Herd Behavior in the FTSE 100: Analyzing Investor Reactions During Periods of Market Volatility.

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DECLARATIONS

Herd Behavior in the FTSE 100: Analyzing Investor Reactions During Periods of Market Volatility.

- I certify that the work contained in this dissertation, submitted for the degree of the MSc in Behavioural Economics and Data Science is my own original work except where explicitly stated otherwise, and has not been previously submitted for a degree at this or any other University.

- This dissertation either does not use data collected by the researcher from human participants, or uses secondary data obtained elsewhere.

- I agree that this dissertation can be used as an example for the instruction of future UEA students.

BASHIR DARAMOLA

12 September 2024

I. Abstract

This dissertation investigates the existence and characteristics of herd behavior among investors in the FTSE 100 Index, with a focus on how it varies during periods of market volatility. Herd behavior, where investors collectively follow the actions of others rather than relying on independent analysis, can lead to market inefficiencies, price distortions, and increased volatility. Using Cross-Sectional Standard Deviation (CSSD) as the primary measure of herding, this study examines stock price movements within the FTSE 100 to assess how herding behavior manifests during both high- and low-volatility periods.

The research finds that herd behavior is present in the FTSE 100, but its intensity varies significantly with market conditions. During high-volatility periods, herding tends to weaken as stock returns become more dispersed, indicating that investors act more independently. Conversely, during low-volatility periods, herd behavior strengthens, with stocks moving more cohesively in response to market trends. Additionally, the study identifies an asymmetry in herding behavior related to market returns: positive market returns (RMp) are associated with weaker herding, while negative returns (RMn) intensify herding, particularly in volatile environments.

The findings contribute to the field of behavioral finance by highlighting how herd behavior fluctuates with market conditions and the psychological factors that drive collective decision-making. This study has practical implications for investors, who can use these insights to manage risk more effectively, and for regulators, who may consider interventions during periods of excessive volatility to stabilize markets. The dissertation concludes by recommending further research into herding across other markets and the use of alternative measures, such as sentiment analysis, to capture the psychological drivers of herd behavior.

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1 Introduction

1.1 Background

Herd behavior in financial markets refers to the tendency of investors to mimic the actions of others rather than relying on their own analysis or beliefs. This behavior often arises from uncertainty and the assumption that others may have more accurate information, leading to collective decision-making. In behavioral economics, herd behavior is a significant concept as it deviates from the traditional notion of rational decision-making assumed in classical finance models. Investors, instead of acting independently and rationally, may follow the crowd, leading to large-scale market movements that are not always grounded in fundamental analysis (Banerjee, 1992).

The significance of herd behavior lies in its potential to create market inefficiencies. When investors collectively rush to buy or sell assets, markets may overreact, pushing prices far beyond their intrinsic values. This can result in the formation of speculative bubbles, where asset prices inflate excessively, only to crash when the herd changes direction. Conversely, during periods of fear, herd behavior can lead to rapid sell-offs and panic, causing prices to plummet, even if the fundamentals of the assets remain unchanged. These dynamics disrupt the normal functioning of financial markets and lead to volatility that is disproportionate to the underlying economic conditions (Bikhchandani & Sharma, 2001).

Major indices such as the FTSE 100, which represent large, well-established companies, are not immune to the effects of herd behavior. In fact, due to the liquidity and visibility of these indices, they can be particularly susceptible to extreme volatility caused by herding. For example, during market downturns or crises, such as the 2008 financial crisis or the Brexit referendum, herd behavior amplified the sell-off in stocks, contributing to significant market declines (Chiang & Zheng, 2010). Similarly, in bullish markets, herd-driven buying can fuel rapid price increases, detaching stock prices from their fundamental values.

Understanding herd behavior is essential in behavioral economics as it highlights the limitations of markets in achieving efficiency and stability. By studying how and why investors follow the crowd, researchers and policymakers can better predict periods of market instability and design regulations that mitigate the impact of such collective behaviors.

1.2 Research Problem

This research focuses on investigating the existence and characteristics of herding behavior among investors in the FTSE 100 Index. Herding, where investors follow the crowd rather than making independent decisions, can lead to market inefficiencies, speculative bubbles, and crashes. The core issue this study seeks to address is whether such herding behavior is present in the FTSE 100 and how it varies across different market conditions, particularly during periods of market volatility.

Market volatility is known to exacerbate irrational behaviors, and herding may intensify during times of uncertainty, when investors rely more on others' actions rather than on their own assessments. By examining both rising and falling market conditions, this research aims to determine whether herding is more pronounced in specific phases of market volatility. Understanding these dynamics is crucial for financial professionals and policymakers, as herding behavior can disrupt the efficiency of markets and contribute to extreme price movements (Bikhchandani & Sharma, 2001). This study will shed light on the behavioral tendencies of investors in one of the most significant stock indices in the world.

1.3 Research Objectives

The primary objective of this research is to investigate the presence and characteristics of herd behavior among investors in the FTSE 100 Index. Specifically, this study aims to identify whether investors exhibit herd-like tendencies and how such behavior impacts market dynamics within this major stock index. The research objectives are as follows:

1. **To examine the presence of herd behavior in the FTSE 100 Index**: This research seeks to determine whether investors in the FTSE 100 engage in herding, which can lead to significant deviations from efficient market behavior and contribute to mispricing of assets.

2. **To explore how herd behavior differs between high and low volatility periods**: Given that market volatility often heightens irrational investor behavior, this objective focuses on analyzing how herd behavior intensifies or diminishes during periods of market turbulence compared to calmer times.

3. **To analyze the relationship between market returns (both positive and negative) and herd behavior using CSSD (Cross-Sectional Standard Deviation)**: This objective seeks to understand how herd behavior interacts with market returns, both in rising and falling markets, and to assess whether investors follow the crowd more during bullish or bearish phases.

1.4 Significance of the Study

The FTSE 100 Index, which comprises the 100 largest companies on the London Stock Exchange, is a vital benchmark for the UK economy and global financial markets. Given its inclusion of various sectors such as financial services, energy, and consumer goods, the FTSE 100 serves as a barometer for investor sentiment, influencing both domestic and international investment decisions. The performance of this index impacts pension funds, institutional investments, and individual portfolios, making it a critical area of focus for market participants (Bikhchandani & Sharma, 2001).

Studying herd behavior in the FTSE 100 is important because it can lead to market inefficiencies, where stock prices deviate significantly from their intrinsic values. When investors follow the crowd rather than relying on independent analysis, markets can experience bubbles, as witnessed during the 2008 financial crisis, or severe sell-offs during panic-induced periods. This phenomenon contributes to volatility and can amplify risks, especially in widely traded indices like the FTSE 100. Research on herding behavior can help investors understand how market sentiment drives price movements and allow them to avoid the pitfalls of following trends without sufficient analysis (Hirshleifer & Teoh, 2003).

From a regulatory standpoint, understanding the presence of herding in major indices like the FTSE 100 can inform policy changes aimed at mitigating volatility and systemic risks. Regulators can introduce measures like circuit breakers or liquidity controls during extreme market conditions to reduce the detrimental effects of herding. For academics, this study adds to the growing body of research on behavioral finance, particularly how psychological factors, rather than purely rational decisions, influence investor behavior and market outcomes. This deepens our understanding of market dynamics beyond traditional financial theories (Shiller, 2003).

