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Calendar Anomalies in Crisis: Intra-Day Volatility Patterns During the GFC and COVID-19

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Abstract – This paper explores how intra-day volatility behaves across different weekdays during periods of major financial stress, focusing specifically on the S&P 500 and NASDAQ-100 indices. The analysis spans two significant market disruptions—the 2008 Global Financial Crisis and the 2020 COVID-19 crash—using one-minute interval data to capture short-term fluctuations. The study applies both parametric and non-parametric statistical techniques to examine whether patterns such as weekday volatility differences and the Monday effect persist, diminish, or shift under varying market regimes. The results indicate that while weekday-based volatility differences are less pronounced during crash and recovery periods, they re-emerge post-crisis, particularly in the S&P 500 index. Mondays typically display lower volatility, whereas Fridays often exhibit heavier tails in their distribution. A weak but statistically meaningful correlation was found between weekday order and volatility, suggesting a slight upward trend in volatility toward the end of the week. These findings contribute to the understanding of temporal risk dynamics and provide useful context for volatility modeling, especially in post-crisis environments where behavioral patterns may return to more predictable rhythms.

Keywords – Intra-day volatility, Calendar Anomalies, Monday Effect, Financial Crisis, Volatility Patterns, High Frequency Trading

I. Introduction

Volatility is a core concept in financial markets, generally referring to the degree of variation in asset prices over time. It serves as a proxy for risk and uncertainty and is widely used in forecasting, portfolio optimization, and trading strategies. While traditional studies often focus on daily or longer-horizon volatility, intra-day volatility—the variability of prices within a single trading day—offers a more granular lens through which to understand short-term market behaviour.

As defined by [1], intra-day volatility captures the "volatility of price changes over short intervals (e.g., 5 minutes) during the trading day, which shows patterns of persistence and predictability over time". This type of volatility reflects how "bumpy" or "calm" the market is throughout the day and is particularly relevant for high-frequency traders, algorithmic strategies, and intraday risk management. Unlike daily closing prices, intraday measures allow researchers and practitioners to observe the temporal distribution of market risk, identify volatile periods during the trading session, and detect behavioral anomalies such as weekday effects that may be obscured in daily aggregates.

While investors often monitor the market closely to formulate strategic investments and manage risks, uncertainties such as the Global Financial Crisis (GFC) and the COVID-19 pandemic are unheralded and difficult to anticipate. In such crises, individuals may resort to impulsive investment decisions, which can either yield unexpected gains or result in significant losses. For the average investor, the primary objective is typically to realize profits from market movements. However, factors such as volatility and trading volume play a crucial role in identifying market patterns and in developing a strategic framework that accounts for these dynamic variables.

A. Background and Context

Volatility in the stock market is a central topic in finance as it reflects the risk and uncertainty associated with asset prices. Although traditional research often models volatility as a continuous process influenced by macroeconomic variables, studies have increasingly found seasonal and calendar-based anomalies, particularly the "day-of-the-week effect"—a pattern where returns and volatilities differ depending on the weekday. For example, early studies by [2] and [3] found that returns on Mondays tend to be lower compared to other days, while Fridays show higher returns.

In addition to returns, volatility itself has been shown to vary by weekday. Several studies using GARCH-based models demonstrated that volatility is often highest mid-week or around economic stress periods, reacting in distinct ways. These findings suggest the need for further exploration, particularly across indices like the S&P 500 and NASDAQ, where composition and investor behavior differ significantly. Financial crises have a large impact on market behavior, market volatility usually ranges between low to moderate during the regular, and there have been studies showing the presence of day of the week volatility ([4], [5]), while these day of the week anomalies are prevailing over the world in different markets, the specificity of a particular day showing the pattern varies in different markets. Now, as the crisis hits the market, volatility surges across the board, and markets experience large swings nearly every day, driven by constant news, policy responses, and changes in investor sentiment.

In these uncertain movements, markets might show deviated behavior from the usual weekday anomalies; it is plausible that different phases of crises might show different behavior towards the weekday anomalies.

B. Problem Statement

Although weekday effects in returns and volatility are well documented, most prior studies focus on daily data or aggregated indices, often overlooking intra-day dynamics. Comparisons between the S&P 500 and NASDAQ are also limited, despite their structural and behavioral distinctions.

Moreover, many studies rely on statistical methods that assume normality, which high-frequency financial data frequently violates. This study addresses these gaps by using both parametric and non-parametric methods to explore weekday-specific intra-day volatility patterns, particularly in the context of major market crises. There are studies on finding the day of the week presence during crisis period based on countries at different market maturity levels [6]. As per our knowledge, there are no relevant studies that specifically examine the U.S. stock market across different phases of a crisis to test for the presence of weekday volatility patterns.

C. *Significance of the Study*

This study contributes meaningfully to both academic research and financial practice by examining how intra-day volatility patterns vary across weekdays and evolve during different regimes of financial crises. While prior literature has extensively documented daily return anomalies such as the Monday effect and Friday premium, this research shifts the focus to high-frequency intra-day volatility, offering a more granular view of market behaviour that is often masked in daily data.

Unlike [7], who explored day-to-day return and volatility behaviour over a 10-year period using dummy variable regression models, this research shifts focus to short-interval price movements, aiming to uncover volatility differences that may be masked in daily summaries. In doing so, the research emphasizes weekday-specific volatility behaviour, aiming to identify whether particular weekday's consistently exhibit higher or lower intra-day volatility across different crisis phases.

By analysing the S&P 500 and NASDAQ indices across six distinct phases tied to the Global Financial Crisis and the COVID-19 market disruption, the study provides a phase-based understanding of how systemic events reshape weekday volatility patterns. It further enhances methodological robustness by using statistical tests, which are well-suited to the characteristics of high-frequency financial data.

In addition to identifying variations in volatility across weekdays, the study explores the persistence and transformation of the Monday effect, a historically observed anomaly, in different crisis regimes. This added dimension helps clarify how behavioral effects fluctuate under stress and recovery, offering practical insights for risk timing and short-term trading strategies during and after market turbulence.

