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DISSERTATION

MEASURING SENTIMENT: THE IMPACT ON FINANCIAL MARKETS VOLATILITY

CAROLINA E SILVA CORREIA DE CARVALHO

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SUPERVISION:

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GLOSSARY

ADF - Augmented Dickey-Fuller.

FRED - Federal Reserve Economic Data.

GER – Germany.

IPO – Initial Public Offering.

OLS – Ordinary Least Squares.

UK – United Kingdom.

USA– United States of America.

ABSTRACT, KEYWORDS AND *JEL* CODES

ABSTRACT: This dissertation provides insights into the impact of sentiment factors on stock market volatility using monthly panel data from Germany, the UK and the US from 2002-2022. The main objective is to understand how the consumer confidence index, the trading volume, the put/call ratio, and the number of IPOs - components of the sentiment index used in this research - affect the volatility of the DAX 40, FTSE 100, and S&P 500 indices, respectively. The results suggest that investor sentiment has impact on market volatility in all three indices. In particular, a higher consumer confidence index correlates with lower volatility, suggesting that positive sentiment stabilizes markets. Conversely, increased trading volume and a higher put/call ratio are associated with increased volatility, reflecting greater market activity and investor uncertainty. In addition, the number of IPOs serves as a sentiment gauge, with increased IPO activity corresponding to a more optimistic market outlook and contributing to lower volatility. Overall, the results underscore the importance of integrating sentiment measures into financial analysis and provide valuable insights for investors and policymakers seeking to understand and manage market fluctuations. This research contributes to the behavioural finance literature by elucidating the complex interplay between investor sentiment and stock market behaviour.

KEYWORDS: sentiment; volatility; stock market.

JEL CODES: G12; G14; G17; C58; E44.

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MEASURING SENTIMENT: THE IMPACT ON FINANCIAL MARKETS VOLATILITY

By Carolina Carvalho

This dissertation examines the impact of sentiment factors on stock market volatility using monthly panel data from Germany, the UK and the US from 2002 to 2022. The study examines how the consumer confidence index, the trading volume, the put/call ratio and the number of IPOs affect the volatility of the DAX 40, FTSE 100 and S&P 500 indices. The results show that higher consumer confidence reduces volatility, while higher trading volume and a higher put/call ratio are correlated with higher volatility. This research highlights the importance of sentiment measures in financial analysis, enhancing the understanding of market behaviour and volatility dynamics.

1. INTRODUCTION

The interaction between investor sentiment and financial market dynamics has received considerable attention in recent years. While traditional financial theories, such as Fama (1970)'s Efficient Market Hypothesis, emphasise that markets are rational and that fundamental analysis is the main driver of market behaviour, it has become increasingly clear that psychological factors play a crucial role in shaping investors' decisions. These factors often lead to market movements that cannot be fully explained by fundamentals alone. Although the relationship between behavioural economics, in particular sentiment measures, and their impact on market fluctuations is still relatively underexplored, there is growing recognition of its importance. In recent years, an increasing number of economists have begun to focus on this area, conducting studies that further support the link between investor sentiment and financial market volatility.

While numerous studies have examined the relationship between market sentiment and price changes, there is limited research focused on the effectiveness of different sentiment indicators in different market environments and countries. This dissertation aims to contribute to fill this gap by analysing how sentiment measures affect market volatility across countries and time periods, particularly during major crisis events such as the 2008 financial crisis and the COVID-19 pandemic.

Market volatility, defined as the extent to which asset prices fluctuate, is a crucial element of financial markets. It often indicates the level of uncertainty, risk and potential instability, making it an essential factor for investors, policymakers and financial analysts. The relationship between market volatility and investor sentiment is complex, as sentiment-driven decisions can lead to market inefficiencies. Episodes of extreme optimism or pessimism can trigger price bubbles, corrections or crashes (Baker & Wurgler, 2006). Understanding the influence of investor sentiment on volatility is essential for forecasting market trends, managing risk and creating more robust financial models.

Despite the increasing attention given to behavioural finance, many conventional models continue to emphasise rational market behaviour, often overlooking the influence of psychological factors on market outcomes. Research, including that of Baker and Wurgler (2007), has shown that changes in investor sentiment can lead to market irregularities, such as overvaluation during periods of heightened optimism and undervaluation during periods of fear. This highlights the need for more integrated models that combine fundamental analysis with sentiment indicators to gain a clearer understanding of market dynamics.

This work examines the correlation between investor sentiment and market volatility in three prominent indices: the S&P 500, the FTSE 100 and the DAX 40. These indices have been chosen for their importance in financial world, as they represent major economies such as the United States, the United Kingdom and Germany respectively. Each market has unique characteristics in terms of liquidity, market structure and investor demographics, providing a comprehensive view of how sentiment affects volatility in different economic contexts.

Investor sentiment can be measured in several ways, each providing different insights into market sentiment. The sentiment indicators include the Put-Call Ratio (PCR), the Consumer Confidence Index (CCI) and the trading volume. The PCR compares the volume of put options to the volume of call options, providing an indication of whether investors are predominantly bearish (buying puts) or bullish (buying calls). In contrast, the CCI measures household confidence in the general economic outlook and acts as a proxy for overall market sentiment. Finally, the trading volume is a direct indicator of market activity, with increased volume often signalling increased investor participation, whether driven by optimism or fear. When analysed together, these indicators provide a complete understanding of how sentiment affects market volatility.