2 Literature Review

2.1 Theoretical Framework: Herd Behavior in Financial Markets

Herd behavior in financial markets is a phenomenon where investors follow what they perceive others are doing rather than relying on their independent analysis. Theories explaining herd behavior encompass psychological triggers, sociological impacts, and economic consequences.

Psychological factors play a pivotal role in driving herd behavior. The fear of missing out (FOMO) and loss aversion prompt individuals to mimic the actions of the majority, often disregarding their own information or analysis. According to Tversky and Kahneman's prospect theory, individuals value gains and losses differently, leading to decisions conditioned more by the possibility of losing than by gaining (Tversky & Kahneman, 1992). This asymmetry makes investors more likely to follow the crowd, especially during periods of high volatility and uncertainty.

Sociological perspectives on herd behavior emphasize the influence of group dynamics and social norms. The concept of informational cascades, as Bikhchandani, Hirshleifer, and Welch (1992) describe, occurs when it is optimal for an individual, having observed the actions of those ahead of them, to follow the behavior of the preceding individual without regard to their own information. This behavior often leads to suboptimal market outcomes where decisions are based not on fundamental information, but on the inference of others' actions.

The economic consequences of herd behavior are significant, leading to asset price bubbles and market crashes. Shiller (2000) discusses how feedback loops from price increases lead to investor enthusiasm, which in turn leads to further increases—a process that often ends in sharp corrections when the reality of overvaluation sets in. The destabilizing effects of herd behavior on financial markets demonstrate its importance in understanding economic cycles and market responses to external shocks.

2.2 Comparative Studies from Other Stock Markets

Herd behavior has been extensively studied across various global stock markets. This section of the literature review focuses on how herd behavior has been observed and analyzed in different market environments and how these findings may apply to the FTSE 100.

Research in emerging markets has often highlighted pronounced herd behavior, primarily due to the higher market volatility and the less mature nature of these markets. Chang, Cheng, and Khorana (2000) provide an in-depth analysis of herd behavior in Asian markets during the 1997 financial crisis. They found significant evidence of herd behavior, particularly during periods of high market stress, which exacerbated market movements. Their methodology involved analyzing the co-movement of stocks and identifying periods where high co-movement was not justified by fundamentals. This study is particularly relevant to the FTSE 100 as it underscores the potential for herd behavior during periods of economic uncertainty, a common occurrence in global markets.

In contrast to emerging markets, developed markets like the U.S. and Europe tend to exhibit less obvious herd behavior, but it is still present during times of market stress or high uncertainty. Hwang and Salmon (2004) focused on the U.S. stock market and used a refined measure of herding that adjusted for market-wide influences. Their findings suggest that herding is less about blindly following others and more about the response to common information. Applying such methodologies to the FTSE 100 can help differentiate between genuine herd behavior and movement driven by common reactions to global news or events.

The methodological diversity in studying herd behavior provides multiple lenses through which to examine the phenomenon. Balcilar, Demirer, and Hammoudeh (2013) employed a regime-switching approach to detect changes in investor sentiment and potential shifts towards herd behavior in both the G7 countries and Brazil, Russia, India, China, and South Africa (BRICS). Their findings indicated that herding effects in stock returns are more pronounced during turbulent periods, suggesting that methodologies sensitive to regime shifts are crucial in identifying and understanding herd dynamics.

These studies offer valuable insights into the dynamics of herd behavior across different types of markets and under various economic conditions. For the FTSE 100, these insights suggest that:

1. **Economic Cycles and Market Stress**: Similar to findings in both emerging and developed markets, the FTSE 100 is likely susceptible to herd behavior during periods of economic downturns and market corrections.

2. **Global Influences**: Given the global interconnectedness of markets, common international triggers can also lead to herd behavior in the FTSE 100, akin to patterns observed in the U.S. and Europe.

2.3 Gaps in Literature

The existing body of research on herd behavior in financial markets provides comprehensive insights into various global stock markets. However, there remain specific gaps, particularly concerning the FTSE 100, which has not been as extensively studied as other major indices like the S&P 500 or Nikkei 225. This section identifies these gaps and details how this dissertation intends to address them.

Despite its critical role as a barometer of the UK economy and a benchmark for global investment, the FTSE 100 has received comparatively less attention in the realm of behavioral finance. This oversight provides a distinctive opportunity for this dissertation to contribute significantly to understanding how herd behavior manifests in the FTSE 100, particularly during periods fraught with Brexit-related uncertainties and global financial upheavals.

Furthermore, there is a clear need for more innovative methodological approaches in studying herd behavior in stock markets. Conventional methods often do not adequately capture the nuanced dynamics of herding, particularly under varying market conditions. Traditional analyses predominantly using daily returns may overlook aspects like skewness and kurtosis in data distribution, potentially leading to biased inferential conclusions. This dissertation addresses this gap by employing logarithmic returns, which offer several advantages, such as stabilizing variance and adjusting for asymmetry in data distribution, making them more suitable for the statistical models that assume normality in error terms.

In addition to logarithmic returns, the adoption of advanced statistical models such as Ordinary Least Squares (OLS) regression is proposed to enhance the robustness of analyzing factors driving herd behavior. This approach is particularly beneficial for distinguishing between reactive herding and instinctive herding based on different market stimuli, thereby enhancing our understanding of herd behavior in the FTSE 100.

These methodological enhancements are expected to provide deeper insights into the predictive power of herding measures and their implications for market efficiency and stability, specifically tailored to the complexities of the FTSE 100. By extending beyond traditional practices and leveraging underutilized methodologies, this dissertation not only aims to fill a significant gap in academic literature but also enhances practical understanding of market dynamics, potentially leading to better-informed investment strategies and policy formulations within the UK financial market.

3. Methodology

3.1 Data Collection

The data collection methodology for this dissertation centers on acquiring extensive historical financial data from Yahoo Finance, focusing on the FTSE 100 index. This data spans an 18-year period, a duration carefully chosen to encompass a variety of economic cycles and significant events, such as financial crises and Brexit. This comprehensive temporal scope is pivotal for analyzing long-term trends and fluctuations in investor behavior within the UK's primary stock market index.

Key data points collected include the daily 'Open', 'Close', and 'Volume' prices for the FTSE 100, which shed light on daily market movements and liquidity levels. Additionally, similar data for the top 100 companies listed on the FTSE 100 is also gathered, allowing for a detailed examination of individual stock performances relative to the overall index. This extended dataset enables an in-depth analysis of how specific sectors and companies contribute to or diverge from broader market behavior, particularly during periods of market volatility or instability.

To ensure the reliability and robustness of the analysis, the dataset undergoes rigorous preprocessing to address any inconsistencies or missing entries. Missing values are typically imputed using the mean of surrounding data points, a method that helps maintain the continuity and integrity of the time series data essential for subsequent econometric analysis. This meticulous approach to data collection and preparation not only enhances the scientific rigor of the study but also ensures that the findings are robust and reflective of true market dynamics.

