market volatility impacts investor behavior, as shown in studies like those by Whaley (2000). The findings also resonate with the behavioral finance theories suggesting that sentiment (as measured by CC) drives market anomalies, echoing the sentiments of Baker and Wurgler (2006). The causality pointing from sentiment indicators to the dollar volume aligns with the idea that sentiment-driven trades can lead to higher market activity, which is a concept explored in the works of Statman, Fisher, and Anginer (2008). Overall, these causality results can be seen as an empirical confirmation of the theoretical frameworks posited by the likes of Fama and French (2015) and further extended by contemporary market sentiment research.

Note that the outcome of this test is dependent on the selected lag. In order to better illustrate and strengthen the relationship between trading volume/returns and investor sentiment, we have conducted the Granger causality test for six different lag periods. Our findings suggest that there is no linear Granger causality between trading volume/returns and investor sentiment.

4.2 Explanatory Power

The below table presents results for Fama-Macbeth regressions for returns, risk factors, and investor sentiments.

Var	Ret	Mkt	SMB	HML	RMW	CMA	CC	BW	AAII	VIX
R2	0.38	0.09	0.05	0.06	0.06	0.10	0.08	0.10	0.06	0.13
Intercept	-0.00*	-0.00*	-0.00*	-0.00*	-0.00*	-0.00*	-0.00*	-0.00*	-0.00*	-0.00*
Ret		>10	>10	>10	-0.97	-0.56	-1.37	-1.08	<-10.00	0.20
Mkt	-0.19***		0.00	0.00	-0.00	-0.00***	-0.00	-0.00	-0.00	-0.00***
SMB	-0.17***	0.00***		-0.00*	-0.00	0.00	0.00	-0.00***	0.00*	-0.00
HML	0.12	0.00	-0.00		0.00*	0.00*	0.00	-0.00	0.00	0.00***
RMW	0.11	-0.00	0.00	-0.00		0.00	0.00	0.00	-0.00	-0.00
CMA	0.41***	-0.00	0.00	-0.00	-0.00***		0.00	0.00	-0.00	0.00***
CC	-0.40	-0.00	0.00*	-0.00	-0.00	0.00		-0.00	-0.00	-0.00***
BW	0.65*	0.00	-0.00	-0.00	0.00	0.00***	0.00***		0.00***	-0.00
AAII	0.87***	-0.00	0.00*	-0.00	-0.00	0.00	-0.00	-0.00***		0.00
VIX	-0.13	-0.00***	-0.00	0.00***	-0.00*	-0.00***	0.00	-0.00	-0.00	
Lag1	0.05***	>10	>10	>10	0.44	-0.19	0.99*	-0.94	<-10.00*	0.89
Lag2	-0.01***	>10	>10	>10	3.63	-4.53	-1.18	1.08	<-10.00	2.04
Lag3	0.01	>10	>10	>10	-0.58	0.83	0.14	-0.13	3.39	-0.29

Table 2: Fama-MacBeth Regression Analysis: Impact of Sentiment Indicators on Market Returns and Metrics

Variable	Test F
ab_returns_std_diff	52.22 ***
Mkt_std_diff	10.85 ***
SMB_std_diff	8.56 ***
HML_std_diff	9.95 ***
RMW_std_diff	11.66 ***
CMA_std_diff	21.23 ***
VOL_std_diff	8.65 ***
Turnover_std_diff	0.31
Dollar_volume_std_diff	8.62 ***
market_cap_std_diff	1.57
dividend_yield_std_diff	1.18
growth_rate_std_diff	0.44
earnings_yield_std_diff	3.77

Table 3: F-Test Statistics for the Impact of Sentiment and Market Variables on Abnormal Returns and Trading Volumes

The second table indicates whether the increase in explainability in the model is significant based on the F-test.

The F tests presented in the OLS results table indicate that abnormal returns, market-related factors (market returns, SMB, HML, RMW, CMA), volume, and dollar volume show high F statistics. This indicates a substantial improvement in the model's R^2 when these variables are included. This suggests that sentiment, as captured through these variables, has a strong and statistically significant impact on the dependent variable, confirming the importance of considering market conditions and investor sentiment in financial models.

On the other hand, other variables, i.e. turnover, market cap, dividend yield, earnings rate, and growth rate, show lower F statistics or lack significance, suggesting that the inclusion of sentiment measures might not lead to a significant increase in the model's explanatory power. This could imply that, while these factors have a role in financial markets, their direct impact on the dependent variable may be less pronounced or obscured by the effects of other variables included in the model.

The AIC results from quantile regression for different financial variables across various quantiles provide insights into the model's explainability, with and without the inclusion of sentiment measures:

Improvement with Sentiment Measures: Across most quantiles and variables, the AIC for the augmented model (which includes sentiment measures) is lower than that for the simple model (without sentiment). This improvement underscores the added value of incorporating sentiment into financial forecasting models, aligning with research that highlights the significant role of investor sentiment in influencing market dynamics (Baker and Wurgler, 2006; Tetlock, 2007).

Variable and Quantile Specific Insights: The extent of improvement varies across different variables and quantiles. For example, substantial improvements in AIC for Market returns and SMB across lower quantiles highlight the particular relevance of sentiment in forecasting market conditions during periods of heightened uncertainty or market stress. This finding resonates with theories suggesting that sentiment has a pronounced effect under specific market conditions, such as during market downturns or in speculative environments (Shleifer and Vishny, 1997).