This paper examines the impact of sentiment indicators on market volatility over a two-decade period, from January 2002 to December 2022. This period includes significant financial events, notably the 2008 global financial crisis and the COVID-19 pandemic in 2020, both of which had a profound impact on investor sentiment and market volatility. By analysing these critical periods, the research aims to improve understanding of how extreme market conditions affect the relationship between sentiment and volatility, providing insights relevant to both typical and crisis market environments.

In terms of methodology, the study uses an Ordinary Least Squares (OLS) regression model to assess the influence of sentiment on volatility. Before running the regressions, the data are tested for stationarity using the Augmented Dickey-Fuller (ADF) test. This step is crucial to ensure that the time series data are suitable for regression analysis and that the results are not biased by trends or seasonal effects (Wooldridge, 2003). For variables identified as non-stationary, such as the logarithm of trading volume, the number of IPOs and Consumer Confidence Index first differences are applied in the regression model to ensure accurate and reliable results. In addition, the research will include robustness checks to validate the consistency of the results across different model specifications, including different lag structures and changes in independent variables.

While the research focuses on three key indices, it recognises the limitations of its geographical focus. A broader analysis including additional countries, such as Portugal, could improve understanding of how investor sentiment influences market volatility in different economic and cultural environments. The inclusion of smaller markets or those with different market structures could allow future studies to determine whether the patterns identified are universal or confined to larger, more established markets. This broader scope would also facilitate comparisons between developed and emerging markets, providing broader insights into the role of sentiment within global financial systems.

The subsequent chapters of this thesis are structured to facilitate a comprehensive exploration of the topic. Chapter 2 provides a detailed literature review, summarising the existing research on investor sentiment and market volatility. Chapter

3 outlines the empirical framework, including the data sources and methodologies used in this study. Chapter 4 presents the analysis of the results, examining the relationships between sentiment indicators and stock market volatility in different contexts. Finally, Chapter 5 discusses the implications of the findings, outlining the main conclusions and suggesting avenues for future research.

Through this research, this thesis aims to deepen the understanding of how investor sentiment shapes financial markets and to contribute to the broader discourse of behavioural finance.

2. Literature Review

Investor sentiment is a psychological factor that influences decision-making and often causes market changes that aren't based purely on fundamental analysis. This literature review examines how sentiment in financial institutions is related to market volatility, discussing key findings and different perspectives.

In this context, Haritha and Rishad (2020) suggest that behavioural finance helps to explain the link between investments and investor psychology. They developed a sentiment index that includes variables such as trading volume, put-call ratio, advance-decline ratio, market turnover, stock turnover and number of IPOs to measure how investor sentiment affects market volatility and stock returns in India from January 2000 to December 2016. Their findings show that investor behaviour is reflected in stock prices, with market fluctuations driven by sentiment. For example, positive investor sentiment has a significant positive effect on excess market returns, leading to more speculative activity and potentially leading to the overvaluation of stocks, which in turn increases market volatility. Moreover, when negative sentiment dominates, investors tend to withdraw from the market due to their pessimistic expectations of future returns.

These conclusions are also supported by Chi et al. (2012), who conducted a study on the Chinese stock market from 2004 to 2009 and found that investor sentiment has a significant impact on stock returns. Their study also shows a statistically significant relationship between stock market volatility and investor sentiment.

Furthermore, Aggarwal (2022) attempted to define and measure investor sentiment to better understand its origins and role in stock market behaviour. After analysing 81 academic papers, the author showed that while behavioural approaches to sentiment have helped explain market mispricing, they still lack the necessary development. Furthermore, the paper highlights the need to incorporate sentiment as a systematic risk factor in asset pricing, as a major limitation in the development of this field has been the fragmented way in which sentiment is treated in decision-making under uncertainty.

In line with this view, Zhou (2018) conducted several surveys from April 2014 to September 2015 to measure investor sentiment, which the author believes is important for both theoretical asset pricing and practical investing. Although his results showed that investors' emotions fluctuate with asset prices, as well as asset values with their economic fundamentals, sentiment has a limited ability to predict overall stock market movements.

On the other hand, Ferreira et al. (2021), in their study on the impact of investor sentiment on Brazilian stock market volatility between 2000 and 2016, show that positive market sentiment is associated with lower volatility due to higher entry of noise traders during optimistic periods, which reduces market volatility. These authors support that "Behavioural Finance argues that investors are creatures of limited rationality who make judgments and decisions under the influence of emotional aspects (sentiments), using mental or heuristic shortcuts that lead to errors or systematic deviations".

Subsequently, in the framework developed by Rocciolo et al. (2019) between 2012 and 2016, optimism is shown to play a role in shaping agents' expectations of market risk premia. As expected, this optimism is influenced by political and socio-economic events. Furthermore, the authors mention that when agents are optimistic, they are more likely to invest in the stock market, leading to an increase in demand and a rise in prices. Conversely, when agents are pessimistic, they may avoid the market, leading to a decrease in demand and increased pressure on the supply side, potentially leading to a decrease in prices.

The effect of sentiment on market volatility may also be related to daily news, especially for more risk-averse investors. In this regard, Hsu et al. (2021), in their study on the impact of financial news on stock market volatility, find that the inclusion of news sentiment significantly improves the accuracy of volatility forecasts. Their results, covering the period between 2011 and 2016, also show that during periods of negative market shocks, the dissemination of information leads to irrational trading behaviour, causing significant price fluctuations.

Similarly, Deveikyte et al. (2022) examined the relationship between daily sentiment measures and market volatility and returns observed the following day by collecting 969.753 news headlines, 12.000 news articles and 545.979 tweets over different periods in 2019. Their results show a correlation between sentiment and stock market movements, with an increase in positive sentiment being associated with a decrease in market volatility.