3.2 Analytical Methods

In this study, the Cross-Sectional Standard Deviation (CSSD) is employed to quantify herding behavior in the FTSE 100, leveraging a methodology inspired by Adem and Sarioğlu (2020), and augmented with logarithmic returns for enhanced statistical rigor, following the approach recommended by Chang, Cheng, and Khorana (2000). This detailed methodological framework is designed to dissect investor behaviors under different market conditions and temporal resolutions.

Model Specification and Data Collection: The foundation of this analysis is built on comprehensive data collection efforts involving daily, weekly, and monthly closing prices of the FTSE 100 Index, alongside a representative sample of stocks from the index. This dataset is pivotal for calculating the CSSD, offering insights into the dispersion of returns as a proxy for market herding behavior. Logarithmic returns, preferred for their properties in stabilizing variance and adjusting for skewness in financial data distributions, are calculated using the formula: $R_t = \ln(\frac{P_t}{P_{t-1}})$ where $R_t$represents the logarithmic return at time t, and P_t and P_{t-1} denote the stock prices at times t and t−1, respectively.

Variable Definition: The study defines key variables to measure market mood:

- RM_{pt} (Return Market positive) is assigned a value of 1 if the daily return of the FTSE 100 is positive, signifying upward market movement, and 0 otherwise.
- RM_{nt} (Return Market negative) is assigned a value of 1 if the daily return is negative, reflecting downward market trends.

CSSD Calculation: The core of this analysis, CSSD, is calculated using the formula:

$$CSSD_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_{i,t} - r_{index,t})^2}$$

where $r_{i,t}$is the return of the ith stock at time t, $r_{index,t}$ is the index return at time t, and N is the number of stocks in the sample. This metric serves as an indicator of the degree to which individual stocks move in concert with the index, with lower values suggesting potential herding behavior.

Statistical Testing and Model Formulation: To understand the influence of market dynamics on CSSD, regression models are formulated for daily, weekly, and monthly data, capturing the effects of positive and negative returns on the dispersion of stock returns:

$$CSSD_t = \beta_0 + \beta_1.RM_{pt} + \beta_2.RM_{nt} + \epsilon_t$$

where β_0, β_1, and β_2 are coefficients estimated through ordinary least squares regression, reflecting the baseline CSSD, the impact of positive returns, and the impact of negative returns, respectively. F-tests and significance testing at the 1% and 5% levels assess the model's robustness and the impact of market conditions.

Data Segmentation by Time Frame and Volatility Segmentation: Herding behavior is analyzed across different temporal resolutions to discern how investor behavior shifts over daily, weekly, and monthly periods. Furthermore, the study period is divided into high and low volatility phases based on a rolling standard deviation of the FTSE 100 returns, enabling a focused examination of herding during turbulent versus stable periods.

4. Data Analysis and Results

4.1 Market Index Returns

The calculation of logarithmic returns for the FTSE 100 index is an essential step in analyzing the market's daily fluctuations through historical price data. Logarithmic returns are preferred in financial analysis due to their properties of symmetry, allowing for the consistent measurement of percentage changes across time. These returns are calculated by taking the natural logarithm of the ratio of consecutive closing prices.

In this analysis, the daily closing prices of the FTSE 100 index were utilized. Logarithmic returns for each day were computed by dividing each day's closing price by the previous day's closing price, then taking the natural logarithm of this ratio. The resulting series of daily log returns was then appended to the original dataset as a new column.

The summary statistics of these logarithmic returns provide insights into the behavior of the market during the study period:

Table 4.1: Summary Statistics of Daily Logarithmic Returns for the FTSE 100 Index

Statistic	Value
count	4544
mean	0.000075
std	0.011474
min	-0.115117
25%	-0.004866
50%	0.000491
75%	0.005597
max	0.093842

These statistics show a mean log return close to zero, indicating a relatively stable average return despite daily price fluctuations. The standard deviation suggests a moderate level of volatility, typical for a major stock index like the FTSE 100. The minimum and maximum values highlight days with significant market moves, both upwards and downwards. The interquartile range, which spans from the 25th to the 75th percentile, quantifies the typical daily return variation, highlighting the most common outcomes excluding more extreme changes.

4.2 Individual Stock Returns

Evaluating the daily logarithmic returns for each of the top 100 companies in the FTSE 100 is a crucial step not only for assessing individual stock performance but also for the broader application of analyzing market dynamics, specifically through the Cross-Sectional Standard Deviation (CSSD). Logarithmic returns are particularly useful for this analysis due to their symmetric properties, which allow for the measurement of relative changes consistently over time.

The process involves calculating the natural logarithm of the ratio of consecutive daily closing prices. This computation generates a series of daily returns for each stock, which are then compiled into descriptive statistics, capturing the mean, standard deviation, and other percentiles that describe the distribution of returns. These statistics provide a granular view of the volatility and performance trends of each stock.

To deepen the analysis, stocks are sorted based on their average returns. Identifying the top and bottom performers within the FTSE 100 allows for a targeted review of which stocks are driving index movements and which are lagging, thus influencing the overall market behavior. The primary goal here is to use these daily returns to calculate the CSSD, which measures the dispersion of individual stock returns around the index return. This dispersion is a key indicator of herding behavior in the market, where high levels of similarity in stock movements suggest that investors might be following each other rather than basing decisions on fundamental or individual stock values.

Table 4.2: Top 5 and Bottom 5 Stocks by Mean Returns

Category	Ticker	Mean Log Returns	Std Dev	Min	25th %	Median	75th %	Max
Top 5 Stocks	FRAS.L	0.001066	0.061766	-0.256591	-0.010505	0	0.011711	3.766552
	JD.L	0.000829	0.02487	-0.261336	-0.010549	0	0.012463	0.231678
	AHT.L	0.000814	0.026462	-0.265318	-0.012086	0.000869	0.014272	0.187893
	DPLM.I	0.000749	0.020443	-0.124097	-0.009195	0	0.010446	0.23857
	RMV.L	0.000659	0.023637	-0.489154	-0.008529	0.000518	0.010281	0.498191
Bottom 5 Stocks	IAG.L	-0.000173	0.050817	-0.943469	-0.014128	0	0.01437	0.913025
	CNA.L	-0.00018	0.018992	-0.210726	-0.008958	0.000379	0.009094	0.155035
	BARC.I	-0.000223	0.030971	-0.394834	-0.012078	-0.000058	0.011653	0.54952
	LAND.I	-0.000223	0.01865	-0.168966	-0.009287	0	0.008886	0.187308
	LLOY.I	-0.000392	0.034831	-0.590225	-0.010595	-0.000157	0.010501	0.568772

4.3 Volatility Analysis

Rolling Standard Deviation

The assessment of market volatility through the calculation of the 21-day rolling standard deviation of the FTSE 100 index provides insights into fluctuations in market behavior over time. This measure captures the average degree to which daily logarithmic returns deviate from their mean, offering a moving window perspective that adapts to recent market conditions. By observing these fluctuations, we can better understand periods of instability or calm in the market dynamics.

Volatility Classification

To further refine the analysis, the methodology involves categorizing days into 'High' or 'Low' volatility based on whether the rolling standard deviation exceeds the 75th percentile threshold of the observed values. This classification system aids in the segmentation of the market conditions into more manageable and analyzable groups, allowing for targeted strategies in trading and risk management.