D. *Research Objective*

This thesis aims to investigate the existence and behavior of weekday-specific intra-day volatility within the S&P 500 and NASDAQ indices, focusing on three distinct market phases:

- Crash Phase: From peak to market bottom,
- Recovery Phase: From bottom to full rebound,
- Post-Recovery Phase: The period after markets return to a new peak.

These phases are studied within the context of two major economic crises—the 2008 Global Financial Crisis and the COVID-19 Market Crash. By isolating these periods, we aim to identify whether intra-day volatility patterns vary by day of the week during market stress, recovery, and stable post-crisis conditions. To achieve this, the study uses non-parametric statistical methods, such as the Kruskal-Wallis test, which allow for robust volatility comparisons without relying on distributional assumptions.

The primary focus is to examine whether volatility varies by weekday, and how these patterns evolve under different market regimes, including crisis and recovery periods associated with the 2008 Global Financial Crisis and the COVID-19 crash. In addition to this broader analysis, the study also explores the relationship between returns and volatility across weekdays, with special attention to the Monday effect — a historically observed pattern where market returns tend to underperform at the beginning of the week. By analysing intra-day return- volatility correlations, this research investigates whether the Monday effect persists under different economic conditions and what role volatility plays in reinforcing or weakening this behaviour.

II. LITERATURE REVIEW

A. *Calendar Anomaly: Stock Market Anomaly*

Calendar anomalies, especially the "day-of-the-week effect," have been studied for decades. [2] and [3] first documented that returns tend to be lower on Mondays and higher on Fridays. Later studies expanded this phenomenon to international markets and different asset classes. [8] and [9] contributed to the robustness of these findings across geographies.

In addition to return patterns, researchers such as [10] and [11] have shown that volatility itself is not constant throughout the week. These studies often use GARCH models to capture the time-varying nature of volatility, finding that volatility tends to cluster around certain weekdays, particularly mid-week. However, most of these studies rely on daily data and aggregate indices, offering limited insight into intra-day behavior.

More recent work, including [7], examines weekday effects in the context of systemic shocks such as COVID-19. They found no statistically significant weekday effect in daily returns across major U.S. indices during the pandemic, but this leaves open the question of whether intra-day volatility might reveal hidden patterns. Our study builds on this gap by exploring short-interval volatility during both the GFC and COVID-19 crises across two major indices.

A. *Economic Crises*

1) 2008-09 Global Financial Crisis: The 2008–09 global financial crisis, triggered by the collapse of the U.S. subprime mortgage market, marked a critical inflection point in the history of financial volatility. It unleashed a cascading economic downturn across the world, severely destabilizing capital markets and significantly increasing investment risk. [12] observed that this crisis led to prolonged high unemployment rates and dramatic equity market declines, notably in indices like the Hang Seng and Jakarta Composite, which recorded sharp losses in October 2008. The globalized nature of financial systems magnified the crisis's contagion effect, allowing shocks from the U.S. to quickly spread to emerging markets. Scholars such as [13] emphasized that BRICS nations, due to their growing foreign capital exposure, were particularly vulnerable during this period. Supporting this view, [14] employed the VIRF framework to analyze volatility transmission from the U.S. to BRICS stock markets, concluding that a similar crisis in today's more interconnected financial environment could cause even greater disruption [15]. Additionally, [16] provided empirical evidence of significant volatility spillovers among both advanced and emerging markets during the crisis. [17] also stressed the importance of incorporating U.S. excess returns and volatilities when studying international markets, as they are strongly linked to volatility and correlation dynamics across global economies [15].

2) COVID-19: The COVID-19 pandemic represented an unprecedented economic shock with rapid and widespread effects on global financial markets. The crisis led to one of the steepest market crashes in history, with the S&P 500 losing over 20% of its value—its worst performance since the 2008 financial crisis [15]. A comparative analysis of BRICS nations revealed a strong positive relationship between rising COVID-19 case numbers and increased stock market volatility, with notable shifts in both average returns and variance observed before and after the outbreak [15]. Notably, China, Brazil, and South Africa experienced heightened market turbulence due to the pandemic, while India and Russia appeared to be more influenced by the 2008 financial crisis, indicating differential sensitivity to economic shocks. [12] documented that global indices such as the Dow Jones, FTSE All-Share, and S&P 500 underwent historic single-day losses in March 2020, with emerging economies facing significant declines as well [12]. Beyond its financial dimensions, the pandemic also disrupted consumer confidence, international trade, and sectoral performance, particularly in industries such as aviation and oil. [18] categorized the COVID-19 outbreak as both a health and financial crisis, highlighting the need for updated risk models and more resilient financial policies to guide investment behavior under such uncertain conditions [18].

B. Monday Effect

A well-documented calendar anomaly in financial markets is the "Monday Effect," where returns tend to be abnormally low or even negative at the beginning of the trading week. One of the earliest contributions was made by [2], who found that between 1953 and 1970, stock prices (particularly the S&P Composite Index) rose more frequently on Fridays than on Mondays, with the percentage of positive returns on Fridays significantly exceeding that of Mondays. This asymmetry was persistent over 18 years and statistically significant. Similarly, [3] analyzed 25 years of data and confirmed consistently negative mean returns on Mondays across all five-year sub-periods, concluding that the phenomenon was inconsistent with both trading time and calendar time models. His findings imply that information released over the weekend—often negative in nature—could play a role, thereby challenging the notion of market efficiency.