Figà-Talamanca and Patacca (2022) analysed the daily closing prices of 150 components of the S&P 500 Index from January 2015 to July 2021, representing over 75% of the index's weight. Their research shows that investor sentiment can influence stock prices, potentially leading to bullish or bearish markets. They also found that measures of sentiment are positively associated with both the returns and volatility of most S&P 500 components.

In addition, Baker and Wurgler (2006) played a key role in highlighting the impact of investor sentiment on financial markets; their research covered the period from 1965 to 2005. They argued that market sentiment leads investors to be overly optimistic or pessimistic when speculating on prices, rather than focusing on fundamental factors. They also developed their index of investor sentiment, which combines data from six proxies. Their results show that high investor sentiment is a strong predictor of low returns, especially for speculative stocks.

Gong et al. (2022) later introduced the New Investor Sentiment Index (NISI), which was constructed by combining many indicators reflecting investor sentiment using partial least squares (PLS). Their model showed that from January 2005 to December 2015, investor sentiment significantly improved the accuracy of predicting stock realised volatility, especially in non-crisis periods.

Cevik et al. (2022) developed a model to analyse investor sentiment and stock market behaviour during the COVID-19 pandemic. Their results showed that positive sentiment not only reduces market volatility but also has a significant impact on G20 stock markets, an international forum of 19 major economies plus the European Union. Manda (2010) collected data from January 2005 to November 2009 and, in her earlier study of stock market volatility during the 2008 financial crisis, found that the volatility of S&P 500 returns was significantly higher during the crisis.

From a different perspective, Liu and Zhang (2015), in their study covering the period from January 1997 to December 2013, showed that increased economic policy uncertainty, rather than sentiment, leads to a significant increase in market volatility. Later, Li et al. (2022) confirmed this from January 1999 to December 2020, finding that economic policy uncertainty indicators provide more accurate forecasts for S&P 500 stocks than market sentiment indicators or financial stress indices in predicting factors affecting market volatility.

On the other hand, Wang et al. (2006) conducted a study that clarifies the relationship between returns, sentiment and realised volatility from 1 February 1990 to 31 December 2001. In particular, the results show that returns, but not sentiment, contain useful information for forecasting volatility. In other words, they did not observe a visible relationship between sentiment measures and realised volatility or returns as predicted by the theoretical literature. The author also cited that "sentiment indicators are driven by returns and that returns predict realised volatility".

Gabaix et al (2006) find similar results when analysing data from 1980 to 2001. The study suggests that institutional investors may have a significant impact on market volatility due to their large size and influence. It also suggests that larger institutional investors may have a greater impact on market volatility. These findings are further validated by Gupta (2018), who highlights that fund manager sentiment is a stronger predictor of volatility than past returns by analysing data from January 2000 to December 2016.

Subsequently, Jiang et al (2017) found a negative correlation between manager sentiment and stock returns, with high sentiment levels associated with lower future market returns. In addition, high manager sentiment may contribute to speculative overvaluation in the market. The author divides the time horizon into two phases, using data from January 2003 to December 2006 for the first estimation period and from January 2007 to December 2014 for the forecast evaluation period.

Audrino et al (2020), in their study focusing on 18 different US companies listed on the NYSE and covering a period from 2004 to 2018, concluded that sentiment and attention variables have predictive power for future volatility, even when controlling for a wide range of economic and financial factors. Specifically, they found that, on average, economic variables are effective in predicting volatility up to a two-week horizon, while sentiment and attention variables improve predictive accuracy for short-term forecasts, particularly one and two days ahead. According to Sias (1996), investors can have a significant impact on market volatility. The author collected data from January 1981 to December 1993 and the results presented show that during this period an increase in institutional holdings can lead to higher volatility in financial markets. In particular, Institutional investors often trade in larger volumes than individual investors, which can contribute to increased volatility. The author even suggests that institutional investors "destabilise" financial markets, so an increase in institutional holdings should lead to even greater volatility.

Building on these insights, the following chapter outlines the data and methodology used in this study, which aims to contribute to the existing literature by providing a comprehensive analysis of the relationship between investor sentiment and stock market volatility.

3. EMPIRICAL FRAMEWORK

3.1. Data

This study examines the relationship between market sentiment indicators and stock market volatility. The analysis is based on a dataset covering the period from January 2002 to December 2022, focusing on three major stock indices: the S&P 500 (United States), FTSE 100 (United Kingdom), and DAX 40 (Germany). The data consists of monthly observations, where each index represents a distinct economy and financial environment. The choice of these indices is motivated by their global importance, representing the financial centres of three major economies which play a key role in global capital flows and investor sentiment.

The dataset incorporates key economic and market activity indicators: Consumer Confidence Index (CCI), Put-Call Ratio (PCR), trading volume, and the number of

Initial Public Offerings (IPOs). The CCI, sourced from FRED, is a measure of household sentiment about future economic conditions. It is included as a proxy for general market sentiment, based on consumers' expectations about their financial situation, their position on the overall economic environment, perceptions of unemployment, and their ability to save (Gong et al., 2022).

The PCR, obtained from Bloomberg, captures investor sentiment by reflecting the balance between bearish (put options) and bullish (call options) market expectations. A high PCR indicates pessimism in the market, while a low PCR reflects optimism. Research by Brown and Cliff (2004), which covers the period from January 1990 to December 2001, has shown that the PCR is a reliable measure of investor expectations in the US stock market, as an increase in the ratio often leads to higher volatility in the S&P 500, in this case.