Number of Days Falling into Each Volatility Category

Table 4.3

Volatility Type	Count
High	1131
Low	3414

The above classification highlights the number of days the market experienced significantly higher fluctuations versus more stable conditions. High volatility days are critical for traders and risk managers who may need to adjust their portfolios quickly to mitigate risks or capitalize on opportunities created by large market movements. Conversely, low volatility days might indicate more stable and predictable market conditions, which could influence long-term investment strategies.

4.4 CSSD and Herd Behavior Analysis

CSSD Over Time

The **Cross-Sectional Standard Deviation (CSSD)** provides a key measure of the dispersion of individual stock returns relative to the FTSE 100 Index. A high CSSD indicates a greater difference in stock performance, potentially signaling reduced herd behavior, while a low CSSD suggests that stocks are moving in unison, which may be indicative of stronger herd behavior.

The descriptive statistics for CSSD over the analyzed period (4547 days) are summarized as follows:

Table 4.4

Metric	Value
Count	4547
Mean	0.016948
Standard Deviation	0.012434
Minimum	0.004888
25th Percentile	0.011594
Median (50th Percentile)	0.01405
75th Percentile	0.017905
Maximum	0.391201

The average CSSD value of 0.0169 suggests relatively low dispersion in individual stock returns relative to the index, indicating that herd behavior might be prevalent during much of the period. However, the spikes in CSSD, such as the maximum value of 0.3912, suggest periods of increased dispersion where individual stocks moved more independently from the index. These spikes likely correspond to market events or external shocks, which often lead to more varied investor behavior and reduced cohesion in the market.

This aligns with findings by Chiang and Zheng (2010), who investigated herd behavior in global stock markets and found that spikes in dispersion of stock returns often coincide with periods of market turbulence. They observed that during global financial crises, stocks tend to exhibit more independent movement as investors react differently to uncertainties, thus reducing herd-like behavior.

Spikes in CSSD and Market Events

Several spikes in CSSD over the period correspond to times of increased market uncertainty or major market events. These periods are marked by higher dispersion between stock returns and the overall market index, suggesting that investors might have reacted differently based on individual risk assessments or news. Such behavior reduces herd behavior and amplifies the dispersion of returns.

Specific periods such as the **2007-2009 global financial crisis** and **Brexit** in 2016 likely contributed to these spikes. For example, Hwang and Salmon (2004) found that financial crises often lead to disintegration of herd behavior as individual investors focus more on firm-specific risks rather than following the market trend. During these times, CSSD would rise significantly as different stocks react in various ways to the external economic shocks.

High-Volatility vs Low-Volatility Periods

To further investigate the relationship between market volatility and herd behavior, the data was split into **high-volatility** and **low-volatility** periods. These periods were classified based on rolling standard deviations, with the 75th percentile used as the threshold to distinguish between high and low volatility.

Descriptive Statistics for CSSD During High and Low Volatility Periods:

Table 4.5

Metric	High Volatility CSSD	Low Volatility CSSD
Count	1131	3414
Mean	0.027	0.012
Standard Deviation	0.015	0.005
Minimum	0.007	0.005
25th Percentile	0.017	0.01
Median (50th Percentile)	0.023	0.012
75th Percentile	0.03	0.015
Maximum	0.391	0.067

The table above clearly shows that CSSD is significantly higher during high-volatility periods (mean = 0.027) compared to low-volatility periods (mean = 0.012). This suggests that during periods of high volatility, herd behavior tends to break down, leading to increased dispersion in stock returns. Investors may react more independently to market events during such times, making stock performance more varied. In contrast, during low-volatility periods, the market exhibits stronger herd behavior, with individual stocks moving more closely in line with the overall market.

These results are consistent with the findings of Hwang and Salmon (2004), who observed that high-volatility environments often cause investors to diverge from the herd as uncertainty rises. Conversely, low-volatility periods reflect a more stable market environment, where investors are more likely to follow the broader market trend, leading to greater cohesion in stock movements.

Market Returns (RMp and RMn) and Volatility

Market returns when positive (**RMp**) and negative (**RMn**) were analyzed to understand how they influence herd behavior. The summary statistics are as follows:

Table 4.6

Metric	RMp Value	RMn Value
Count	4545	4545
Mean	0.003886	-0.00381
Standard Deviation	0.006813	0.007456
Minimum	0	-0.115117
25th Percentile	0	-0.004865
Median (50th Percentile)	0.000491	0
75th Percentile	0.005595	0
Maximum	0.093842	0

These statistics show that both **RMp** and **RMn** have relatively small mean values, with a slight positive mean for RMp and a slight negative mean for RMn. This reflects typical stock market behavior, where returns tend to be small on average but highly variable during periods of market movement. The larger standard deviation for RMn reflects the increased variability in returns when the market is declining, which is consistent with periods of panic selling and heightened market stress.

CSSD in High vs. Low Volatility Periods

Rolling Standard Deviation and Volatility Classification

To assess market volatility, the 21-day rolling standard deviation of the log returns for the FTSE 100 Index was calculated. Days were categorized into **high** and **low volatility** based on the 75th percentile of the rolling standard deviation:

- **High Volatility**: Days where the rolling standard deviation was above the 75th percentile.
- **Low Volatility**: Days where the rolling standard deviation was below the 75th percentile.

This classification helps analyze how market conditions shift between calm and turbulent periods, and how herd behavior (as measured by CSSD) responds to these shifts.

Regression Analysis: High vs. Low Volatility Periods

Regression analysis was performed to explore how the market return factors **RMp** (market return when positive) and **RMn** (market return when negative) explain the variation in CSSD during high- and low-volatility periods.

Regression Results for High Volatility Periods:

Table 4.7

Metric	Coefficient	Std. Error	t-statistic	P-value	95% Confidence Interval
Constant	0.0168	0	37.032	0	[0.016, 0.018]
RMp	0.4248	0.031	13.719	0	[0.364, 0.486]
RMn	-0.3949	0.028	-13.921	0	[-0.451, -0.339]

- **R-squared**: 0.201
- **F-statistic**: 141.7 ($P < 0.0001$)
- **Observations**: 1,131

Interpretation:

- The coefficient for **RMp** (0.4248) suggests that during high-volatility periods, positive market returns lead to an increase in CSSD, indicating weaker herd behavior. Stocks move more independently as investors react to firm-specific factors.
- The coefficient for **RMn** (-0.3949) indicates that during periods of negative returns in high-volatility environments, CSSD decreases, implying stronger herd behavior. Investors tend to act in unison, likely driven by collective fear or panic. This pattern aligns with the findings of Chiang and Zheng (2010), who reported increased herding during market downturns and turbulent periods.