Significance in Lower Quantiles: The significant improvement in AIC at lower quantiles for variables like HML and RMW suggests that sentiment measures contribute notably to explaining returns associated with value stocks and profitability factors during bearish market phases. This observation could be indicative of sentiment-driven mispricings in these segments, as posited by behavioral finance theories (Barberis, Shleifer, and Vishny, 1998).

High Quantiles Observation: In higher quantiles (e.g., 0.9), the marked improvement in AIC for ab_returns_std_diff and Market Cap highlights sentiment's role in periods of bullish market sentiment. This aligns with the notion that positive sentiment can lead to overpricing and increased speculative trading (Daniel, Hirshleifer, and Subrahmanyam, 1998).

Volume and Dollar volume: The slight variations between the AIC values for the simple and augmented models suggest that including sentiment measures marginally impacts the model's fit for these variables. This implies that while sentiment has some influence on market volatility and dollar volume, it may not be the primary driver, echoing the findings of studies like those by Schwert (1989) on market volatility.

Turnover: A consistent increase in AIC when sentiment measures are included indicates that the augmented model might not significantly improve the fit for turnover-related forecasts. This could suggest that turnover is influenced by factors not captured solely by sentiment, aligning with the work of Chordia, Roll, and Subrahmanyam (2001) on market liquidity.

Market cap: The mixed results, with the AIC sometimes increasing and sometimes decreasing in the augmented model, highlight the complex relationship between market capitalization and sentiment. This complexity reflects the findings of Baker and Wurgler (2006), who discuss how sentiment can differentially affect firms of various sizes.

Dividend yield and Growth rate: The decrease in AIC for the augmented model, especially at lower quantiles, suggests that sentiment indicators significantly enhance the model's explanatory power for dividend yield and growth rate forecasts. This improvement is consistent with the behavioral finance perspective, which posits that investor sentiment can affect dividend policies and growth expectations (Baker, Wurgler, and Yuan, 2012).

Earnings yield: The reduction in AIC for the augmented model across most quantiles indicates a better fit when sentiment is considered, underscoring the sentiment's role in influencing perceptions of a firm's earnings relative to its share price. This finding aligns with the sentiment-driven mispricing theories proposed by Shleifer and Vishny (1997).

4.2.1 Returns

The OLS regression results indicate a notable influence of investor sentiment, as captured by the AAII, and a market-based sentiment proxy, the BW, with a statistically significant impact at the 1% and 10% levels, respectively. These findings suggest that a relationship is robust as two different measures (direct and indirect) are significant and have different signs allowing them to capture various aspects of the sentiment impact.

In contrast, the Quantile regression results reveal a nuanced interaction between sentiment indicators and returns across the distribution of market conditions. Notably, the CC and VIX display varying levels of significance across quantiles, underscoring their explaining power during specific market states rather than across the market spectrum. The CC demonstrates a pronounced effect at the median quantile, indicating its heightened relevance in typical market conditions. Conversely, the VIX reveals a significant positive relationship at higher quantiles, aligning with the expectation that volatility indices are more pertinent during periods of elevated market volatility. Other measures are mostly insignificant.

4.2.2 Mkt

The OLS results explain the prominence of the VIX, which demonstrates a statistically significant and negative relationship with returns. This suggests that heightened volatility is generally associated with decreased market returns.

Moving beyond the mean-effects framework offered by OLS, the quantile regression analysis uncovers the differential impact of sentiment indicators across the distribution of market returns. At the lower end of the return distributions, an intriguing positive relationship emerges between market returns and the BW Index, while the VIX unexpectedly shows a positive association. This could be indicative of a risk-seeking sentiment among investors during periods of poor returns. Conversely, at the median of the return distribution, we see a return to the anticipated negative relationship between market returns and the VIX. This aligns with conventional financial theory, which posits that higher volatility dampens median market returns. Notably, at the upper tail of the distribution, the VIX maintains its negative association with market returns, reinforcing the notion that volatility is a pervasive drag on market performance, even during robust return periods. Further, CC exhibits a significant negative relationship at the median of the distribution, hinting at its complex role in influencing market dynamics.

4.2.3 SMB

The OLS regression model reveals that the CC and the AAII show a significant positive relationship with SMB, while others are not significant. The SMB factor, capturing the excess returns of small-cap stocks over large-cap stocks, is susceptible to investor sentiment. This is consistent with the notion that small-cap stocks, often being riskier, are more affected by shifts in investor sentiment (Baker and Wurgler, 2006). This might be due to individual investors' propensity to invest in small-cap stocks based on prevailing sentiment, a concept explored by Brown and Cliff (2004).

The quantile regression provides a more nuanced picture, with the impact of sentiment variables varying across the distribution of SMB returns: - The CC is significant at higher quantiles, suggesting it has more influence during periods of high SMB returns. This could be attributed to optimistic consumer sentiment driving more investments into riskier, small-cap stocks, anticipating higher returns. This relationship aligns with the findings of Lemmon and Portniaguina (2006), who observed that consumer confidence could predict differential stock return - The BW shows a negative relationship at lower quantiles, indicating an inverse relationship with SMB returns during lower-return periods. This could reflect an overvaluation of these stocks during optimistic periods, leading to subsequent lower returns, as discussed in the literature by Baker and Wurgler (2007). - The AAII is consistently positive across most quantiles, indicating a stable positive relationship with SMB returns across various market conditions. This might be due to individual investors' propensity to invest in small-cap stocks based on prevailing sentiment, a concept explored by Brown and Cliff (2004). - The VIX shows significance mainly at higher quantiles, implying its relevance increases during high SMB return periods. This could indicate that in times of high market volatility, investors' sentiment towards small-cap stocks becomes more pronounced, potentially due to perceived higher risk-reward scenarios during volatile periods.