Trading volume, also sourced from Bloomberg, represents the overall level of market activity. Increased trading activity often signals higher market participation, which can lead to greater price fluctuations and, consequently, higher market volatility. In contrast, lower trading volumes may indicate reduced liquidity and more stable price movements. Baker and Stein (2004) argue that trading volume is a good proxy for investor sentiment in their study of the US stock market over a 41-year period starting in 1960.

The number of IPOs, sourced from the respective national stock exchanges (New York Stock Exchange for the S&P 500, London Stock Exchange for the FTSE 100, and Deutsche Börse for the DAX 40), can be interpreted as an indicator of market optimism. Companies are more likely to go public when market conditions are favourable, and fewer IPOs may indicate market uncertainty or some aversion to risk, which can increase volatility. Baker and Wurgler (2006) suggest that IPOs are a key measure of market sentiment, reflecting both investor confidence, i.e. bullish market sentiment. In this analysis, IPO data were originally available on an annual basis but were converted to monthly data, which presents some limitations due to the smoothing of data across time.

Table 1 - Descriptive Statistics Germany, 2002-2022.

Variable	Mean	Std. Error	Median	Std. Dev.	S²	Kurt.	Skew.	Min.	Max.	Obs	ADFstat
Volatility_GER	0.0695	0.0024	0.0590	0.0384	0.0015	6.1552	2.1435	0.0220	0.2727	252	-6.4821***
CCI_GER	-7.8563	0.4813	-5.7500	7.6403	58.3736	-0.6305	-0.6355	-29.4000	2.8000	252	14.1359***
PCR_GER	1.3930	0.0162	1.3770	0.2566	0.0658	-0.0071	0.2778	0.7924	2.1131	252	-3.4132**
No.IPOs_GER	0.7421	0.0375	0.5833	0.5954	0.3545	1.8137	1.4606	0.0833	2.5000	252	15.7490***
ln(Vol_GER)	9.3416	0.0082	9.3284	0.1298	0.0168	0.6275	0.5724	9.0128	9.8156	252	-3.2582**

Table 2 - Descriptive Statistics UK, 2002-2022.

Variable	Mean	Std. Error	Median	Std. Dev.	S²	Kurt.	Skew.	Min.	Max.	Obs	ADFstat
Volatility_UK	0.0552	0.0021	0.0471	0.0333	0.0011	10.5488	2.6664	0.0155	0.2642	252	-6.9084***
CCI_UK	-10.6857	0.5875	-7.3000	9.3263	86.9799	0.7042	-1.0828	-43.5000	3.6000	252	14.8940***
PCR_UK	1.5469	0.0209	1.5286	0.3323	0.1104	1.1461	0.7723	0.8901	2.8943	252	-5.9503***
No.IPOs_UK	10.8730	0.7164	7.0000	11.3724	129.3304	4.7628	2.0624	0.0000	62.0000	252	-4.4938***
ln(Vol_UK)	10.3318	0.0099	10.2918	0.1577	0.0249	-1.1373	0.3292	10.0030	10.6469	252	-5.6377***

Table 3 - Descriptive Statistics US, 2002-2022.

Variable	Mean	Std. Error	Median	Std. Dev.	S²	Kurt.	Skew.	Min.	Max.	Obs	ADFstat
Volatility_USA	0.0562	0.0024	0.0456	0.0387	0.0015	14.9717	3.1569	0.0141	0.3223	252	-6.9929***
CCI_USA	88.9938	0.8440	91.2400	13.3981	179.5097	-0.6746	-0.5263	53.7972	111.6830	252	13.8728***
PCR_USA	1.7352	0.0134	1.7502	0.2121	0.0450	0.4996	-0.0054	1.1001	2.4862	252	-4.5077***
No.IPOs_USA	21.3175	1.0252	18.0833	16.2743	264.8543	9.5586	3.0142	5.1667	86.2500	252	15.7480***
ln(Vol_USA)	10.8304	0.0118	10.8807	0.1873	0.0351	-0.0451	-0.8044	10.3885	11.2100	252	10.8224***

The descriptive statistics show that Germany's DAX 40 had an average monthly volatility of 6.95%, with moderate fluctuations (standard deviation of 3.84%). However, it experienced extreme volatility spikes, reflected in high kurtosis (6.15) and positive skewness (2.14), indicating frequent periods of high volatility, especially during crises.

In the UK, the FTSE 100 had a lower average volatility of 5.52%, but with even higher kurtosis (10.55) and skewness (2.66), signalling that extreme volatility events were more common. Volatility ranged from 0.0155 to 0.2642, showing sharp fluctuations during unstable periods.

The S&P 500 in the US had a similar average volatility of 5.62%, with a standard deviation of 3.54%. It had fewer extreme events (kurtosis of 3.16) compared to Germany and the UK, and its skewness (0.94) was lower, but it recorded the highest maximum volatility (0.3233), indicating severe spikes during major crises.

The correlation matrix for these variables can be found in the appendix, providing further insights into the relationships between volatility and other key factors.

3.2. Methodology

Regarding the methodology, this analysis employs a least squares regression model to investigate the impact of the independent variables mentioned above on the volatility of the S&P 500, FTSE 100, and DAX 40, respectively over the period from January 2002 to December 2022.