Regression Results for Low Volatility Periods:

Table 4.8

Metric	Coefficient	Std. Error	t-statistic	P-value	95% Confidence Interval
Constant	0.0136	0	43.503	0	[0.013, 0.014]
RMp	0.2306	0.051	4.485	0	[0.130, 0.331]
RMn	-0.3244	0.045	-7.212	0	[-0.413, -0.236]

- **R-squared**: 0.016
- **F-statistic**: 27.64 ($P < 0.0001$)
- **Observations**: 3,414

Interpretation:

- The coefficient for **RMp** (0.2306) is lower during low-volatility periods than in high-volatility periods. This indicates that positive market returns result in a smaller increase in CSSD, implying that herd behavior is stronger when markets are calm.
- Similarly, the coefficient for **RMn** (-0.3244) is less negative compared to high-volatility periods. This suggests that, while herd behavior is present during negative returns in low-volatility periods, it is not as strong as during high-volatility downturns. These results are consistent with findings from Christie and Huang (1995), who found that herding behavior tends to intensify during periods of market stress, particularly in declining markets.

Key Insights from the Regression Models

- **High-volatility periods** show stronger deviations from the market trend, with greater independent stock movements during positive returns and more pronounced herd behavior during negative returns. The higher R-squared value (0.201) for high-volatility periods indicates that CSSD is more closely tied to market returns during turbulent times.
- **Low-volatility periods**, on the other hand, exhibit more uniform stock movements regardless of market returns, suggesting that herd behavior is more prevalent during calm markets. The lower R-squared value (0.016) reflects the reduced impact of market returns on CSSD in stable periods, as investor behavior is more cohesive.

4.5 Regression Results Analysis

The regression models were applied to the Cross-Sectional Standard Deviation (CSSD) as the dependent variable, with **RMp** (market return when positive) and **RMn** (market return when negative) as the independent variables. The regression analysis was conducted on daily, weekly, and monthly data, revealing key insights about the relationship between market returns and herd behavior.

Daily Data Regression Results

Table 4.9

Metric	Coefficient	Std. Error	t-statistic	P-value	95% Confidence Interval
Constant	0.0135	0	56.778	0	[0.013, 0.014]
RMp (Positive Returns)	0.456	0.027	16.933	0	[0.403, 0.509]
RMn (Negative Returns)	-0.448	0.025	-18.203	0	[-0.496, -0.400]

R-squared: 0.095

Adjusted R-squared: 0.095

F-statistic: 239.5

P(F-statistic): 1.26e-99

Observations: 4545

Interpretation:

- The constant (0.0135) represents the average CSSD when the market returns are neutral.
- The coefficient for RMp (0.4560) suggests that during periods of positive market returns, CSSD increases, indicating weaker herd behavior. When the market rises, stocks tend to move more independently, resulting in higher dispersion. This corresponds with the findings of Christie and Huang (1995), who also reported that stock return dispersion increases during market rallies as investors focus on firm-specific factors.

- The coefficient for RMn (-0.4480) shows a negative relationship between negative market returns and CSSD. During market declines, CSSD decreases, indicating stronger herd behavior. Investors tend to react similarly during downturns, likely driven by fear or panic, causing stocks to move more cohesively. This pattern echoes the observations made by Chiang and Zheng (2010), who found that herd behavior intensifies during periods of market stress, especially during downturns.

The R-squared value of 0.095 indicates that about 9.5% of the variability in CSSD is explained by the model. While this is relatively low, it is typical for models analyzing complex behavioral phenomena in financial markets.

Weekly Data Regression Results

Table 5.0

Metric	Coefficient	Std. Error	t-statistic	P-value	95% Confidence Interval
Constant	0.0113	0	26.187	0	[0.010, 0.012]
RMp (Positive Returns)	0.8153	0.074	11.029	0	[0.670, 0.960]
RMn (Negative Returns)	-0.6589	0.062	-10.686	0	[-0.780, -0.538]

R-squared: 0.221

Adjusted R-squared: 0.220

F-statistic: 133.2

P(F-statistic): 1.20e-51

Observations: 940

Interpretation:

- The coefficient for RMp (0.8153) is much higher for weekly data than for daily data, indicating that during positive weekly returns, stocks deviate more from the index. This suggests that when the market performs well over a week, stocks are more likely to be influenced by company-specific factors, weakening herd behavior.

- The coefficient for RMn (-0.6589) is also higher in magnitude than in the daily regression, suggesting that during weeks of negative returns, herd behavior becomes even more pronounced, with stocks moving together more closely in response to bad news. Chiang and Zheng (2010) also found that herding behavior is more apparent during bearish markets, where investor reactions are more uniform due to risk aversion.

The R-squared value of 0.221 indicates that the model explains 22.1% of the variation in CSSD at the weekly level, a significant improvement over the daily model. This implies that herd behavior is more predictable at the weekly level compared to daily movements, where randomness may play a larger role.

Monthly Data Regression Results

Table 5.1

Metric	Coefficient	Std. Error	t-statistic	P-value	95% Confidence Interval
Constant	0.0097	0.001	14.203	0	[0.008, 0.011]
RMp (Positive Returns)	1.1483	0.236	4.856	0	[0.682, 1.614]
RMn (Negative Returns)	-0.7614	0.176	-4.326	0	[-1.108, -0.414]

R-squared: 0.449

Adjusted R-squared: 0.444

F-statistic: 87.16

P(F-statistic): 2.05e-28

Observations: 217

Interpretation:

- At the monthly level, the coefficient for RMp (1.1483) is the highest, suggesting that during months of positive returns, there is a significant divergence in stock behavior, with stocks becoming less correlated with the overall market. Investors seem to place more emphasis on firm-specific news or events during longer periods of market growth, reducing herd behavior.

- The coefficient for RMn (-0.7614) shows that herd behavior intensifies during months of market decline. Investors may exhibit panic-selling behavior, leading to more uniform stock movements. This is consistent with findings from Christie and Huang (1995), who identified stronger herding behavior during market downturns when fear dominates investor decision-making.

The R-squared value of 0.449 indicates that the model explains 44.9% of the variation in CSSD at the monthly level, showing a clear improvement over both daily and weekly models. This suggests that herd behavior is more predictable over longer periods, and market returns have a greater impact on stock dispersion when aggregated over months.

Interpretation of Coefficients for RMp and RMn

Across all three models (daily, weekly, and monthly), the coefficient for RMp is positive, while the coefficient for RMn is negative. This indicates a consistent pattern where:

- RMp (Positive Returns): As market returns rise, the CSSD increases, indicating weaker herd behavior. Investors are more likely to differentiate between stocks, possibly reacting to firm-specific information or sector-specific factors. This effect is strongest at the monthly level (coefficient = 1.1483), where the dispersion is more pronounced.
- RMn (Negative Returns): As market returns fall, the CSSD decreases, signaling stronger herd behavior. Investors tend to react similarly during market downturns, leading to more cohesive stock movements. This effect is also strongest at the monthly level (coefficient = -0.7614).

The increasing R-squared values from daily (9.5%) to weekly (22.1%) to monthly (44.9%) suggest that herd behavior is more clearly observed over longer time horizons. This is likely because, over daily periods, stock movements are more influenced by short-term noise or random fluctuations, whereas longer periods capture more systematic behavior driven by broader market trends and investor psychology.

5. Conclusions and Recommendations

5.1 Key Findings

This study analyzed the presence and characteristics of herd behavior within the FTSE 100 Index, focusing on how it responds to varying market conditions. The findings indicate that herd behavior is prevalent among investors in the FTSE 100, but its intensity fluctuates based on market volatility and returns.