Expanding on this, [19] confirmed the presence of the Monday Effect across individual stocks and treasury bills using S&P 500, value-weighted, and equal-weighted indexes from 1962 to 1978. Their results showed that Monday returns were uniformly low or negative across almost all Dow Jones 30 stocks, and even after adjusting for heteroscedasticity, the effect remained strong. Additionally, treasury bills exhibited a similar pattern, suggesting that institutional peculiarities alone could not explain the anomaly. Their study also highlighted the implications of these patterns for tests of market efficiency, emphasizing the necessity of incorporating weekday effects into asset pricing models. Together, these studies underscore the robustness and consistency of the Monday Effect across decades and asset classes

III. Data and Methodology

A. *Data and Data Source*

The data used in this study comprises high-frequency (one-minute interval) intra-day stock prices collected from the academically accessible database available at Skyskraper.AI. The dataset includes constituent stocks from the S&P 500 (SPX) and NASDAQ-100 (NDX) indices, covering the period from October 2007 to December 2022. The Global Financial Crisis (2008) and the COVID-19 crash (2020) are used in this study due to their unparalleled depth, speed, and systemic nature. Both events triggered historic market declines, required extraordinary policy responses, and caused widespread shifts in economic and investor behavior. Their impact was global, synchronized, and well-documented in academic and regulatory literature, making them ideal candidates for analyzing volatility behavior across crisis, recovery, and post-recovery phases. Unlike shorter or localized market corrections, these events offer segmented periods that reflect different volatility regimes, allowing for a robust examination of weekday effects and behavioral anomalies such as the Monday effect. To ensure consistency across crisis periods, the analysis focuses on the S&P 500 (SPX) and NASDAQ-100 (NDX) indices, which were selected for their broad market representation and historical relevance. Only data from standard U.S. trading hours (9:30 AM to 4:00 PM) were used. The high-frequency data Minute-level index prices were processed to compute logarithmic returns, which were then aggregated daily to calculate both daily return and daily realized volatility. The latter was defined as the square root of the sum of squared intra-day log returns, enabling a high-frequency measure of volatility suitable for weekday-level and phase-based comparisons. Due to the unavailability of high-frequency volume data in selected academic databases and the lack of accessible open-source alternatives, this study primarily focuses on price-based volatility and its behavior across weekdays.

A. *Crisis Phases and Periods*

To investigate how intra-day volatility varies by day of the week and market condition, six phases were selected based on historical stock market behavior around the 2008 Global Financial Crisis (GFC) and the COVID-19 Crash.

These phases were defined based on market peaks, bottoms, and recovery periods, as outlined in widely accepted economic research frameworks.

The six crisis phases and their respective time frames are listed in Table 1:

These phases were selected based on major turning points in U.S. financial markets, and they represent distinct economic and behavioral environments. The segmentation allows us to isolate and compare how intra-day volatility patterns shift across different types of market regimes—crisis, recovery, and post-recovery, both for short-lived (COVID) and long-drawn (GFC) economic events. The table defining these phases is adapted from publicly available academic resources and financial crisis chronology used in market research and investment banking archives.

B. *Data Handling*

High-frequency financial data, such as minute-by-minute stock prices, often contains significant market microstructure noise, which arises from bid-ask bounce, discrete price movements, and asynchronous trading. This noise contaminates the observed prices and distorts volatility estimates, particularly when very fine sampling intervals are used. As rigorously demonstrated by [20], realized volatility computed from high-frequency returns is upwardly biased in the presence of microstructure noise, leading to inaccurate representations of the underlying price variation. To address this issue, several noise-robust estimators have been proposed. [20] introduced the Two-Scale Realized Volatility estimator, which blends high and low frequency data to reduce bias. [21] recommended approaches such as optimal sparse sampling using five-minute intervals and pre-averaging to mitigate noise while preserving information. Additionally, [22] developed the volatility signature plot as a diagnostic tool to identify the optimal sampling frequency and proposed kernel-based estimators to handle persistent microstructure effects.

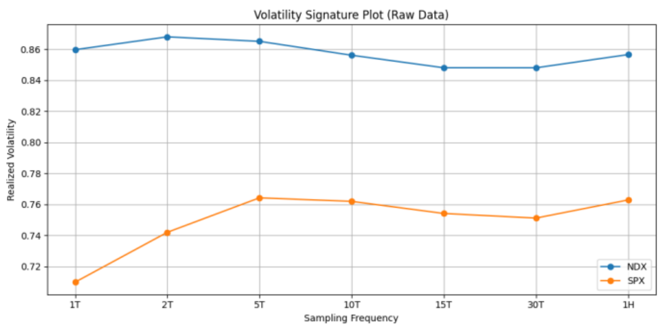

Figure 1 : Volatility Signature Plot

To assess the presence and severity of microstructure noise in the high-frequency price data, we applied three standard diagnostics: the volatility signature plot, the lag one autocorrelation of one-minute log returns, and the Two-Scale Realized Variance (TSRV) estimator. The volatility signature plot Fig.1 visualizes realized volatility across a range of sampling intervals, from one minute up to one hour, for both the NDX and SPX indices, shown in Table 2. A typical indicator of microstructure noise is a sharp decline in realized volatility as the sampling frequency decreases, since noise-induced fluctuations tend to be averaged at coarser intervals. However, our results show only minimal variation in volatility across frequencies. For the SPX index, the realized volatility has a difference of 7.65 percent between the one-minute and 5-minute intervals, while the NDX index shows a similarly small change of around 0.63 percent. This limited sensitivity to sampling frequency suggests that the high-frequency price series are not materially distorted by noise. This finding is consistent with prior literature, indicating that highly liquid and mature indices tend to exhibit minimal microstructure frictions ([20] [23] To validate this interpretation using a more statistically robust approach, we computed the TSRV, which adjusts realized volatility for the effects of high frequency measurement error by using multiple sub-sampling scales [20]. For the NDX index, the TSRV was estimated at 0.60824, compared to a realized volatility of 0.73898. For the SPX index, the TSRV was 0.46560 against a realized volatility of 0.50397. These values imply that the noise component is moderate in NDX and minimal in SPX, with the signal remaining dominant in both series. The relative gap between standard and adjusted volatility is approximately 17.7 percent for NDX and 7.6 percent for SPX, further supporting the inference that noise contamination is not severe.