The dependent variable in this study is monthly market volatility**,** which was calculated using the standard deviation of daily percentage returns for each index. As outlined by Poon and Granger (2003), to compute volatility, the following steps were used:

A. Daily Percentage Returns:

Daily returns for each index were calculated as the percentage change in price from one trading day to the next. The formula used is:

$$R_t(\%) = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \times 100 \qquad (1)$$

Where R_t (%) is the daily percentage return on day *t*, P_t is the price of the index on day *t*, and P_{t-1} is the price of the index on the previous trading day.

B. Mean daily return (μ):

$$\mu = \frac{1}{N}\sum_{t=1}^{N} R_t \qquad (2)$$

Where N is the number of trading days in the month.

C. The standard deviation of percentage daily returns:

$$\sigma_{daily\ retuns} = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(R_t - \mu)^2} \qquad (3)$$

D. Monthly volatility:

By multiplying the standard deviation of daily returns by the square root of the number of trading days (n) in the month, monthly volatility is obtained:

$$Volatility = \sqrt{30} \times \sigma_{daily\ returns} \qquad (4)$$

Before the regression analysis, the ADF test was performed on the independent variables to assess their stationarity, as noted by Campbell and Perron (1991). The test showed that for the US and the UK, the CCI, the logarithm of the trading volume and the number of IPOs were non-stationary at their levels, i.e. their statistical properties varied over time. To correct this and to ensure the reliability of the regression results, the first differences of these variables were used in the regression model, as recommended by Stock and Watson (1988). However, for Germany, the logarithm of trading volume was stationary at its level, so it was included in its original form for that market. The PCR was also found to be stationary for all markets, allowing it to be included without any transformation. This approach ensures that only the relevant changes in these indicators are modelled for each country, reflecting the idea that changes in sentiment or market activity are often more impactful on volatility than their absolute levels.

The model for the S&P 500 and FTSE 100 takes the following form:

$$Volatility_t = \propto + \beta_1(\Delta CCI_t) + \beta_2(PCR_t) + \beta_3 \Delta \ln(Vol_t) + \beta_4(\Delta No.IPOs_t) + \varepsilon_t \qquad (5)$$

For the DAX 40, where the log of trading volume is stationary, the model is adjusted to:

$$Volatility_t = \propto + \beta_1(\Delta CCI_t) + \beta_2(PCR_t) + \beta_3 \ln(Vol_t) + \beta_4(\Delta No.IPOs_t) + \varepsilon_t \qquad (6)$$

In both models:

- $Volatility_t$ is the monthly market volatility,
- ΔCCI_t is the first difference in the Consumer Confidence Index,
- PCR_t is the Put-Call Ratio,
- $\Delta \ln(Vol_t)$ is the first difference in the logarithm of trading volume (for the US and UK), while $\ln(Vol_t)$ is used for Germany,
- $\Delta No.IPOs_t$ is the first difference in the number of IPOs, and
- ε_t is the error term.

The regression models were estimated using Ordinary Least Squares (OLS) due to its straightforward application in linear models and its capacity to provide efficient and unbiased parameter estimates, as suggested by Wooldridge (2003). Given the nature of financial time series data, it is important to ensure robustness. To test this, the baseline model was compared with a lagged model. The consistency of the coefficients in both models suggests that the relationships between volatility and the independent variables remain stable, confirming the robustness of the analysis.

Table 4 – Coefficient Comparison Between Baseline and Lagged Models.

	GER		UK		US	
Variable	Baseline Model	Lagged Model	Baseline Model	Lagged Model	Baseline Model	Lagged Model
Intercept	-0.7876	-0.4837	-0.0746	0.0584	0.1356	0.1057
ΔCCI	-0.0039	-0.0016	-0.0018	-0.0009	-0.1919	-0.0007
PCR	-0.0302	-0.0348	-0.126	-0.0022	-0.0461	-0.0287
ΔNo.IPOs	-0.0178	-0.0110	-0.0001	-0.0002	-0.0002	-0.0002
ln(Vol)/ Δln(Vol)	0.0962	0.064380	0.0747	0.0111	0.1437	0.0727

4. Analysis and Discussion of Results

The analysis and discussion of results section will be divided into two parts; the first one consists of a detailed analysis of the results by country and the second includes a comparison across the three countries analysed.

4.1. Impact of sentiment on index volatility

The regression results for Germany (DAX 40) show several key relationships between the independent variables and market volatility (Table 4).

Table 5 – OLS for the effects of sentiment in DAX 40

Variable	Coefficient	Std. Error	*t* statistic	P-value (significance)
Intercept	-0.7876	0.1613	-4.884	0.0000***
ΔCCI_GER	-0.0039	0.0011	-3.6491	0.0003***
PCR_GER	-0.0302	0.0085	-3.5586	0.0004***
ΔNo.IPOs_GER	-0.0178	0.0102	-1.7474	0.0818*
ln(Vol_GER)	0.0962	0.0169	5.6768	0.0000***
R- squared	0.250316	Mean dependent var		0.0699454
Adjusted R- squared	0.238126	S.D. dependent var		0.038480
S.E. of regression	0.033588	Akaike info criterion		-3.929592
Sum squared resid	0.277521	Schwarz criterion		-3.859364
Log likelihood	498.1639	Hannan-Quin criter.		-3.901331
F-statistic	20.53452	Durbin-Watson stat		0.612840
Prob(F-statistic)	0.000000			

Note: (a) *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

The PCR has a negative coefficient (-0.030194) and is statistically significant at a 1% level, with a t-statistic of -3.585596 and a p-value of 0.0004. This indicates that a higher PCR, which reflects more bearish sentiment in the market, tends to reduce volatility. A higher PCR is generally associated with rising investor fear and typically leads to increased volatility. This negative relationship suggests that investors might engage in more effective hedging strategies during bearish periods, thereby stabilizing the market. This finding aligns with studies by Baker and Wurgler (2007) who argue that investor sentiment plays a crucial role in stabilizing volatility, particularly when investors anticipate downturns.