4.2.4 HML

In the OLS regression, HML's relationship with sentiment measures is generally weak, except the VIX, which shows a significant positive impact, indicating higher HML spreads with increasing market volatility sentiment. This can be interpreted within the framework that value stocks might be more appealing or perceived as safer during times of increased market volatility, as investors might turn to value stocks as a defensive strategy against uncertainty.

Quantile regression reveals that the impact of sentiment on HML varies across different quantiles. At the lower quantiles, conservative investment sentiment (BW) has a notably negative impact, while at the higher from median, market volatility sentiment (VIX) is significantly positive. The results from the analysis, highlighting the nuanced impact of investor sentiment on the HML factor across different market conditions, can be seen as a confirmation and extension of the theories proposed by Loughran and Hough (2006) and Baker et al. (2011). Loughran and Hough (2006) delve into the performance of value versus growth stocks and argue that investor sentiment has a differential impact on these categories of stocks. Specifically, their work suggests that growth stocks, often characterized by higher volatility and speculative opportunities, tend to perform better in high sentiment periods, while value stocks perform relatively better when sentiment is low. Baker et al. (2011), on the other hand, discuss the predictive power of investor sentiment on future stock returns and emphasize how sentiment-driven trading can lead to significant deviations in stock prices from their fundamental values. The significant positive relationship between the VIX and HML spreads at higher quantiles can be seen as an empirical manifestation of their theory, particularly during turbulent market periods characterized by high volatility. This relationship underscores the idea that investor sentiment, especially fear or risk aversion as captured by the VIX, can amplify the value premium, as investors demand higher returns for holding riskier value stocks during uncertain times.

4.2.5 RMW

The sentiment measures in the OLS model do not show strong or consistent statistical significance, with coefficients being small and the majority not marked with significance stars, except for CMA showing highly significant negative values, indicating an inverse relationship with RMW at lagged periods. This inverse relationship hints at the possible perception among investors that conservative investment strategies may underperform in periods following high profitability.

The findings from the Quantile Regression analysis provide deeper insights, particularly highlighting the behavior of sentiment measures and market factors across different distribution points of stock returns. The significant negative coefficients for the intercept and RMW at lower quantiles suggest that in conditions of low profitability, there is a stronger inverse relationship with conservative investment strategies. This could reflect market conditions where investors are pessimistic or conservative, especially in scenarios of low profitability. As we observe shifts in sentiment impact across the quantiles, with BW and AAII showing positive effects at mid-quantiles that diminish at higher quantiles, it indicates a changing investor sentiment influence on stock returns from pessimistic to optimistic market conditions. The diminishing effect at higher quantiles could imply that the predictive power of these sentiment indicators weakens in extremely optimistic or bullish market conditions. Notably, the VIX consistent negative impact across most quantiles, particularly at the median, underscores its critical role as a predictor of stock returns. This aligns with existing literature that views VIX as a fear gauge, where higher volatility or fear levels are associated with lower stock returns. The significance of VIX across quantiles suggests that market volatility sentiment is a consistent predictor of stock returns, regardless of the market conditions reflected by the quantiles. These results, particularly the nuanced findings from quantile regression, resonate with theories and prior research mentioned in the previous section.

4.2.6 CMA

In the OLS regression for CMA, the sentiment measure BW significantly positively influences CMA, while VIX has a negative effect. This aligns with established financial theories and previous empirical findings, see Baker and Wurgler (2006, 2007)

The quantile regression findings further illuminate the complex dynamics between sentiment measures and CMA across the distribution. The consistency of BW as a positive predictor across several quantiles, especially around the median, underscores the nuanced influence of investor sentiment on investment strategies. This could imply that median levels of conservative versus aggressive investment strategies are particularly sensitive to overall market sentiment. Conversely, the consistent negative impact of VIX across most quantiles highlights the pervasive influence of market volatility on investment strategy preferences. This suggests that as market uncertainty increases, as indicated by higher VIX levels, there is a systematic shift towards more conservative investment strategies across the spectrum of CMA.

4.2.7 CC in the returns model

For CC the coefficient, the BW index has a positive and highly significant coefficient, indicating a strong positive relationship with CC. This relationship shows that optimism in the survey index is consistent with the movement of the market index. The mixed results from lagged variables, particularly the significance of the first lag and the third lag suggest complex feedback loops between market outcomes and consumer confidence. This is in line with the adaptive market hypothesis, which considers how investors learn and adapt based on past market performance and external economic indicators. The significance of lagged effects highlights the temporal dynamics in the sentiment-CC relationship, indicating that recent sentiment changes can have a more immediate impact on consumer confidence.

The quantile regression provides a more nuanced view by examining different points of the conditional distribution of the dependent variable. Conditional Effects at Different Market States, i.e. that the impact of returns and other sentiment measures varies across different states of the CC distribution. This finding underscores the conditional nature of sentiment effects on market indicators, suggesting that certain sentiment measures may only influence consumer confidence under specific market conditions. For example, the significant positive effect of returns at lower quantiles implies that in periods of general market pessimism or lower consumer confidence, returns might play a more critical role in shaping future consumer sentiment. From the sentiment measures, there are varying levels of significance for the BW and the VIX across quantiles. The BW index has a significant positive coefficient at the median and higher quantiles, while the AAII shows significance at some lower quantiles but not consistently across the spectrum. Further, it demonstrates the heterogeneity in how different facets of investor sentiment interact with consumer confidence. This is particularly relevant for understanding how general market sentiment versus specific market volatility indicators contribute to shaping overall economic outlooks as reflected in consumer confidence levels.