Finally, we examined the lag one autocorrelation of one-minute log returns, a commonly used diagnostic for detecting short-term return reversals associated with bid-ask bounce. The autocorrelation was measured at 0.02588 for NDX and 0.06809 for SPX. These values are close to zero and fall within commonly accepted bounds for low-noise signals [21], although the slightly higher value for SPX may reflect some mild noise-related reversal effects. Taken together, the evidence from all three diagnostics—the stability of the volatility signature plot, the modest adjustment required by the TSRV, and the near-zero autocorrelation—indicates that the presence of microstructure noise in our dataset is negligible. Therefore, we proceed with the raw price and return series for all subsequent volatility analysis, without applying additional denoising techniques.

Following data cleaning and noise reduction, the minute-level stock price data was structured into a star schema to support volatility analysis. The dataset included OHLC prices for two major indices, along with time-stamps, index identifiers, and market phase labels.

A temporal dimension was created by merging date and time into a single datetime field, from which year, month, day, day, hour, minute, and weekday were derived. Each timestamp was assigned a surrogate key for efficient joins. Similarly, index names were standardized and mapped to unique IDs in an index dimension.

Market phase labels were normalized and grouped into broader categories like “During Crisis”,” Recovery”, and “Post Crisis” for macro-level comparisons. The central fact table combined minute-level observations with foreign key references to all dimensions, enabling scalable and granular analysis of volatility across time and economic regimes.

Each trading day was tagged with its corresponding weekday and assigned to a crisis phase label based on its date, allowing for analysis by day of the week within each market regime. The dataset was normalized and structured to support statistical testing, as well as correlation analysis between return and volatility.

Sampling Interval	NDX RV	NDX % Change from 1T	SPX RV	SPX % Change from 1T
1 Minute (1T)	0.85964	—	0.70991	—
2 Minutes (2T)	0.86793	+0.96%	0.74202	+4.52%
5 Minutes (5T)	0.86504	+0.63%	0.76424	+7.65%
10 Minutes (10T)	0.85607	−0.42%	0.76197	+7.33%
15 Minutes (15T)	0.84802	−1.35%	0.75416	+6.23%
30 Minutes (30T)	0.84800	−1.35%	0.75119	+5.81%
1 Hour (1H)	0.85649	−0.37%	0.76288	+7.46%

Table 1 Realized Volatility for Both Indices

Table 2 Crisis Phases

Crisis Phase	Description	Date Range
1. GFC Crash Phase	Peak to market bottom during the 2008 financial meltdown	Oct 9, 2007 – Mar 9, 2009
2. GFC Recovery Phase	Market rebounding from the bottom to full recovery	Mar 10, 2009 – Mar 28, 2013
3. Post-GFC Recovery Period	Stable post-recovery period before COVID	Mar 29, 2013 – Feb 19, 2020
4. COVID Crash Phase	Market panic and sharp decline due to COVID-19 outbreak	Feb 20, 2020 – Mar 23, 2020
5. COVID Recovery Phase	Recovery from COVID lows to the previous market peak	Mar 24, 2020 – Aug 18, 2020
6. Post-COVID Recovery Period	Post-recovery expansion phase, prior to 2022 downturn	Aug 19, 2020 – Dec 31, 2022

C. *Exploratory Data Analysis:*

To examine underlying price dynamics across distinct market regimes, we constructed empirical distribution plots of closing prices for the SPX and NDX indices. Figure 2 presents close price distributions segmented by regime—During Crisis, Recovery, and Post-Crisis—while Figure 3 displays regime-specific and index-specific distributional characteristics, respectively.

The results reveal systematic shifts in price distributions across phases. During crisis periods, both indices exhibit compressed valuations and distributional clustering at lower price levels, consistent with broad-based selloffs, deleveraging, and risk aversion. The recovery regime is characterized by wider dispersion and heavier tails, reflecting transitional volatility and uncertain price discovery as markets respond to policy interventions and shifting investor expectations.

Importantly, the post-crisis regime distributions closely resemble the full-sample distributions for both indices, suggesting that this phase represents a baseline state of market behaviour. This finding reinforces our hypothesis that calendar anomalies, including weekday-based volatility patterns, are most reliably observed in post-crisis environments where market microstructure conditions have stabilized and noise is minimized.

Moreover, the NDX consistently displays higher central tendencies and greater dispersion compared to the SPX across all regimes. This aligns with its growth-heavy composition, particularly its concentration in the technology sector, and reflects its higher sensitivity to macroeconomic shifts and investor sentiment, making it a valuable comparator in regime-specific volatility analysis.

In particular, the outlier rates presented in Table 3 ranged approximately between 5% and 7% during crisis periods, moderating to roughly 3% to 4% in recovery and post-crisis phases. These elevated outlier frequencies during crisis periods align closely with previous empirical findings highlighting increased return volatility, kurtosis, and clustering of extreme observations during financial stress episodes [24], [25]. Rather than representing data anomalies, these extreme volatility observations likely reflect authentic market responses to news shocks, heightened uncertainty, liquidity constraints, and structural market frictions [26]. Consequently, excluding or smoothing these data points without a clear economic rationale risks artificially understating the actual volatility and obscuring meaningful market dynamics.

D. *Return and Volatility Construction*

To quantify daily return variation and intra-day volatility in a high-frequency setting, we construct minute-level log returns and aggregate them into daily realized volatility (RV) measures. The realized volatility for each trading day is computed by summing the squared minute-wise log returns and taking the square root, thereby capturing the total return variation throughout the trading day. This estimation follows the frameworks established by [11] and [22], which are widely adopted in volatility modelling using high-frequency data.

$$RV_t = \sqrt{\sum_{i=1}^{n_t} r_{t,i}^2}$$

Where:

- RV_t: Realized volatility on trading day t
- $r_{t,i}$: Log return in the i^{th} minute of day t
- n_t: Number of intraday intervals on day t

E. *Weekday Volatility Patterns and Statistical Testing*

To evaluate the presence of systematic weekday volatility effects, we analyze the daily realized volatility across different weekdays. This analysis is conducted separately for each market phase—During Crisis, Recovery, and Post-Crisis—and for each index, namely SPX and NDX. Our initial tests assess whether average daily volatility differs significantly across the market phases.