The analysis shows that herd behavior is present in the FTSE 100 Index, with investors often making collective decisions, particularly during market downturns. This behavior leads to stock price movements that deviate from their fundamental values, creating inefficiencies in the market. Investors tend to follow the actions of others rather than relying on independent analysis, which is particularly noticeable during periods of uncertainty. Herding was measured using the Cross-Sectional Standard Deviation (CSSD) of returns, which highlighted significant clustering of stock movements around market trends.

Volatility plays a crucial role in the intensity of herd behavior. During high-volatility periods, herd behavior weakens as individual stock returns show greater dispersion. In these turbulent times, investors react more independently, likely due to heightened uncertainty and diverse responses to risk. Conversely, in low-volatility periods, herd behavior strengthens. Investors are more inclined to follow broader market trends when the market is stable, leading to more cohesive stock movements. The study revealed that herding is more predictable in calm markets, whereas high-volatility periods disrupt collective behavior.

The study also examined the influence of positive market returns (RMp) and negative market returns (RMn) on herd behavior. During periods of positive returns, herd behavior weakens as investors become more confident in making independent decisions. This effect is particularly evident in high-volatility periods, where positive returns lead to wider dispersion in stock movements. Conversely, during negative returns, herd behavior intensifies, with investors acting more uniformly. This collective reaction is especially strong during high-volatility periods, where fear and uncertainty prompt investors to follow the crowd.

5.2 Theoretical Implications

The findings of this research contribute significantly to the field of behavioral economics by deepening the understanding of herd behavior in financial markets. Herd behavior, where investors make decisions based on the actions of others rather than independent analysis, challenges the traditional efficient market hypothesis, which assumes rational behavior. This study, focusing on the FTSE 100 Index, highlights how investors tend to exhibit herding tendencies under certain market conditions, particularly during periods of volatility and downturns.

Behavioral economics emphasizes the role of psychological and social factors in decision-making. Herding behavior aligns with this perspective, demonstrating how emotions such as fear and uncertainty can override rational analysis, leading to collective behavior that exacerbates market inefficiencies. This study's findings show that during high-volatility periods, herd behavior tends to weaken as dispersion in stock returns increases, suggesting that heightened uncertainty pushes investors toward independent decisions. Conversely, during low-volatility periods, herd behavior strengthens as investors are more likely to follow market trends, reflecting the confidence and stability in the market.

By exploring the asymmetric responses to positive and negative returns, this research contributes to the understanding of how herding behavior is not constant but varies with market conditions. During negative returns, herd behavior intensifies, suggesting that fear and risk aversion lead to more uniform actions among investors. This insight is valuable for understanding how behavioral biases influence market dynamics, supporting the notion that financial markets are not always driven by rationality but are often swayed by psychological factors.

This study aligns with previous research, such as the findings of Adem and Sarioğlu (2020) on the Istanbul Stock Exchange (ISE), which demonstrated that herding behavior intensifies during periods of market stress, particularly when market volatility is high. In both studies, negative market returns are associated with stronger herding behavior, as investors react collectively to market downturns. The FTSE 100 findings support this by showing that during periods of heightened volatility, herd behavior becomes more prominent during negative returns, reflecting increased risk aversion.

Both the ISE study and this research on the FTSE 100 reveal asymmetric behavior in how investors react to market conditions. In both cases, herd behavior is stronger during market downturns compared to periods of rising prices. This is consistent with behavioral finance theory, which posits that investors are more likely to engage in collective behavior during periods of fear or uncertainty (Bikhchandani & Sharma, 2001). The FTSE 100 findings, like those from the ISE, show that investors act more independently during positive returns, resulting in less herd behavior.

The ISE study emphasizes that daily data reveals more pronounced herding behavior compared to weekly or monthly data. Similarly, this study found that daily CSSD data from the FTSE 100 demonstrated stronger herding patterns, particularly during periods of negative returns. While weekly and monthly data also reflected herding behavior, the effects were more pronounced in daily observations, suggesting that short-term market fluctuations heighten collective reactions.

Both the FTSE 100 study and the ISE research show that herding is statistically significant during negative returns but less so during positive returns. This finding supports the theory that investors are more prone to following the crowd during market declines, driven by panic and uncertainty, while during positive returns, they are more likely to act independently, relying on firm-specific information.

The alignment between the findings of this study and previous research, such as that of Adem and Sarioğlu (2020), strengthens the validity of the observed patterns in herd behavior. Both studies highlight the asymmetry in investor behavior, with herding more prevalent during market downturns and periods of volatility. This research not only contributes to behavioral economics by offering new insights into how investors behave in the FTSE 100 but also underscores the broader applicability of these findings across different market contexts.

5.3 Practical Implications

Understanding herd behavior is crucial for investors, particularly in managing risk during volatile market periods. Herd behavior occurs when investors follow the actions of others instead of conducting independent analyses, leading to overreactions in both bullish and bearish market conditions. Recognizing these collective tendencies can help investors avoid getting caught up in market irrationality, which often leads to mispricing and increased market risk. For instance, during market rallies, herd behavior can inflate asset prices beyond their intrinsic values, leading to bubbles that eventually burst, as was the case during the dot-com bubble (Shiller, 2003).

By being aware of herd behavior, investors can adopt a more contrarian approach, making decisions based on fundamental analysis rather than following market trends blindly. This strategy is particularly valuable during high-volatility periods, where the risks associated with herd behavior are amplified. For example, when markets experience sharp declines, herd behavior can intensify the sell-off as fear spreads among investors. By recognizing this pattern, investors can make more calculated decisions, such as holding their positions or even taking advantage of panic selling to acquire undervalued assets. Additionally, investors can use tools like cross-sectional standard deviation (CSSD) to monitor market dispersion and assess the strength of herding in real-time, enabling more informed decision-making in dynamic market conditions (Banerjee, 1992).

Regulators play a critical role in ensuring the stability of financial markets, especially during periods of extreme volatility when herd behavior can exacerbate market fluctuations. Herd behavior, particularly during downturns, can lead to systemic risks as large groups of investors engage in panic selling, causing sharp declines in asset prices and eroding market confidence. Regulators need to closely monitor herding patterns to identify signs of market instability and intervene when necessary. For example, during the 2008 financial crisis, herd behavior contributed to the rapid unwinding of positions, further destabilizing the global economy (Bikhchandani & Sharma, 2001).

One potential regulatory intervention to mitigate the effects of herd behavior is the implementation of circuit breakers, which temporarily halt trading during significant market declines. This mechanism can prevent herd-driven panic selling by giving the market time to recover and allowing investors to reassess their decisions more rationally. Another approach could be the regulation of high-frequency trading (HFT), which can accelerate herd behavior by amplifying short-term market trends. Monitoring and placing constraints on HFT activity during periods of volatility could help regulators reduce the risk of market distortions caused by herding (Hirshleifer & Teoh, 2003).

Additionally, regulators can focus on improving market transparency to mitigate herd behavior. When investors have access to clear, accurate, and timely information, they are more likely to make independent, informed decisions rather than following the crowd. Educational campaigns promoting financial literacy, and the importance of independent analysis could also reduce the prevalence of herd behavior, contributing to a more stable financial system.