4.2.8 BW in the returns model

The OLS regression results for the BW index show the lack of significance for returns suggesting that they may not be a reliable predictor for changes in investor sentiment as measured by BW in this context. However, the significant relationship of the SMB and AAII with BW underscores the relevance of size premium and individual investor sentiment in explaining variations in the BW index. This aligns with Baker and Wurgler's (2006) seminal work on investor sentiment, which illustrates the impact of sentiment on market outcomes, suggesting that factors such as size and investor optimism can significantly influence sentiment. The significance of lagged BW variables indicates potential autocorrelation, implying that past sentiment levels influence current sentiment. This reflects the persistence of sentiment effects in financial markets, a phenomenon explored in the literature on the dynamics of investor sentiment (Antweiler and Frank, 2004; Tetlock, 2007).

Quantile regression results offer a nuanced view, revealing the negative Impact of CC at lower quantiles. The significant negative relationship of the CC at lower quantiles suggests that decreases in consumer confidence have a more pronounced negative effect on investor sentiment in periods of pessimism or market downturns. This is consistent with the behavioral finance theory that negative economic outlooks can disproportionately affect investor sentiment (Lemmon and Portniaguina, 2006). The stable negative relationship of returns across several quantiles (0.2, 0.3, 0.5, 0.6) suggests that returns may have a uniformly negative impact on sentiment across a broad spectrum of market conditions. This could indicate that investors interpret abnormal returns as signs of market overextension or potential reversals, affecting sentiment accordingly. The positive impact of RMW and VIX at the median underscores the complexity of sentiment drivers, indicating that both profitability factors and market volatility can positively influence investor sentiment in median market conditions. This could be interpreted within the framework of risk-return trade-offs, where investors may view higher profitability and volatility as opportunities for higher returns, boosting sentiment (Fama and French, 2015).

4.2.9 AAII in the returns model

In the OLS regression, the significant predictors, including the first lag of AAII and the BW variable, suggest a reliance on past sentiment levels and broader market sentiment as captured by Baker and Wurgler's index for explaining current sentiment shifts. This could reflect the persistent nature of sentiment and its influence by historical trends and general market conditions, consistent with the literature on investor behavior and sentiment analysis.

The quantile regression's findings provide a more gratified view, revealing how different factors become relevant at various points in the AAII distribution. The significance of different variables across quantiles—from the 10th percentile highlighting returns, SMB, and BW, to the median where HML, RMW, CMA, CC, and VIX become significant—illustrates the conditional nature of sentiment drivers. This variation suggests that investor sentiment, as measured by AAII, is influenced by a complex interplay of market returns, size, value, profitability, investment, consumer confidence, and market volatility factors, depending on the sentiment level. The presence of significant variables across the spectrum, especially in lower and median quantiles, underscores the multifaceted influences on investor sentiment. At lower sentiment levels, immediate market returns and size factors seem more influential, possibly reflecting reactive sentiment to recent market performance and preference for small-cap stocks. At the median, the broader range of significant predictors suggests a more balanced sentiment influenced by a comprehensive set of market conditions, including value, profitability, and market volatility.

4.2.10 VIX in the returns model

The OLS regression analysis, showing that market factors such as Mkt, HML, and CMA significantly explain the Volatility Index, underscores the intricate relationship between market conditions and volatility. The significant coefficients for these variables align with the foundational financial theories that posit a direct link between market performance, value factors, and overall market volatility. For example, the negative market beta might indicate that as market returns decrease, VIX increases, a relationship that is well-documented in financial literature (French et al. 1987). The significance of the lagged VIX variables indicates the autocorrelation present in market volatility, suggesting that past volatility is a strong predictor of future volatility. This finding is consistent with the volatility clustering phenomenon described by Engle (1982) in the Autoregressive Conditional Heteroskedasticity (ARCH) model, where volatility tends to cluster in periods, leading to persistent effects over time. Moreover, CC negatively affects VIX, which means that positive sentiment can cause less uncertainty in the market.

Quantile regression's nuanced view, showing variable significance and signs across quantiles, reflects the non-linear and conditional nature of the relationship between market variables and volatility. The positive significance of returns and Mkt at lower quantiles and their negative significance at higher quantiles suggest that the impact of market returns on volatility differs across the volatility distribution. This could be interpreted through the lens of the leverage effect, where negative market returns increase future volatility more than positive returns decrease it (Black, 1976). The reversal in the direction of the relationship between market variables and the VIX across different quantiles of the VIX distribution also highlights the complex dynamics that govern market volatility. This finding supports the conditional heteroskedastic models, which suggest that volatility is influenced by a range of market conditions and can behave differently under varying economic scenarios (Bollerslev, 1986). VIX is the only measure that is fully not affected by other sentiment measures in quantile regression.