To determine whether volatility significantly varies across weekdays within each phase and index, the one-way ANOVA is used to test for differences in mean realized volatility across weekdays. The Kruskal–Wallis H-test, a non-parametric alternative to ANOVA, is employed when return distributions

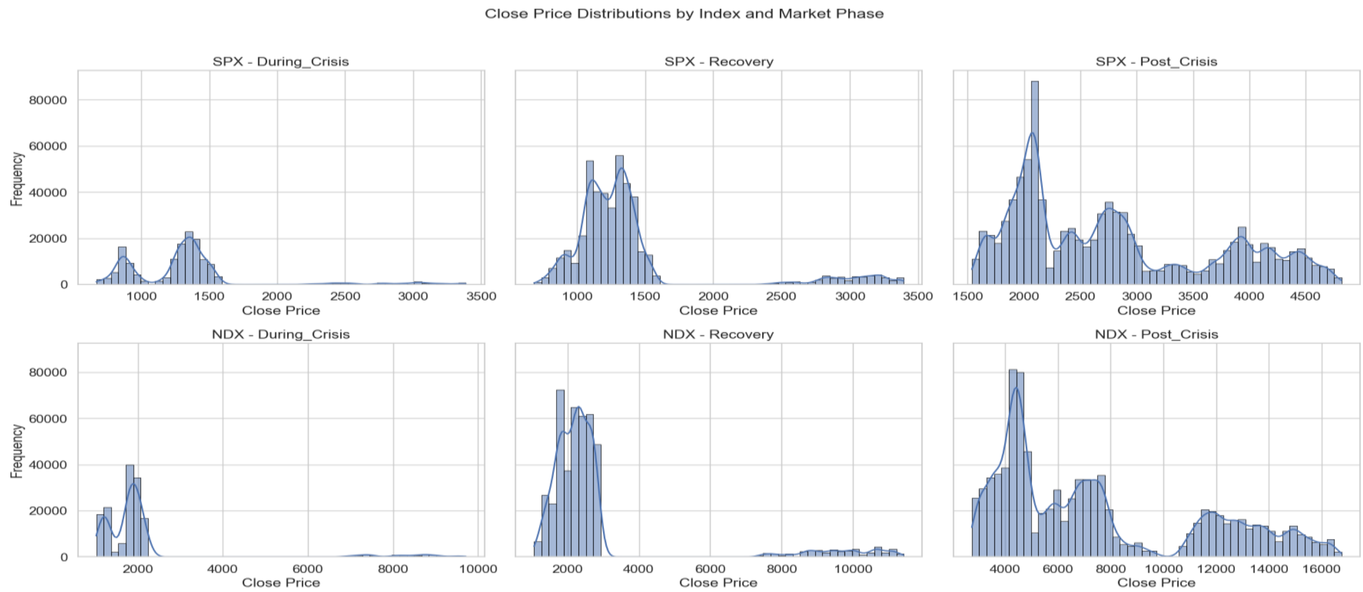

Figure 2 : Distribution of close Price during different Market regimes

deviate from normality or contain outliers. It tests whether the distributions of realized volatility values are the same across weekdays. Additionally, Mann–Whitney U tests are conducted for all pairwise weekday comparisons to identify specific day-to-day differences.

We complement these tests with a series of visual diagnostics to illustrate weekday-wise patterns in realized volatility. Box-plots, violin plots, and line charts are used to visualize volatility distributions and mean behavior across weekdays within each market regime and for each index. These visualizations aid in identifying trends and confirming statistical findings. To capture potential monotonic trends in volatility across the trading week, we use the Spearman rank correlation

Figure 3 : Distribution of close price for SPX and NDX

Table 3 : Outlier Analysis by Market Phase and Index

Index	Phase Group	Total Observation	Outliers Count	Outliers %
NDX	During Crisis	379	26	6.86%
NDX	Post Crisis	2389	96	4.02%
NDX	Recovery	1,124	39	3.47%
SPX	During Crisis	379	19	5.01%
SPX	Post Crisis	2,389	105	4.40%
SPX	Recovery	1124	44	3.91%

between ordinal weekday values and daily realized volatility. This non-parametric measure helps detect increasing or decreasing volatility patterns from Monday through Friday, without assuming a linear relationship.

To further examine weekday-specific differences in volatility, we conduct pairwise Mann–Whitney U tests for each index. This approach enables robust comparison of realized volatility distributions between individual weekdays, providing insights into specific days where volatility behavior diverges significantly.

In addition to analysing volatility patterns, we explore the relationship between daily return and realised volatility. This analysis focuses exclusively on Mondays to examine whether the start of the trading week exhibits unique behavioural or informational effects. Pearson and Spearman correlation coefficients are calculated to evaluate both linear and monotonic relationships between Monday returns and volatility.

To deepen this analysis, we segment the return-volatility relationship by market phase. Pearson and Spearman correlations between daily return and realized volatility are computed for Mondays within each crisis phase, separately for SPX and NDX. This allows us to assess whether the strength or direction of the return–volatility association varies across different market regimes. Subsamples with insufficient observations are excluded to ensure statistical validity.

