Evidence of Market Non-Normality: Insights from SPY Data Analysis

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Introduction

Traditional analysis and predictions in the financial markets have historically relied on the normality assumption, expecting price changes to follow a Gaussian distribution. However, numerous empirical studies have shown deviations from this anticipated model. This report delves into the analysis of SPY (SPDR S&P 500 ETF Trust) data from January 1, 2000, to January 1, 2024, to investigate the presence of non-normality in the market. The paper focus on three separate events, 2008 and 2020 when the market experienced serious deviation from its normal distribution to highlight the severity of each deviation.

Data Description and Methodologies

The SPY dataset used in this analysis comprises daily closing prices spanning over two decades. Each data point represents the adjusted closing price of the SPY ETF, which tracks the performance of the S&P 500 index, a widely followed benchmark for the U.S. equity market.

The data used for 2008-2009 period ranged from 2008/01/01 - 2009/12/31.
The data used for 2020 analysis ranged from 2020/01/01 - 2020/12/31.

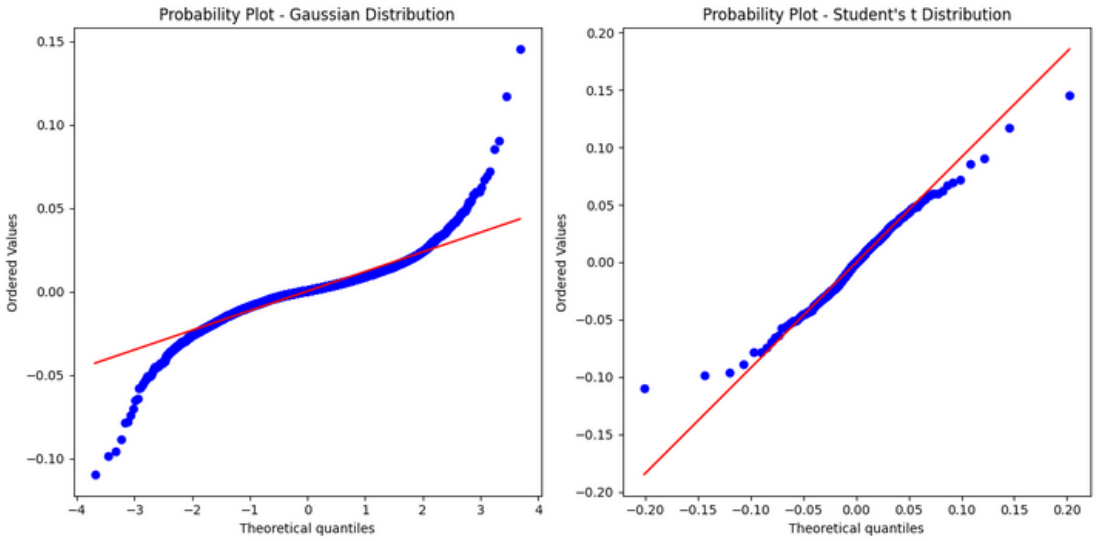
Table 1:

	2008	2020	Total
Mean	-0.021	0.089	0.0345
Median	0.06	0.226	0.0654
Standard Deviation	2.19	2.104	1.24
Skew	0.418	-0.608	-0.008
Kurtosis	7.13	7.33	11.46

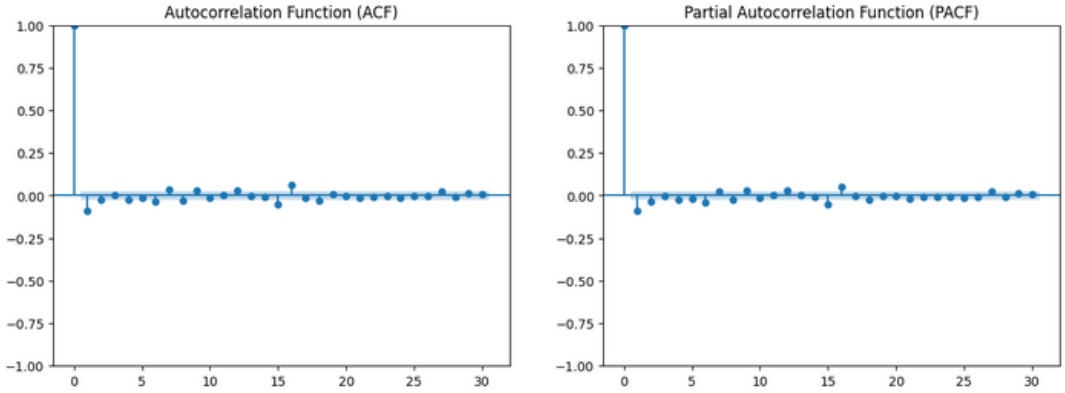
Market Non-Normality Analysis

Examination of SPY data reveals periods of non-normality characterized by extreme volatility and erratic price movements. These deviations from the expected distribution highlight the presence of market inefficiencies and the influence of external factors such as geopolitical events, economic crises, and other unpredictable factors.