4.2.11 Volume

Dep	VOL	Turnover	Dol Vol	Cap	Dividend	Growth	Earnings	CC	BW	AAII	VIX
R2	0.09	0.03	0.10	0.20	0.26	0.08	0.25	0.0725	0.07	0.06	0.10
Intercept	1.32	0.02*	4.34	0.01***	0.04***	-0.00	0.01***	-0.00	0.00	0.00	-0.0000
VOL		-0.03*	>10	>10***	0.06***	0.04***	0.02***	<-10	<-10	>10	>10***
Turnover	-1.30		1.51	-0.00	0.00	-0.01***	-0.00	<-10	<-10	<-10	<-10*
Dol Vol	-1.37	-0.03*		>10***	0.06***	0.04***	0.02***	>10	>10	<-10	<-10
Cap	>10	-0.01	>10		0.01***	0.01***	-0.00	>10	>10	<-10	>10
Dividend	>10	-0.01	>10	0.02***		-0.01	-0.01	>10	<-10	<-10	<-10*
Growth	2.84	-0.00	>10***	-0.01	-0.00		-0.00	>10	>10	>10	>10
Earnings	3.99	0.00	>10	-0.00	-0.00	-0.00		>10	>10	<-10	>10
CC	>10	0.00	>10	-0.00	0.00	-0.00	0.01		-0.00	-0.00	-0.00
BW	>10***	0.00	>10***	-0.01***	0.00	-0.00	0.00	0.00***		0.00*	0.00
AAII	0.27	0.00	-0.52	0.00	-0.00	-0.00	0.00	-0.00***	0.00***		-0.00***
VIX	>10	0.00	>10*	-0.01***	0.00	-0.00	0.01***	0.00	0.00***	-0.00***	
Lag1	>10	0.05*	>10	0.02***	0.04***	0.01	-0.00	>10	>10	<-10	>10
Lag2	>10	-0.03	>10	-0.00	-0.01	-0.01	-0.00	<-10	>10	>10	<-10
Lag3	3.96	-0.00	1.15	0.01	0.03***	-0.02	-0.00	<-10	>10	<-10	>10*

Table 4: Fama-MacBeth Regression Analysis: Impact of Sentiment Indicators on Volume

4.2.12 Volume

The analysis of trading volume through the OLS regression offers significant insights into the dynamics of financial markets, in line with theoretical expectations and previous empirical findings. The theory suggests that volume is influenced by the liquidity of the market, information asymmetry among traders, and transaction costs (O'Hara, 1995). The significant predictors in the OLS model, such as market cap (indicative of size and liquidity) and dividend yield (potentially reflecting information asymmetry on future earnings), align with the theory's predictions. The negative coefficient for the BW index might reflect the role of investor sentiment in volume, where a higher sentiment divergence could lead to increased trading as investors act on their diverse beliefs about future performance (Karpoff, 1987).

Quantile regression's ability to uncover different relationships at various points in the VOL distribution provides a more nuanced understanding of how trading volume is influenced by market conditions. The variation in the influence of market cap across quantiles, from negative in the median to positive in the upper quantile, could reflect the liquidity preference in trading, where larger firms tend to have more stable trading patterns but might see surges in volume due to specific market events or news releases. The significant negative influence of dividend yield in the OLS model and its variation across quantiles in the quantile regression might be interpreted through the lens of the dividend signaling theory, where changes in dividend yields could signal future profitability or firm health, impacting trading volume as investors react to these signals (Bhattacharya, 1979). The significant negative influence of BW on trading volume could indicate that extreme sentiment might lead to a reduction in trading volume, possibly due to market consensus or periods of market uncertainty when investors prefer to hold rather than trade. This finding contributes to the literature on the impact of investor sentiment on market dynamics, highlighting the complex role sentiment plays in trading behavior.

4.2.13 Turnover

The negative relationship between VOL and Dollar volume with Turnover observed in the OLS results aligns with theoretical expectations about market liquidity. Higher volume and dollar volume typically indicate higher liquidity, potentially leading to lower turnover rates as securities are more easily traded without significant price impacts (Amihud and Mendelson, 1986). The positive coefficient for Turnover lag 1 underscores the persistence in trading activity, suggesting that past turnover can be a predictor of future turnover, a concept explored in the literature on market microstructure and liquidity (O'Hara, 1995). The quantile regression analysis reveals that the impact of market factors like VOL, Dollar volume, market cap, dividend yield, and growth rate on Turnover varies significantly across the distribution. This variation could reflect different trading behaviors under varying market conditions, such as investors reacting more strongly to these factors during periods of lower liquidity or heightened market uncertainty. The stronger negative relationship at lower quantiles suggests that in periods of low turnover, factors like volume and dollar volume have a more pronounced negative impact, possibly due to the increased importance of liquidity in these conditions.

4.2.14 Dollar Volume

The negative significance of market capitalization in the OLS regression is consistent with the notion that larger firms, despite their size, may not always see proportionately higher trading volumes, possibly due to their stability and lower relative news flow compared to smaller firms. This aligns with theories suggesting that smaller firms are subject to higher informational asymmetries, leading to more trading as information gets incorporated into prices (Kyle, 1985). The positive significance of dividend yield and BW's sentiment index indicates that higher dividend yields and positive investor sentiment can drive trading volume. This could be interpreted through the dividend signaling theory, where higher dividends may signal firm strength, attracting more trading (Bhattacharya, 1979), and the role of investor sentiment in driving market participation (Baker and Wurgler, 2006). The negative coefficient for VIX, representing market volatility, suggests that higher volatility may deter trading to some extent, possibly due to increased uncertainty or risk aversion among investors. This is in line with the mixture of distributions hypothesis, which posits that volatility and volume are jointly determined by the flow of information (Clark, 1973).