F. *Robustness Checks and Sensitivity Analyses*

To assess the robustness of weekday volatility patterns, we constructed additional daily volatility estimators based on high, low, open, and close price data, along with jump-robust methods. Specifically, we included the Parkinson, Garman–Klass, Rogers–Satchell, and Bi-power Variation estimators, which are widely used in financial econometrics for their efficiency and robustness in high-frequency settings. Kruskal–Wallis tests were applied across weekdays within each market phase using these alternative volatility measures, and the results were compared with those obtained from the baseline realized volatility. The consistency of statistical outcomes across all estimators reinforced the validity of the weekday volatility patterns identified in our primary analysis. Furthermore, we computed the average difference in volatility between Mondays and the rest of the week under each estimator to evaluate the persistence and directional bias of the Monday effect. To further evaluate the sensitivity of weekday volatility effects to the choice of

Index	Phase	N	Mean	Std Dev	Min	Max	Q25	Median	Q75	Skewness	Kurtosis
SPX	*During Crises*	379	0.0162	0.0110	0.0031	0.0858	0.0089	0.0123	0.0205	1.943	*8.237*
	Recovery	1,124	0.0080	0.0044	0.0019	0.0398	0.0050	0.0069	0.0097	2.159	*10.682*
	Post Crises	2,389	0.0059	0.0034	0.0012	0.0317	0.0035	0.0049	0.0073	1.785	*7.499*
NDX	*During Crises*	379	0.0182	0.0107	0.0037	0.0766	0.0113	0.0149	0.0215	2.112	*8.896*
	Recovery	1,124	0.0090	0.0042	0.0025	0.0482	0.0062	0.0081	0.0108	2.366	*14.466*
	Post Crises	*2,389*	*0.0076*	*0.0042*	*0.0017*	*0.0406*	*0.0048*	*0.0063*	*0.0095*	*1.804*	*7.878*

Table 4 Descriptive Statistics by Market Phase and Index

Index	H-statistic	P-value	Sig. at $\alpha = 0.1$	Sig. at $\alpha = 0.05$	Sig. at $\alpha = 0.01$
SPX	0.9834	0.912305	No	No	No
NDX	0.6162	0.961247	No	No	No

Table 5 Weekday Effect Analysis – During Crisis (Kruskal–Wallis Test)

Index	H-statistic	P-value	Sig. at $\alpha = 0.1$	Sig. at $\alpha = 0.05$	Sig. at $\alpha = 0.01$
SPX	8.3779	0.078676	Yes	No	No
NDX	5.1847	0.268863	No	No	No

Table 6 Weekday Effect Analysis – Recovery Phase (Kruskal–Wallis Test)

Index	H-statistic	P-value	Sig. at $\alpha = 0.1$	Sig. at $\alpha = 0.05$	Sig. at $\alpha = 0.01$
SPX	21.0578	0.000308	Yes	Yes	Yes
NDX	15.9256	0.003121	Yes	Yes	Yes

Table 7 Weekday Effect Analysis - Post Crisis (Kruskal-Wallis Test)

sampling frequency, we computed daily volatility measures using resampled intraday bars at 1-minute, 5-minute, and 15-minute intervals. For each frequency level, we estimated both realized volatility and bi-power variation and performed Kruskal–Wallis tests across weekdays within each market phase. This enabled us to determine whether observed weekday patterns are stable across temporal resolutions. In the post-Crisis regime, we also calculated effect sizes using epsilon-squared (ε^2) statistics to assess the proportion of variability attributable to weekday clusters. To complement this, we conducted post-hoc pairwise comparisons using Dunn's test with false discovery rate (FDR) adjustment, identifying specific weekday combinations that contributed to the overall significance.

IV. Results

A. *Descriptive Statistics and Market Phase Characteristics*

The descriptive statistics in Table 4 reveal distinct volatility regimes across the three market phases for both indices. Crisis phases exhibit the highest volatility levels (SPX: mean = 0.0182), followed by Recovery as an intermediate regime (SPX: mean = 0.0080, NDX: mean = 0.0090), with post-Crisis periods showing the lowest volatility (SPX: mean = 0.0059, NDX: mean = 0.0076). This hierarchical pattern occurs consistently across both indices.

All phases display positive skewness and excess kurtosis, with crisis and recovery periods showing more pronounced distributional characteristics. NDX consistently demonstrates higher volatility levels than SPX across all market phases.

B. *Statistical Validation of Market Phase Distinctions*

Both parametric and non-parametric tests show significant volatility differences across market phases. For SPX: ANOVA F-statistics = 720.66 ($p = 5.85\times10^{-267}$), Kruskal-Wallis H = 828.36 ($p = 1.33\times10^{-180}$). For NDX: ANOVA F-statistics = 673.73 ($p = 5.91\times10^{-252}$), Kruskal-Wallis H = 742.30 ($p = 6.47\times10^{-162}$).

C. *Weekday Volatility Patterns by Market Phase*

1) Overall Weekday Trends: ANOVA tests reveal marginal significance for SPX (F = 2.29, p = 0.057) but no significant weekday effects for NDX (F = 1.54, p = 0.189) across the complete sample period. Spearman rank correlations show SPX exhibits a weak positive correlation (ρ = 0.043, p = 0.007), while NDX shows no significant relationship (ρ = 0.018, p = 0.269).

Most significant pairwise differences occur between Monday and mid-week trading days: SPX Monday vs Wednesday (p = 0.000076), Monday vs Thursday (p = 0.000089); NDX Monday vs Wednesday (p = 0.000109), Monday vs Thursday
(p = 0.000591).

2) Crisis Period: No significant weekday effects observed for either index(Table 5). SPX: Kruskal-Wallis H = 0.98 (p = 0.912), ANOVA F = 0.38 (p = 0.822). NDX: H = 0.62 (p= 0.961), F = 0.31 (p = 0.875). Spearman correlations non-significant for both indices (SPX: ρ = 0.032, p = 0.534; NDX: ρ = 0.017, p = 0.745). The outcomes of the pairwise statistical comparisons between weekdays during crises are summarized in Table 11.

3) Recovery Period: SPX shows marginal weekday effects (H = 8.38, p = 0.079), NDX shows none (H = 5.18, p = 0.269) (Table 6). SPX exhibits significant Spearman correlation (ρ = 0.061, p = 0.041), while NDX remains non-significant (ρ = 0.024, p = 0.421). For SPX, Monday volatility differs significantly from Wednesday (p = 0.023) and Thursday (p = 0.006). The outcomes of the pairwise statistical comparisons between weekdays during the recovery period are summarized in Table 12.