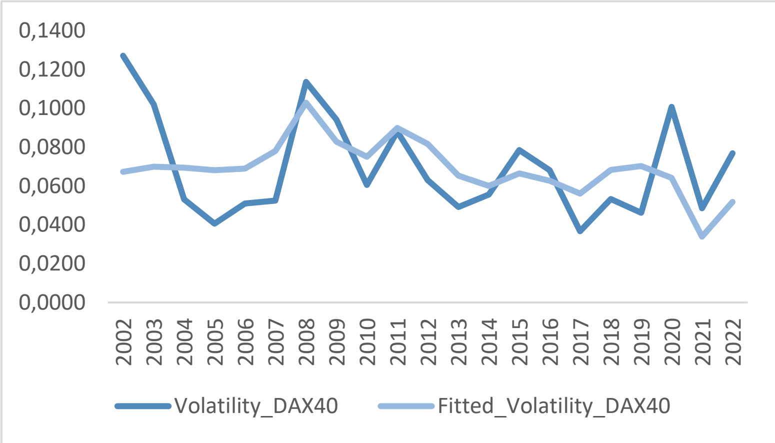
The relationship between trading volume and volatility in DAX 40 is positive, with a coefficient of 0.096229 and a highly significant t-statistic of 5.677675. This suggests that higher trading activity amplifies market volatility, a result consistent with traditional financial theory, where increased trading reflects heightened market uncertainty and leads to greater price fluctuations. Gabaix et al. (2006) and Manda (2010) highlight similar dynamics, noting that institutional trading volume contributes significantly to volatility, especially during periods of market stress.

The coefficient for changes in the number of IPOs is negative (-0.017854), with a marginal p-value of 0.0818. This suggests that an increase in IPO activity is associated with lower volatility. This result implies that increased IPOs may signal stronger market confidence, leading to a more stable market environment.

Lastly, the CCI has a significant negative coefficient, with a t-statistic of -3.649151 and a p-value of 0.0003. This indicates that higher consumer confidence is associated with lower market volatility in Germany, periods of increased confidence in economic growth and stability tend to reduce market uncertainty.

The overall fit of the model, with an R-squared of 0.250316, suggests that approximately 25% of the variation in German market volatility is explained by these variables.

Figure 1 - Actual vs. fitted volatility for the DAX 40.



The chart in Figure 1 compares actual and fitted volatility for the DAX 40, showing that the regression model captures overall trends well during stable periods (such as 2002–2007 and 2013–2017). This indicates that variables like the PCR, trading volume, number of IPOs, and the CCI effectively explain volatility in normal market conditions. However, during periods of intense market stress, for instance, the 2008 financial crisis and the 2020 COVID-19 pandemic, the model underestimates volatility, most probable because extreme market shocks are difficult to capture with standard regression models.

Table 6 - OLS for the effects of sentiment in FTSE 100.

Variable	Coefficient	Std. Error	*t* statistic	P-value (significance)
Intercept	-0.0746	0.0098	7.5561	0.0000***
ΔCCI_UK	-0.0018	0.0008	-2.2883	0.0003***
PCR_UK	-0.126	0.0062	-2.0218	0.0004***
ΔNo.IPOs_UK	-0.0001	0.0002	-0.7490	0.0818*
Δln(Vol_UK)	0.0747	0.0230	3.2485	0.0000***
R- squared	0.073719	Mean dependent var		0.055219
Adjusted R- squared	0.058658	S.D. dependent var		0.033329
S.E. of regression	0.032337	Akaike info criterion		-4.005520
Sum squared resid	0.257230	Schwarz criterion		-3.935291
Log likelihood	507.6927	Hannan-Quin criter.		-3.977258
F-statistic	4.894557	Durbin-Watson stat		0.606550
Prob(F-statistic)	0.000817			

Note: (a) *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

In the UK (FTSE 100), the PCR has a negative coefficient (-0.012642) and is statistically significant, with a t-statistic of -2.021818 and a p-value of 0.0443 (Table 6). Similar to Germany, this result suggests that as bearish sentiment increases, market volatility tends to decrease.

The trading volume variable shows a positive and statistically significant relationship with volatility in the FTSE 100, with a coefficient of 0.047790 and a t-statistic of 3.248503. This indicates that higher trading volumes lead to increased market volatility, a finding that mirrors the results for Germany.

In contrast, changes in the number of IPOs have an insignificant effect on volatility in the UK, as indicated by a p-value of 0.4546. This result suggests that IPO activity in the more mature markets does not significantly impact volatility. This is because the UK market, being mature and stable, can easily absorb new IPOs without significant fluctuations. In such large, liquid markets, IPOs represent a smaller share of activity, and well-established companies have a greater impact on overall volatility, reducing the influence of new listings.

The CCI has a significant negative effect on volatility, with a coefficient of -0.001830 and a p-value of 0.0230. This finding is in line with the results for Germany and supported by Haritha and Rishad (2020), who show that higher consumer confidence tends to reduce uncertainty, leading to more stable market conditions. As consumer confidence rises, markets generally expect improved economic performance, which reduces the likelihood of large price swings.