Quantile regression's variability across different quantiles highlights the conditional nature of the relationships between market variables and dollar volume. For instance, the larger positive coefficients for VOL and dividend yield at the lower quantile contrast with their diminished or reversed effects at higher quantiles, suggesting that factors driving trading activity vary in different market conditions or segments of trading activity.

4.2.15 Market Cap

The significant coefficients for dividend yield and growth rate in the OLS regression, particularly the strong negative relationship of the growth rate with Market Cap, resonate with the lifecycle theory of firms. This theory posits that firms' growth opportunities and dividend policies are closely related to their lifecycle stage, where mature firms tend to pay higher dividends and have lower growth rates (DeAngelo, DeAngelo, and Stulz, 2006). The significant impact of VIX underscores the sensitivity of Market Cap to market volatility. This aligns with the risk-return trade-off inherent in financial markets, where higher market volatility is often associated with higher required returns by investors, potentially affecting firm valuations negatively (Black, 1972; Merton, 1973).

Quantile regression's varying relationships across different levels of Market Cap reveal the heterogeneous impact of financial and economic variables on firms of different sizes. For instance, the consistent significance of VOL and Turnover across several quantiles suggests that trading activity and liquidity are crucial determinants of Market Cap across firms of various sizes. The more pronounced impact of lagged Market Cap variables at higher quantiles could indicate that larger firms' size is more persistently influenced by their historical sizes, possibly due to the compounding effects of their market presence and operational scale.

4.2.16 Dividend Yield

The significant estimators identified in the OLS regression, such as market capitalization market cap and past dividend yields, support the dividend signaling theory. This theory posits that dividends convey information about a firm's prospects and profitability (Bhattacharya, 1979; Miller and Rock, 1985). The positive relationship between past dividend yields and the current dividend yield change suggests that firms maintaining or increasing dividends signal confidence in their future earnings. The significance of volume and dollar volume in affecting dividend yield changes underscores the impact of trading activity and liquidity on dividend policy. High trading activity may reflect investor sentiment and market conditions, influencing firms' decisions on dividend payouts (Amihud and Li, 2006).

Quantile regression provides a deeper understanding by highlighting how the influence of these variables varies across the distribution of dividend yields. In lower quantiles, the stronger influence of variables like VOL and market cap suggests that in firms with lower dividend yields, external market factors and firm size play a more significant role in determining dividend changes. This could reflect liquidity constraints or different payout policies among smaller firms or firms in specific market conditions. Moving to higher quantiles, the change in significance and influence of variables indicates that for firms with higher dividend yields, internal factors or past dividend policies (as indicated by the significance of lagged dividend yields) may have a more substantial impact on dividend yield changes.

4.2.17 Growth Rate

The positive significance of trading volume and dollar volume in relation to the growth rate in the OLS model is in line with the liquidity-preference theory, suggesting that higher trading activity is often associated with higher growth expectations by investors (Amihud and Mendelson, 1986). This could be because firms with higher trading activity are more visible and potentially more attractive to investors seeking growth opportunities. The positive association between market capitalization and growth rate suggests that larger firms, contrary to some growth constraint theories, still present substantial growth opportunities, possibly due to their ability to exploit economies of scale and market dominance (Penrose, 1959). This finding could also reflect the market's perception of stability and lower risk associated with larger firms, translating into higher expected growth rates. The negative significance of turnover with growth rate hints at a potential liquidity-overhang issue where higher turnover might indicate speculative trading rather than investment in growth opportunities, possibly leading to lower growth rates (Shleifer and Vishny, 1997).

Quantile regression provides deeper insights into the growth dynamics of firms under varying market conditions. In lower quantiles, the diminished significance of variables like dollar volume and VOL suggests that for firms experiencing lower growth rates, external market activities such as trading volume may have less influence on their growth potential, possibly overshadowed by internal or sector-specific challenges. In median quantiles, the emergence of earnings yield as a significant predictor at the median suggests that profitability metrics become more relevant for firms with moderate growth rates, aligning with fundamental analysis principles that link firm profitability directly with growth potential (Graham and Dodd, 1934). The regained significance of VOL and dollar volume at higher quantiles, albeit with smaller coefficients, could indicate that market activities and liquidity return as important factors for firms with higher growth rates, potentially due to increased investor interest and speculation in high-growth firms.

4.2.18 Earning Rate

The significant impact of VOL, dollar volume, and turnover on earnings yield can be interpreted through the lens of liquidity and market activity's effect on firm valuation. Higher trading volume and turnover are often associated with increased investor attention and potentially higher demand for a firm's shares, which can influence its earnings yield. This relationship underscores the liquidity-preference theory, suggesting that securities with higher liquidity command a premium (Amihud and Mendelson, 1986). The significance of the first lag across OLS and quantile regressions reflects the information effect, where past earnings yield data provide relevant information that influences future yields. This is consistent with the efficient market hypothesis, suggesting that all available information is reflected in stock prices and yields (Fama, 1970).

Quantile regression reveals the conditional nature of these relationships across the distribution of earnings yield, showing how the impact of market activity and firm characteristics varies at different points of the yield distribution. The negative coefficients for variables like VOL at lower quantiles may indicate that in environments of low earnings yield, higher market activity could be associated with negative pressures on yield, possibly due to speculative trading. At higher quantiles, the changing sign or reduced negativity of coefficients for variables such as VOL suggests a different market dynamic, where higher volume may coincide with positive developments or optimistic investor sentiment influencing earnings yield positively.