4) Post-Crisis Period: Strong weekday effects observed for both indices(Table 7). SPX: Kruskal-Wallis H = 21.06 (p < 0.001), ANOVA F = 3.19 (p = 0.013). NDX: H = 15.93 (p = 0.003), F = 2.33 (p = 0.054). SPX maintains significant Spearman correlation (ρ = 0.050, p = 0.014).

Monday consistently shows the lowest volatility levels, while Wednesday exhibits peak levels. Most significant pairwise comparisons: SPX Monday-Wednesday (p < 0.001), Monday-Thursday (p < 0.001); NDX Monday-Wednesday (p < 0.001), Wednesday-Friday (p = 0.006).

The outcomes of the pairwise statistical comparisons between weekdays during the post-crises period are summarized in Table 13.

B. Monday Return-Volatility Relationship

Monday return-volatility correlations show significant negative relationships for both indices (Table 9). Overall sample: SPX Pearson r = −0.247 (p = 1.38×10^{-11}), Spearman r = −0.166 (p = 6.30×10^{-6}); NDX Pearson r = −0.256 (p = 2.08×10^{-12}), Spearman r = −0.188 (p = 3.19×10^{-7}).

1) Phase-Specific Analysis: The crisis period shows the strongest correlations: NDX Pearson r = −0.334 (p = 0.004), SPX r = −0.237 (p = 0.043). The recovery period exhibits the weakest associations with no significant correlations at conventional levels. Post-crisis period demonstrates re-established significance: SPX Pearson r = −0.265 (p = 1.38×10^{-8}), NDX r = −0.120 (p = 0.011) (Table 10 & 8).

Table 8 8 Monday Return-Volatility Correlations

Index	Pearson r	Spearman r
SPX	−0.247***	−0.166***
NDX	−0.256***	−0.188***
	*** p < 0.001	

C. Robustness Analysis

Alternative volatility estimators (Parkinson, Garman-Klass, Rogers-Satchell, Bi-power Variation) show high correlations with realized volatility (0.855-0.996). Post-crisis weekday effects remain consistent across estimators: BV shows the strongest concordance (SPX: H = 19.93, p < 0.001; NDX: H = 15.45, p = 0.004). Monday exhibits consistently lower volatility across all estimators, ranging from −0.0298% (Parkinson) to −0.0550% (Bi-power Variation).

Sampling frequency analysis (1-, 5-, 15-minute intervals) demonstrates pattern stability at higher frequencies. SPX shows significant effects at 1-minute (p = 0.008) and 5-minute (p = 0.033) intervals using Bi-power Variation, with attenuation at 15-minute intervals (p = 0.118).

Effect size analysis reveals weekday factors explain modest proportions of volatility variance in post-crisis periods (SPX: ε^2 = 0.004, NDX: ε^2 = 0.003). Post-hoc tests with FDR adjustment confirm Monday-Thursday (adjusted p = 0.011) and Monday-Wednesday (adjusted p = 0.011) as most robust effects for SPX, with Monday-Wednesday (adjusted p = 0.027) primary for NDX.

Table 9 9 Overall Monday Return-Volatility Correlations

Index	Correlation Type	*Correlation (r)*	p-value	Sign at α=**0.05**
SPX	Pearson	−0.2469	0.00000	Yes
SPX	Spearman	−0.1664	0.00001	Yes
NDX	Pearson	−0.2564	0.00000	Yes
NDX	Spearman	−0.1880	0.00000	Yes

V. DISCUSSION

This study provides novel insights into the fundamental nature of calendar anomalies by demonstrating their systematic disappearance and re-emergence across crisis phases. The findings challenge traditional views of market anomalies as persistent inefficiencies and reveal them as regime-dependent phenomena that reflect underlying market microstructure dynamics.

A. *Theoretical Implications for Market Efficiency*

The complete absence of weekday effects during crisis periods fundamentally alters our understanding of the Monday effect and related calendar anomalies. Traditional efficient market theory suggests anomalies should either persist due to structural factors or disappear through arbitrage [27]. Our findings reveal a third possibility: anomalies can be temporarily suppressed by extreme market conditions while retaining their underlying structural foundations.

This pattern suggests that calendar anomalies arise from institutional factors—such as fund flows, settlement cycles, and information processing patterns—that remain dormant during crises but reassert themselves as markets normalize. The systematic re-emergence of these patterns with similar magnitudes to pre-crisis levels indicates they reflect fundamental aspects of market architecture rather than temporary inefficiencies.

The heterogeneous recovery between SPX and NDX indices further illuminates the institutional foundations of weekday effects. Broad market indices appear more sensitive to the restoration of normal trading patterns, likely reflecting their greater exposure to institutional portfolio re-balancing and systematic trading strategies that drive calendar anomalies.

Table 10 Monday Return-Volatility Correlations by Market Phase

Index	Phase Group	Pearson r	Pearson p-value	Spearman r	Spearman p-value	Count
SPX	During Crisis	−0.2371	0.0434	−0.2583	0.0273	73
SPX	Recovery	−0.0935	0.1771	−0.0139	0.8413	210
SPX	Post Crisis	−0.2647	0.0000	−0.2196	0.0000	446
NDX	During Crisis	−0.3336	0.0039	−0.1631	0.1678	73
NDX	Recovery	−0.1132	0.1018	−0.0207	0.7080	210
NDX	Post Crisis	−0.1197	0.0114	−0.2462	0.0000	446

B. *Crisis-Induced Microstructure Transformation*

The volatility hierarchy observed across phases—crisis exhibiting highest levels, followed by recovery, then post-crisis stability—reveals how extreme events fundamentally alter market microstructure. During crises, the normal weekly rhythm of trading activity becomes overwhelmed by continuous information processing and heightened uncertainty, creating a more homogeneous volatility environment across weekdays.

This transformation extends beyond simple volatility amplification to encompass the complete breakdown of temporal trading patterns. The finding that alternative volatility estimators produce consistent results across this transformation validates that the observed patterns reflect genuine microstructure changes rather than measurement artifacts.