5.4 Study Limitations

A primary limitation of this study is the reliance on **Cross-Sectional Standard Deviation (CSSD)** as the sole measure of herd behavior. While CSSD is a well-established metric, it may not capture all dimensions of herding, especially in the presence of market anomalies or noise. Additionally, CSSD focuses on the dispersion of returns, which may not always fully reflect investor behavior, particularly during subtle market shifts. An alternative measure, such as the **Cross-Sectional Absolute Deviation (CSAD)**, could have provided further insights. CSAD is considered more robust in detecting nonlinear relationships between returns and herding and might have offered a more nuanced view of herd behavior in volatile markets. Incorporating both CSSD and CSAD would have enhanced the robustness of the analysis by capturing different aspects of herding dynamics.

This study is also limited by its focus on the **FTSE 100 Index**, which consists of large-cap UK companies. While the FTSE 100 is a major indicator of market trends, the results may not be generalizable to other stock markets or smaller indices with different investor compositions. For example, emerging markets, which tend to have higher volatility and less institutional participation, may exhibit different herding patterns. Future research should apply this methodology to other indices and regions to assess whether the findings are consistent across diverse market environments.

5.5 Recommendations for Future Research

Future research should extend the methodology used in this study to other stock markets, both in developed and emerging economies, as well as other indices within the UK. While the FTSE 100 represents the largest companies in the UK, applying the methodology to other UK indices such as the FTSE 250 or FTSE All-Share Index could reveal differences in herding behavior across different segments of the UK market. Smaller indices might exhibit stronger or weaker herding due to variations in liquidity, market capitalization, and investor composition. Replicating the study in these UK indices, as well as in international markets like the Nikkei 225, DAX 30, or Brazil's Bovespa, would help assess whether the patterns of herding observed in the FTSE 100 are consistent across different market environments (Hwang & Salmon, 2004). This comparative approach would provide insights into how market structures, cultural factors, and economic conditions influence herd behavior.

While Cross-Sectional Standard Deviation (CSSD) is a widely accepted method for measuring herding behavior, future studies should incorporate other metrics such as the Cross-Sectional Absolute Deviation (CSAD) and sentiment analysis to gain a more comprehensive understanding of investor behavior. CSAD can help identify nonlinear relationships, while sentiment analysis can provide insights into the emotional drivers behind investor decisions by analyzing data from news reports, social media, and financial statements. Incorporating sentiment analysis would allow researchers to capture the psychological aspect of herding, especially in high-volatility periods where market emotions are heightened (Baker & Wurgler, 2007).

The role of media and social media in influencing herd behavior deserves further exploration. In the modern market environment, real-time information dissemination through platforms like Twitter, Reddit, and financial news outlets can act as catalysts for herding behavior, especially during periods of market stress. Future research should investigate how different forms of media affect herd behavior in high-volatility periods and assess whether these effects differ across markets and indices. By examining how media narratives and information cascades contribute to or mitigate herding, researchers could offer deeper insights into the role of external factors in driving collective investor behavior (Tetlock, 2007). Understanding these dynamics could be critical for investors and policymakers alike, offering tools to better anticipate market movements driven by herd behavior.

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IV. APPENDIX

```
Regression Results for Daily Data:
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.095
Model:                            OLS   Adj. R-squared:                  0.095
Method:                 Least Squares   F-statistic:                     239.5
Date:                Mon, 09 Sep 2024   Prob (F-statistic):           1.26e-99
Time:                        16:59:56   Log-Likelihood:                 13719.
No. Observations:                4545   AIC:                        -2.743e+04
Df Residuals:                    4542   BIC:                        -2.741e+04
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0135      0.000     56.778      0.000       0.013       0.014
RMp            0.4560      0.027     16.933      0.000       0.403       0.509
RMn           -0.4480      0.025    -18.203      0.000      -0.496      -0.400
==============================================================================
Omnibus:                     7586.939   Durbin-Watson:                   1.324
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         11299585.857
Skew:                          10.914   Prob(JB):                         0.00
Kurtosis:                     246.293   Cond. No.                         168.
==============================================================================
```

```
Regression Results for Weekly Data:
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.221
Model:                            OLS   Adj. R-squared:                  0.220
Method:                 Least Squares   F-statistic:                     133.2
Date:                Mon, 09 Sep 2024   Prob (F-statistic):           1.20e-51
Time:                        17:00:06   Log-Likelihood:                 3234.3
No. Observations:                 940   AIC:                            -6463.
Df Residuals:                     937   BIC:                            -6448.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0113      0.000     26.187      0.000       0.010       0.012
RMp            0.8153      0.074     11.029      0.000       0.670       0.960
RMn           -0.6589      0.062    -10.686      0.000      -0.780      -0.538
==============================================================================
Omnibus:                      932.901   Durbin-Watson:                   1.444
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            47325.337
Skew:                           4.599   Prob(JB):                         0.00
Kurtosis:                      36.522   Cond. No.                         296.
==============================================================================
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.449
Model:                            OLS   Adj. R-squared:                  0.444
Method:                 Least Squares   F-statistic:                     87.16
Date:                Mon, 09 Sep 2024   Prob (F-statistic):           2.05e-28
Time:                        17:00:06   Log-Likelihood:                 854.18
No. Observations:                 217   AIC:                            -1702.
Df Residuals:                     214   BIC:                            -1692.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0097      0.001     14.203      0.000       0.008       0.011
RMp            1.1483      0.236      4.856      0.000       0.682       1.614
RMn           -0.7614      0.176     -4.326      0.000      -1.108      -0.414
==============================================================================
Omnibus:                       97.061   Durbin-Watson:                   1.021
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              348.913
Skew:                           1.869   Prob(JB):                     1.72e-76
Kurtosis:                       7.962   Cond. No.                         862.
==============================================================================
```

```
                Rolling_Std                                              \
                      count      mean       std       min       25%       50%
Volatility_Type
High                 1131.0  0.017461  0.007286  0.011578  0.012819  0.015162
Low                  3393.0  0.007398  0.001980  0.002536  0.005805  0.007207

                                     Log_Returns                              \
                      75%       max      count      mean       std       min
Volatility_Type
High             0.019137  0.050682     1131.0  0.000501  0.018586 -0.115117
Low              0.008937  0.011558     3413.0 -0.000064  0.007799 -0.039610


                      25%       50%       75%       max
Volatility_Type
High            -0.008865  0.001502  0.010611  0.093842
Low             -0.004402  0.000322  0.004555  0.034134
```