4.2.19 CC by VOL

The significant impact of investor sentiment indices (BW and AAII) on consumer sentiment underscores the interconnectedness between market sentiment and broader economic expectations. This relationship is well-documented in financial literature, with Baker and Wurgler (2006) demonstrating how investor sentiment can significantly affect asset prices and market dynamics. Their work suggests that shifts in investor sentiment, whether optimistic or pessimistic, can influence consumer confidence through its effects on market conditions and economic outlooks. The significant negative coefficients for lagged consumer sentiment suggest that past sentiment levels can influence future changes. This finding echoes the concept of sentiment momentum or persistence, where previous sentiment states, whether positive or negative, can have a lasting impact on future sentiment levels. This concept of sentiment persistence aligns with the broader literature on behavioral finance, which examines how psychological factors and heuristic biases influence financial markets and economic indicators.

The quantile regression analysis offers a granular view of how the relationship between market variables and consumer sentiment varies across different sentiment levels. The significance of variables like turnover and market cap at lower quantiles, and dividend yield at median quantiles, suggests that these factors may have differential impacts on consumer sentiment depending on the prevailing economic and market conditions. This nuanced understanding is critical for financial analysts and policymakers who seek to gauge the economic outlook based on prevailing market conditions.

4.2.20 BW by VOL

The significance of lagged BW index variables in the OLS model underscores sentiment's persistent influence over time, a phenomenon Baker and Wurgler (2007) extensively document. Their research demonstrates how investor sentiment, once established, can have a lasting impact on asset prices and trading volumes, affecting market dynamics over subsequent periods. This persistence highlights the importance of historical sentiment in shaping current market conditions, reflecting the psychological and behavioral underpinnings of financial markets.

The nuanced dynamics revealed by quantile regression, particularly at extreme quantiles, highlight the non-linear relationship between sentiment and market variables. This is consistent with findings from Ljungqvist, Nanda, and Singh (2006), who explore how investor sentiment can disproportionately affect market outcomes under different sentiment states. Such non-linear effects emphasize that the impact of sentiment on market variables can vary significantly across different market conditions, with sentiment having a more pronounced impact during periods of high uncertainty or extreme market states.

4.2.21 AAII by Turnover

The significant but divergent effects of VOL and turnover on AAII sentiment highlight the complex relationship between market activity and investor sentiment. The positive impact of volume could be interpreted as increased market activity bolstering investor optimism, while the negative impact of turnover might reflect higher trading activity associated with market uncertainty or profit-taking, which could dampen sentiment.

The application of quantile regression allows for a deeper examination of how the influence of market variables on investor sentiment varies across different sentiment levels. The variable effects' fluctuation across quantiles, especially noted in the upper quantiles for VOL and turnover suggests that the impact of these market variables on investor sentiment is conditional upon the prevailing sentiment levels. This is particularly important for understanding the dynamics of investor sentiment during extreme market conditions, whether overly optimistic or pessimistic.

4.2.22 VIX by VOL

The positive association between trading volume and VIX reflects the widely acknowledged relationship between trading activity and market volatility. Higher trading volumes are often indicative of heightened market activity which can lead to increased volatility, a relationship supported by the mixture of distributions hypothesis (Clark, 1973) and the sequential arrival of information hypothesis (Copeland, 1976). The negative coefficient for Turnover might suggest that in certain contexts, higher turnover rates, representing the ratio of trading volume to the number of outstanding shares, could be associated with decreased volatility. This could be interpreted through the lens of liquidity provision and market depth, where higher turnover signifies more robust trading activity, potentially stabilizing prices and reducing volatility.

The variability in the impact of predictors across different quantiles observed in the quantile regression results underscores the conditional nature of these relationships. Specifically, the changing influence of VOL and Turnover across volatility levels suggests that at lower levels of volatility, trading activity might play a different role compared to periods of high volatility, possibly due to differing investor reactions and market conditions. The conditional impact of market variables on volatility, as revealed by quantile regression, aligns with theories suggesting that market responses to information and trading activity are not linear and can vary significantly under different conditions (Engle, 1982; Bollerslev, 1986).

4.3 Forecasting

Table 5: Diebold-Mariano Test Results for Forecast Models Incorporating Sentiment Measures

Variable	DM stat
ab_returns	1.0614
Mkt	1.5399
HML	2.5499 ***
SMB	8.1859 ***
RMW	4.8851 ***
CMA	0.8835
Turnover	5.9110 ***
VOL	2.5100 ***
Dollar volume	2.5094 ***
dividend yield	3.3917 ***
market cap	1.2090
earnings yield	0.5046
growth rate	6.3030 ***

The OLS results, marked by significant DM stats for variables like RMW, HML, SMB, Turnover, VOL, and Dollar Volume, underscore the multifaceted impact of these factors on the financial markets.

Returns and market returns: DM for these variables is insignificant, which means that the returns itself are not better predicted when the sentiment is included in the model.

RMW and SMB: High DM statistics with significant levels (*** for RMW and SMB) suggest that the model's forecasts for these Fama-French factors are substantially different from, and presumably more accurate than, those of a naïve benchmark model. This aligns with Fama and French (2015), where these factors are critical in explaining stock returns and can be significantly influenced by investor sentiment.

Turnover, VOL, and Dollar Volume: These variables show high DM statistics with significance, indicating the model's effectiveness in forecasting market liquidity and trading activity. Prior research has highlighted the importance of these factors in reflecting market sentiment and investor behavior (Lee and Swaminathan, 2000), suggesting that our model captures essential aspects of market dynamics influenced by investor sentiment.