The distribution of returns exhibits fatter tails and aligns more closely with a Student's t distribution rather than a Gaussian distribution.



Autocorrelation analysis highlights a significant lag at both lag 1 for both the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). This suggests a high degree of serial correlation in the data, indicating persistent patterns in returns over time.



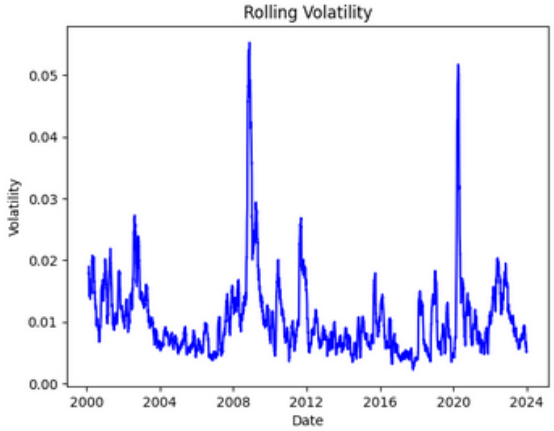
Volatility Cluster:

Alpha (1) and beta (1) parameters in the GARCH model yield a t-statistic of 3.385 and 9.773 ($p < 0.001$), provide insights into the persistence and clustering behavior of volatility. These findings suggest that SPY data exhibit characteristics of non-normality, with heavier tails and significant autocorrelation in returns.

Turmoil Events

Going back to Table 1. we can observed the significantly higher volatility during 2008 and 2020 with standard deviation of 2.19 and 2.104 respectively, comparing to the total standard deviation of the market 1.24.

Both 2008 and 2020 had similar kurtosis values (7.13 and 7.33, respectively), indicating heavy-tailed distributions and heightened likelihood of extreme returns compared to a normal distribution. However, the total dataset exhibited higher kurtosis (11.46), indicating even heavier tails and a greater propensity for extreme market events over the entire period.



Abnormal return refers to the difference between an asset's actual return and its expected return over a specific time period, typically derived from a benchmark index or a predictive model. Cumulative Abnormal Return (CAR) represents the accumulation of abnormal returns over a series of consecutive periods.

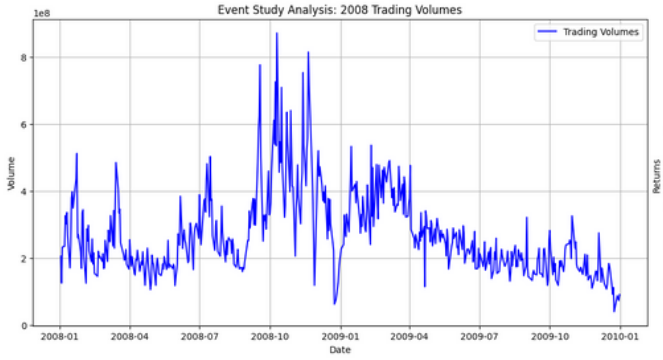
Trading volume refers to the total number of shares, contracts, or units of a financial asset that are bought and sold during a specific period, typically within a trading day or over a given time frame. It is a key metric used to measure the level of market activity and liquidity for a particular security or financial instrument.

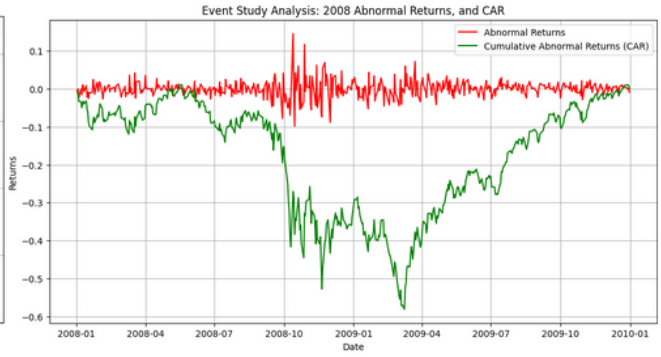
We observed the surge in trading volume alongside declining Cumulative Abnormal Returns (CAR) during the 2008 and 2020 crisis, which indicates a strong correlation between market activity and security performance. As CAR declines, reflecting significant investor losses, trading volume rises as market participants react to deteriorating conditions by buying and selling securities. This relationship between trading volume and CAR underscores heightened investor uncertainty and intense market dynamics typical of crisis periods. Moreover, the spike in trading volume may exacerbate price movements and volatility, as large volumes of transactions amplify market reactions, potentially worsening market downturns.