Regression Results for High Volatility Periods:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   CSSD   R-squared:                       0.201
Model:                            OLS   Adj. R-squared:                  0.199
Method:                 Least Squares   F-statistic:                     141.7
Date:                Mon, 09 Sep 2024   Prob (F-statistic):           1.27e-55
Time:                        17:02:44   Log-Likelihood:                 3544.0
No. Observations:                1131   AIC:                            -7082.
Df Residuals:                    1128   BIC:                            -7067.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0168      0.000     37.032      0.000       0.016       0.018
RMp            0.4248      0.031     13.719      0.000       0.364       0.486
RMn           -0.3949      0.028    -13.921      0.000      -0.451      -0.339
==============================================================================
Omnibus:                      855.776   Durbin-Watson:                   1.025
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            24806.805
Skew:                           3.185   Prob(JB):                         0.00
Kurtosis:                      25.042   Cond. No.                         110.
------------------------------------------------------------------------------
```

Regression Results for Low Volatility Periods:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   CSSD   R-squared:                       0.016
Model:                            OLS   Adj. R-squared:                  0.015
Method:                 Least Squares   F-statistic:                     27.64
Date:                Mon, 09 Sep 2024   Prob (F-statistic):           1.23e-12
Time:                        17:02:44   Log-Likelihood:                 10242.
No. Observations:                3414   AIC:                        -2.048e+04
Df Residuals:                    3411   BIC:                        -2.046e+04
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0136      0.000     43.503      0.000       0.013       0.014
RMp            0.2306      0.051      4.485      0.000       0.130       0.331
RMn           -0.3244      0.045     -7.212      0.000      -0.413      -0.236
==============================================================================
Omnibus:                     6267.158   Durbin-Watson:                   1.407
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          13361484.947
Skew:                          13.245   Prob(JB):                         0.00
Kurtosis:                     308.332   Cond. No.                         278.
==============================================================================
```

CSSD

In [42]:

```
import pandas as pd
import numpy as np

index_log_returns = ftse100_summary['Log_Returns']

difference = close_data_log_returns.subtract(index_log_returns, axis=0)

cssd = difference.std(axis=1)

# Now, you can check for NaN values in 'cssd'
nan_count_cssd = cssd.isna().sum()
print(f"Number of NaN values in CSSD: {nan_count_cssd}")
print (cssd.head())
# Impute NaN values with the mean of the CSSD values
cssd = cssd.fillna(cssd.mean())

# Print the imputed CSSD values to verify
print("Imputed CSSD values:")
print(cssd.head())
print (cssd.describe())
```

RMp (Market return when positive) for rising markets and RMn (Market return when negative) for falling markets

In [34]:

```
index_log_returns = ftse100_summary['Log_Returns']

difference = close_data_log_returns.subtract(index_log_returns, axis=0)

# Calculate the standard deviation of these differences across all stocks for each day (CSSD)
cssd = difference.std(axis=1)

# Now, you can check for NaN values in 'cssd'
nan_count_cssd = cssd.isna().sum()
print(f"Number of NaN values in CSSD: {nan_count_cssd}")
print(cssd.head())

# Impute NaN values with the mean of the CSSD values
cssd = cssd.fillna(cssd.mean())
```

```
# Print the imputed CSSD values to verify
print("Imputed CSSD values:")
print(cssd.head())

# Calculate RMp (Market return when positive) for rising markets
ftse100_summary['RMp'] = np.where(ftse100_summary['Log_Returns'] > 0, ftse100_summary['Log_Returns'],
0)

# Calculate RMn (Market return when negative) for falling markets
ftse100_summary['RMn'] = np.where(ftse100_summary['Log_Returns'] < 0, ftse100_summary['Log_Returns'],
0)

# Display the calculated RMp and RMn values to verify
print("RMp (Market return when positive):")
print(ftse100_summary[['Log_Returns', 'RMp']].head())

print("RMn (Market return when negative):")
print(ftse100_summary[['Log_Returns', 'RMn']].head())

# Optional: Check if RMp and RMn are correctly calculated
print("Summary of RMp (positive returns) and RMn (negative returns):")
print(ftse100_summary[['RMp', 'RMn']].describe())
```

regression model for daily data

In [35]:

```
# Ensure that ftse100_summary has the columns 'CSSD', 'RMp', and 'RMn'
# 'cssd' is the already calculated CSSD for each day

# Step 1: Align the indices of ftse100_summary and cssd
X_daily, y_daily = ftse100_summary[['RMp', 'RMn']].align(cssd, join='inner', axis=0)

# Step 2: Add a constant to the model for the intercept
X_daily = sm.add_constant(X_daily)

# Step 3: Run the OLS regression for daily data
model_daily = sm.OLS(y_daily, X_daily).fit()

# Step 4: Print the summary of the regression model for daily data
print("Regression Results for Daily Data:")
print(model_daily.summary())
```

regression model for weekly data and regression model for monthly data

In [36]:

```
import statsmodels.api as sm
import pandas as pd

# Resample to weekly using the mean
ftse100_summary_weekly = ftse100_summary.resample('W').mean()
cssd_weekly = cssd.resample('W').mean()

# Resample to monthly using the mean
ftse100_summary_monthly = ftse100_summary.resample('M').mean()
cssd_monthly = cssd.resample('M').mean()

# Step 2: Align the indices of ftse100_summary and cssd for weekly data
X_weekly, y_weekly = ftse100_summary_weekly[['RMp', 'RMn']].align(cssd_weekly, join='inner', axis=0)

# Add a constant to the model for the intercept
X_weekly = sm.add_constant(X_weekly)

# Step 3: Run the OLS regression for weekly data
model_weekly = sm.OLS(y_weekly, X_weekly).fit()

# Print the summary of the regression model for weekly data
print("Regression Results for Weekly Data:")
print(model_weekly.summary())

# Step 4: Align the indices of ftse100_summary and cssd for monthly data
X_monthly, y_monthly = ftse100_summary_monthly[['RMp', 'RMn']].align(cssd_monthly, join='inner', axis=0)

# Add a constant to the model for the intercept
X_monthly = sm.add_constant(X_monthly)

# Step 5: Run the OLS regression for monthly data
model_monthly = sm.OLS(y_monthly, X_monthly).fit()

# Print the summary of the regression model for monthly data
print("Regression Results for Monthly Data:")
print(model_monthly.summary())
```

High Volatility Periods and Low Volatility Periods

In [41]:

```
import statsmodels.api as sm

cssd_df = cssd.to_frame(name='CSSD')
cssd_df = cssd_df.reindex(ftse100_summary.index, fill_value=np.nan)  # Reindexing and filling missing values

# Now segregate the data into high and low volatility datasets
high_vol_data = ftse100_summary[ftse100_summary['Volatility_Type'] == 'High']
low_vol_data = ftse100_summary[ftse100_summary['Volatility_Type'] == 'Low']

# Filter the CSSD values for high and low volatility periods using the same indices
cssd_high = cssd_df.loc[high_vol_data.index, 'CSSD']
cssd_low = cssd_df.loc[low_vol_data.index, 'CSSD']

# Prepare the regression data for high volatility
X_high = high_vol_data[['RMp', 'RMn']]
y_high = cssd_high
X_high = sm.add_constant(X_high)  # Adding a constant for the intercept

# Prepare the regression data for low volatility
X_low = low_vol_data[['RMp', 'RMn']]
y_low = cssd_low
X_low = sm.add_constant(X_low)  # Adding a constant for the intercept

# Perform OLS regression for high volatility periods
model_high = sm.OLS(y_high, X_high, missing='drop').fit()  # Using missing='drop' to handle any NaNs that per
sist

# Perform OLS regression for low volatility periods
model_low = sm.OLS(y_low, X_low, missing='drop').fit()  # Using missing='drop' to handle any NaNs that persis
t

# Print the results
print("Regression Results for High Volatility Periods:")
print(model_high.summary())

print("\nRegression Results for Low Volatility Periods:")
print(model_low.summary())
```