The R-squared for the UK model is relatively low at 0.073719, indicating that only about 7.37% of the variation in market volatility is explained by the model's independent variables. This suggests that other factors, potentially international economic events or for instance, Brexit, may play a significant role in driving volatility in the UK market.

Figure 2 - Actual vs. fitted volatility for the FTSE 100.

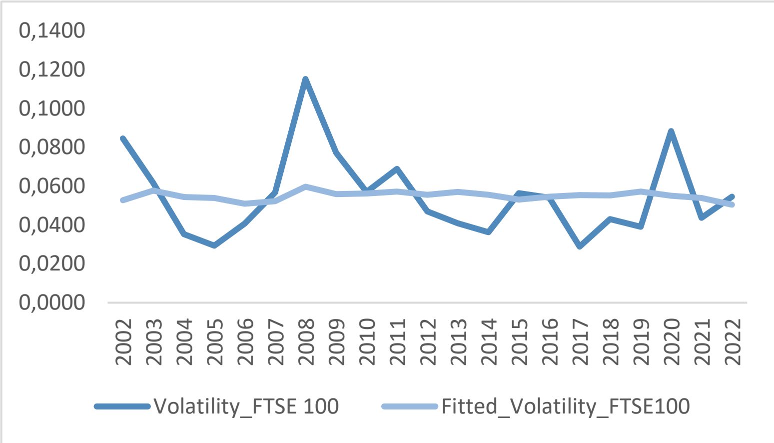


Figure 2 shows the comparison between actual and predicted volatility for the FTSE 100 from 2002 to 2022. The actual volatility shows significant variation, with pronounced peaks around 2008 and 2020, corresponding to periods of market distress similar to those experienced by the DAX 40. Conversely, the fitted volatility line shows a more consistent trajectory, suggesting that the model performs adequately during periods of stability, particularly between 2010 and 2017, when it closely tracks actual volatility values. However, it fails to accurately reflect the intensity of volatility spikes during crisis periods.

The model's tendency to underestimate these sharp volatility spikes becomes apparent during turbulent market conditions. This observation implies that while the model is successful in capturing overall trends, it does not fully capture the magnitude of extreme market events - an essential factor in assessing financial risk in times of crisis.

Table 7 - OLS for the effects of sentiment in S&P 500.

Variable	Coefficient	Std. Error	*t* statistic	P-value (significance)
Intercept	0.1356	0.0186	7.2658	0.0000***
ΔCCI_USA	-0.1919	0.0005	-3.9671	0.0001***
PCR_USA	-0.0461	0.0107	-4.3106	0.0000***
ΔNo.IPOs_USA	-0.0002	0.0004	-0.4890	0.6252
Δln(Vol_USA)	0.1437	0.0326	4.4036	0.0000***

R- squared	0.168934	Mean dependent var	0.056246
Adjusted R- squared	0.155420	S.D. dependent var	0.038738
S.E. of regression	0.035600	Akaike info criterion	-3.813200
Sum squared resid	0.311778	Schwarz criterion	-3.742972
Log likelihood	483.5566	Hannan-Quin criter.	-3.784938
F-statistic	12.50131	Durbin-Watson stat	0.732684
Prob(F-statistic)	0.000000		

Note: (a) *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Turning to the USA (S&P 500), the PCR has a significant negative relationship with volatility, with a coefficient of -0.046071 and a t-statistic of -4.310565 (Table 7). This finding indicates that the PCR is a strong predictor of reduced volatility in the US.

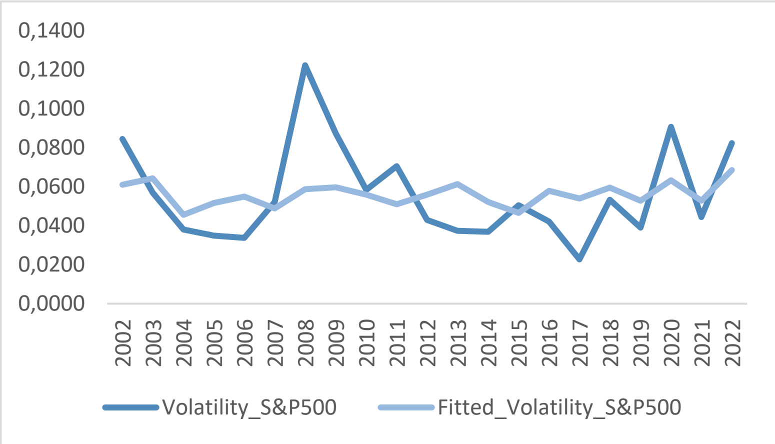
Trading volume has the largest positive effect on volatility in the US, with a coefficient of 0.143672 and a t-statistic of 4.430565, highlighting the importance of trading activity in driving market volatility. Higher trading volume often coincides with periods of uncertainty or significant market events, leading to greater volatility as prices adjust to new information.

Similar to the UK, changes in the number of IPOs do not have a significant impact on volatility, as evidenced by a p-value of 0.6252. This reflects the findings of Zhou (2018), who suggests that in highly liquid markets like the S&P 500, IPO activity does not significantly influence volatility, given the wide range of factors that affect such a large and diverse market.

The CCI is negatively and significantly related to volatility in the US, with a coefficient of -0.001911 and a t-statistic of -3.967068. In the same way, the results from the other two countries analysed also suggest that higher consumer confidence reduces market uncertainty and reduces volatility.

The R-squared for the US model is 0.168934, meaning that about 16.89% of the variation in volatility is explained by the variables that constitute the sentiment index.