2008:

The financial crisis of 2008, often referred to as the Great Recession, was one of the most severe economic downturns in modern history. Stemming from the collapse of the subprime mortgage market in the United States, the crisis quickly spread globally,

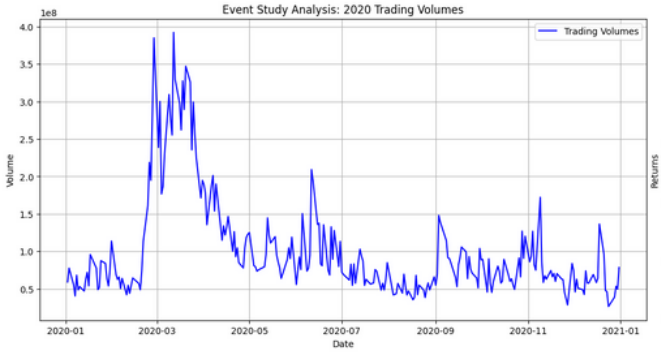
resulting in widespread bank failures, plummeting stock markets, and a sharp decline in economic activity. The crisis was characterized by a liquidity crunch, with financial institutions facing insolvency and credit markets freezing up.

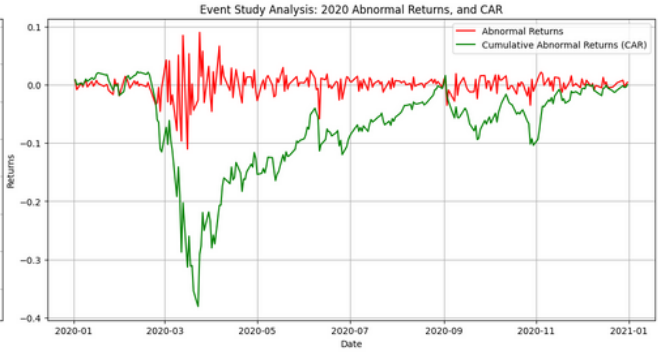




2020:

The COVID-19 pandemic triggered an unprecedented crisis in 2020, with far-reaching implications for public health, economies, and financial markets worldwide. Stock markets experienced extreme volatility, with major indices recording steep declines in a matter of weeks. The pandemic-induced recession resulted in mass unemployment, business closures, and significant economic contractions across sectors.





Conclusion

This project provides a comprehensive analysis of market non-normality using SPY data from 2000 to 2024, with a focus on three significant turmoil events in 2008 and 2020. Through various statistical methods and modeling techniques, we have highlighted the presence of non-normality in market returns, characterized by fat tails, volatility clustering, and persistent serial correlation. By comparing the metrics of these turmoil events to the overall dataset, we have demonstrated the severity of market disruptions during these periods, as evidenced by sharp declines in Cumulative Abnormal Returns (CAR) and spikes in trading volume. The analysis highlights the unpredictable nature of financial markets and the importance of adapting risk management strategies to evolving conditions.

Future research could focus on exploring additional factors contributing to market non-normality, such as behavioral biases, algorithmic trading, and systemic risk.

Appendices

Constant Mean - GARCH Model Results

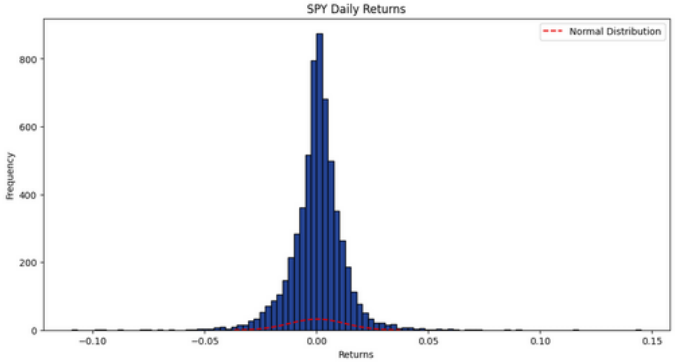
Dep. Variable:	Return	R-squared:	0.000
Mean Model:	Constant Mean	Adj. R-squared:	0.000
Vol Model:	GARCH	Log-Likelihood:	4335.16
Distribution:	Normal	AIC:	-8662.33
Method:	Maximum Likelihood	BIC:	-8635.50
		No. Observations:	6036
		Df Residuals:	6035
		Df Model:	1

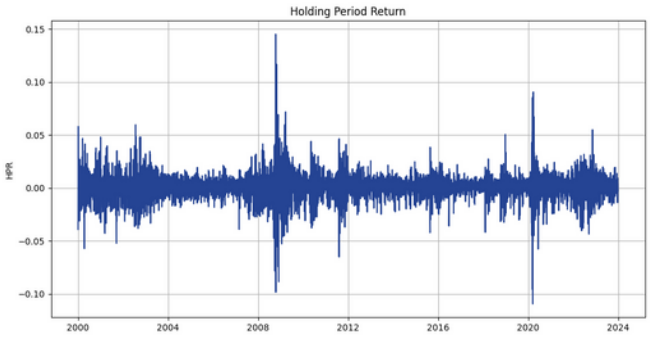
Mean Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
mu	0.1168	1.215e-03	96.199	0.000	[0.114, 0.119]

Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	2.5920e-05	2.228e-04	0.116	0.907	[-4.107e-04,4.625e-04]
alpha[1]	0.2494	7.366e-02	3.385	7.106e-04	[0.105, 0.394]
beta[1]	0.7302	7.471e-02	9.773	1.473e-22	[0.584, 0.877]





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