Dividend Yield and Growth Rate: The positive DM statistics for dividend yield and growth rate indicate that the model can effectively predict growth rate dynamics, possibly capturing the optimistic sentiment about future corporate earnings and the company growth.

Market Cap and Earnings Yield: These variables show non-significant and negative DM statistics, respectively, indicating that the model's performance in forecasting these factors is not significantly better than the benchmark. This could be due to the inherent stability of larger firms (market cap) or the nuanced relationship between earnings yield and market conditions.

Overall, these results emphasize the importance and impact of investor sentiment on market dynamics, however, not on the results itself.

Test results across various quantiles offer an intricate view of the forecasting accuracy of our model in relation to market and investor sentiment variables:

Table 6: Diebold-Mariano Test Results for Forecast Models Incorporating Sentiment Measures by Quantiles

Quantile	Returns	Market	SMB	HML	VOL	Turnover
0.1	0.34	1.02	0.88	1.45	1.84*	1.22
0.2	1.48	0.96	0.87	1.40	1.21	1.38
0.3	0.74	0.89	0.86	1.33	0.84	2.49**
0.4	-0.11	0.80	0.83	1.22	1.70*	1.99**
0.5	-0.17	0.51	0.55	0.42	2.43**	2.58**
0.6	0.70	0.83	1.26	1.14	1.52	0.47
0.7	0.92	0.87	1.33	1.13	1.51	0.84
0.8	0.84	0.91	1.34	1.12	0.80	0.61
0.9	1.18	0.95	1.34	1.12	0.54	0.08

Higher Significance in Lower Quantiles (0.1 to 0.3): Variables like VOL, Dollar Volume, and Dividend Yield showing significance (*) and (**) at lower quantiles suggest that our model is particularly adept at forecasting market dynamics under conditions of pessimism. This could reflect the model's sensitivity to early indicators of market downturns or stress, capturing the preemptive adjustments by investors.

Broad Significance Across Mid to Higher Quantiles (0.4 to 0.9): The spread of significance across these quantiles for variables like Market Cap, Growth Rate, and Earnings Yield, with many reaching (***) levels, indicates a strong forecasting performance in varied market conditions, from neutral to highly optimistic. This performance aligns with theories suggesting that market cap and growth prospects are critical in periods of market recovery and optimism, influencing investor sentiment and trading volume.

Notable Results for Turnover and VOL: The consistent significance of Turnover and VOL across multiple quantiles highlights their role as key indicators of market sentiment. This supports previous research indicating that trading volume can serve as a proxy for investor sentiment, with increased trading activity often reflecting heightened market interest or speculative trading.

Moreover, the quantile-specific results enhance understanding of sentiment's varying impact across different market states, emphasizing the conditional nature of sentiment's influence on financial markets. This nuanced approach offers a deeper insight into the complexities of market behavior, echoing the multifaceted analysis proposed by Fama and French (2015) in their five-factor model, which accounts for different dimensions of stock returns, including market conditions influenced by investor sentiment.

5 Conclusion

The research culminates in several pivotal findings that augment our comprehension of the dynamics governing financial markets. Through rigorous analysis utilizing Fama-MacBeth and quantile regression methodologies, this study illuminates the multifaceted impact of investor sentiment on stock returns and trading volume, offering a nuanced perspective on market behavior.

Firstly, it reveals that for both, returns and volume, using all sentiment measures the explainability of the model increases. The relationship is more nuanced in quantile regressions. The extent of improvement varies across different variables and quantiles. For example, substantial improvements in AIC for Market returns and SMB across lower quantiles highlight the particular relevance of sentiment in forecasting market conditions during periods of heightened uncertainty or market stress.

Secondly, the investigation confirms the predictive capacity of investor sentiment indicators on market returns and volumes, underscoring sentiment's vital role in financial market dynamics. Notably, different sentiment measures—including the VIX, Consumer Confidence (CC), and the Baker-Wurgler Index (BW)—exhibit diverse effects on market outcomes. For example, returns cannot be predicted better by sentiments while volume can be using three chosen metrics.

Thirdly, the study's findings highlight the conditional influence of sentiment across market conditions. The application of quantile regression reveals that the impact of sentiment on market variables varies significantly across the distribution of returns and volumes. This evidential variance underscores the complexity of sentiment's role, demonstrating its non-linear and state-dependent effects on financial markets.

Moreover, the research delineates the differential impact of investor sentiment across various financial metrics, such as SMB, HML, RMW, and CMA factors, each responding distinctively to sentiment indicators. These results enrich the theoretical discourse on market efficiency and behavioral finance, illustrating how sentiment-driven anomalies can emerge and persist in financial markets.

Importantly, the study's empirical insights provide a foundation for practical applications in portfolio management and investment strategy. By elucidating the nuanced relationship between sentiment and market outcomes, investors and financial analysts can better anticipate market movements and adjust strategies accordingly to mitigate risks and enhance returns.

In conclusion, this study substantiates the significant and complex role of investor sentiment in explaining and forecasting market anomalies. Its findings not only contribute to the academic literature in behavioral finance but also offer valuable guidance for market practitioners. Future research may further explore the mechanisms underlying sentiment's impact on financial markets, potentially uncovering novel strategies for navigating the ever-evolving landscape of investment and risk management.

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University of Warsaw
Faculty of Economic Sciences
44/50 Długa St.
00-241 Warsaw
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