Figure 3 - Actual vs. fitted volatility for the S&P 500.



The graph in Figure 3 compares the actual and fitted volatility of the S&P 500 from 2002 to 2022. The actual volatility shows significant spikes during major financial events, such as the 2008 financial crisis and the COVID-19 pandemic in 2020. The fitted volatility estimated by the model generally tracks the actual volatility but smooths out extreme spikes. During the 2008 crisis and the pandemic, the fitted volatility increases but underestimates the severity of the peaks observed in the actual data.

4.2. Comparison Across Countries

When comparing the results across Germany, the UK, and the US, several common patterns and notable differences emerge. In all three markets, the PCR has a significant negative relationship with volatility, which aligns with the findings of Baker and Wurgler (2007) and Cevik et al. (2022), who argue that bearish sentiment often leads to stabilizing market effects as investors hedge their positions. However, the strength of this relationship is notably stronger in the US, where the PCR has the largest impact on reducing volatility.

Trading volume consistently shows a positive and significant relationship with volatility across all three markets, though the magnitude of the effect is very small in the UK.

The number of IPOs only has a marginally significant effect in Germany, while it is insignificant in both the UK and the US. This may indicate that IPO activity plays a more significant role in smaller or less liquid markets. In more established and liquid markets like the UK and the US, the impact of IPOs on volatility appears to be minimal.

Finally, the CCI has a consistently negative and significant relationship with volatility in all three markets, emphasising the importance of sentiment in stabilizing market conditions.

In conclusion, while there are common drivers of volatility across the three markets, such as the negative relationship between sentiment indicators like PCR and CCI with volatility, there are also prominent differences, particularly in the role of trading volume and IPO activity. The US market, with its larger trading volume, appears to be more sensitive to trading fluctuations, while the German market shows a more pronounced sensitivity to IPO activity. These differences highlight the diverse market environments, as reflected in the statistical results.

5. Conclusion

In this paper, we have examined the relationship between investor sentiment and stock market volatility, demonstrating how psychological factors can play a significant role in shaping financial markets. Through an extensive analysis of existing literature and empirical data, we highlight the importance of incorporating behavioural economics into the study of financial markets.

The results of this study suggest that investor sentiment is a crucial factor in determining market volatility. Specifically, this analysis has revealed several important findings. First, measures such as the Put-Call Ratio (PCR) consistently show a negative relationship with market volatility across different settings. This suggests that when bearish sentiment is high, it can have a stabilising effect as investors hedge their positions, challenging the traditional assumption that increased pessimism automatically leads to higher volatility.

Second, the evaluation of the trading volume reinforces its function as a dependable measure of market activity and investor sentiment. The findings indicate that elevated trading volume is associated with increased market volatility. This implies that greater participation in trading, frequently influenced by sentiment, can lead to more substantial price fluctuations and heightened volatility, especially in times of uncertainty.

Third, the analysis of consumer confidence, as indicated by the Consumer Confidence Index (CCI), shows a notable negative effect on market volatility. This underscores the significance of investor psychology in influencing market dynamics, as a rise in consumer confidence generally contributes to market stability and diminishes uncertainty.

Despite these valuable findings, some limitations and areas for future research should be acknowledged. A key limitation is that the study focuses on historical data from a limited number of countries. Extending the analysis to more countries, such as Portugal, would provide a broader perspective and enhance the understanding of how sentiment affects market volatility in different economic contexts. In addition, while traditional sentiment measures such as the PCR and CCI are used, there is considerable scope for incorporating real-time data sources such as social media and news sentiment to better capture dynamic changes in investor behaviour. Future research could benefit from the use of these more immediate sentiment indicators, as well as the use of more sophisticated models, such as GARCH, to better capture the complexity and volatility of financial markets, particularly in times of crisis.

In conclusion, this study contributes to the growing behavioural finance literature by exploring the complex relationship between investor sentiment and stock market volatility. By bridging the gap between psychological factors and market behaviour, this research deepens our understanding of the forces that drive financial markets. As the field evolves, further research is needed to explore the multifaceted nature of investor sentiment and its implications for market stability and efficiency, in particular by including more countries to strengthen the generalisability of the findings.

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APPENDIX

Table A1 - Correlation Matrix Germany, 2002-2022.

Sentiment	Volatility_GER	CCI_GER	PCR_GER	No.IPOs_GER	ln(Vol_GER)
Volatility_GER	1				
CCI_GER	-0.3932	1			
PCR_GER	-0.2798	0.2519	1		
No IPOs_GER	-0.3053	0.3331	0.2063	1	
ln(Vol_GER)	0.4015	0.0146	-0.2084	0.1546	1

Table A2 - Correlation Matrix UK, 2002-2022.

Sentiment	Volatility_UK	CCI_UK	PCR_UK	No.IPOs_UK	ln(Vol_UK)
Volatility_UK	1				
CCI_UK	-0.2090	1			
PCR_UK	-0.0999	-0.1096	1		
No.IPOs_UK	-0.2985	0.3214	0.1957	1	
ln(Vol_UK)	0.2979	0.1968	0.0356	0.4059	1

Table A3 - Correlation Matrix US, 2002-2022.

Variable	Volatility_USA	CCI_USA	PCR_USA	No.IPOs_USA	ln(Vol_USA)
Volatility_USA	1				
CCI_USA	-0.4383	1			
PCR_USA	-0.2082	0.2293	1		
No.IPOs_USA	-0.1385	0.0802	0.1510	1	
ln(Vol_USA)	0.3435	-0.4996	-0.0475	0.0802	1