The leverage effect's evolution across phases provides additional insight into crisis-period dynamics. The strengthening of Monday return-volatility correlations during crises suggests that the start-of-week information processing role becomes more pronounced when market stress is elevated, consistent with theories of heightened attention and information sensitivity during turbulent periods.

C. *Integration with Existing Literature*

These findings extend the seminal work of [2] and [3] volatility and comparing across crisis types, we demonstrate that the suppression of calendar anomalies represents a general crisis phenomenon rather than a These findings extend the seminal work of [2] and [3] by demonstrating that the Monday effect is not a static phenomenon but varies systematically with market conditions. While previous studies have documented the Monday effect's persistence across decades, our high-frequency analysis reveals its dynamic nature and institutional foundations.

The temporary disappearance of weekday effects during crises reconciles apparently contradictory findings in the literature. Studies reporting the absence of calendar anomalies during specific periods may have inadvertently captured crisis-influenced time-frames, while those documenting persistent effects likely reflected normal market conditions.

Our results also complement recent work by [7], who found no significant weekday effects during COVID-19 using daily data. By extending this analysis to intraday volatility and comparing across crisis types, we demonstrate that the suppression of calendar anomalies represents a general crisis phenomenon rather than a COVID-specific anomaly.

D. *Broader Implications for Financial Theory*

The systematic evolution of weekday patterns across market phases suggests that market efficiency itself may be regime-dependent. Rather than viewing efficiency as a static property, these findings support a dynamic conception where the effectiveness of arbitrage mechanisms varies with market conditions.

During crisis periods, the resources and attention of arbitrageurs become focused on fundamental valuation discrepancies rather than calendar-based trading opportunities. This temporary suspension of anomaly-correcting forces allows fundamental uncertainty to dominate price formation, creating the homogeneous volatility environment we observe.

The re-emergence of patterns in post-crisis periods indicates that the underlying institutional and behavioral factors driving calendar anomalies reassert themselves as markets stabilize. This suggests that calendar anomalies represent an equilibrium outcome of institutional trading patterns rather than exploitable inefficiencies.

E. *Limitations and Future Directions*

Although this study focuses on two major systemic crises—the Global Financial Crisis (GFC) and the COVID-19 pandemic—the consistency of observed patterns across these structurally distinct events strengthens the validity and potential generalizability of the findings. However, to rigorously assess the universality of these temporal volatility dynamics, future research can extend the analysis to include additional types of crises such as geopolitical shocks and policy-induced disruptions, as well as international markets characterized by varying institutional frameworks and trading behaviors

A significant limitation of the present study is the unavailability of intraday trading volume data, which likely plays a crucial role in shaping return volatility through mechanisms such as order flow imbalances, liquidity variation, and institutional trading cycles. Incorporating high-frequency volume metrics in future research may provide deeper insights into the micro-structural determinants of weekday volatility effects.

In addition, integrating exogenous explanatory variables such as macroeconomic indicators, firm-level financial fundamentals, and real-time news sentiment could improve the explanatory power of the model and facilitate a more nuanced interpretation of behavioral and informational influences.

The analytical framework proposed in this study may also be extended to examine other calendar-based market anomalies, including turn-of-the-month effects, holiday-related patterns, and earnings announcement cycles, particularly in contrasting crisis and non-crisis regimes. Such extensions would contribute to understanding whether the attenuation of market anomalies during crises reflects a broader phenomenon with implications for market efficiency and investor behavior under conditions of systemic stress.

VI. Conclusion

This study aims to contribute to the literature on financial market volatility and calendar anomalies by examining weekday-specific intra-day volatility patterns in the S&P 500 and NASDAQ indices across two major crisis events: the Global Financial Crisis and the COVID-19 market crash. Using high-frequency data and robust statistical methods, the study seeks to understand how volatility behavior changes across distinct market phases—crisis, recovery, and post-recovery—and whether familiar patterns, such as the Monday effect, persist or evolve during these regimes.

The results indicate that while weekday-based volatility differences are less pronounced during crash and recovery periods, they re-emerge during post-crisis, particularly in the S&P 500 index. Mondays typically display lower volatility, whereas Fridays often exhibit heavier tails in their distribution. A weak but statistically meaningful correlation was found between weekday order and volatility, suggesting a slight upward trend in volatility toward the end of the week.

The findings contribute to a deeper understanding of temporal risk dynamics and offer critical insights for volatility modeling, particularly in post-crisis contexts where behavioral patterns tend to normalize. Moreover, they provide a valuable framework for investors seeking to interpret market behavior during unforeseen crisis events.

VII. Acknowledgments

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Appendix A:
Additional Results

Table 11 Pairwise Weekday Comparisons of Volatility - During Crisis

Index	Comparison	p-value	$\alpha = 0.1$	$\alpha = 0.05$	$\alpha = 0.01$
SPX	Tuesday vs Wednesday	0.961089	No	No	No
SPX	Tuesday vs Thursday	0.894891	No	No	No
SPX	Tuesday vs Friday	0.925864	No	No	No
SPX	Tuesday vs Monday	0.424096	No	No	No
SPX	Wednesday vs Thursday	0.917157	No	No	No
SPX	Wednesday vs Friday	0.950062	No	No	No
SPX	Wednesday vs Monday	0.446376	No	No	No
SPX	Thursday vs Monday	0.802125	No	No	No
SPX	Friday vs Monday	0.527589	No	No	No
SPX	Thursday vs Friday	0.386057	No	No	No
NDX	Tuesday vs Wednesday	0.858027	No	No	No
NDX	Tuesday vs Thursday	0.845092	No	No	No
NDX	Tuesday vs Friday	0.755046	No	No	No
NDX	Tuesday vs Monday	0.567663	No	No	No
NDX	Wednesday vs Thursday	0.796946	No	No	No
NDX	Wednesday vs Friday	0.975732	No	No	No
NDX	Wednesday vs Monday	0.680739	No	No	No
NDX	Thursday vs Monday	0.629259	No	No	No
NDX	Friday vs Monday	0.746418	No	No	No
NDX	Thursday vs Friday	0.485156	No	No	No

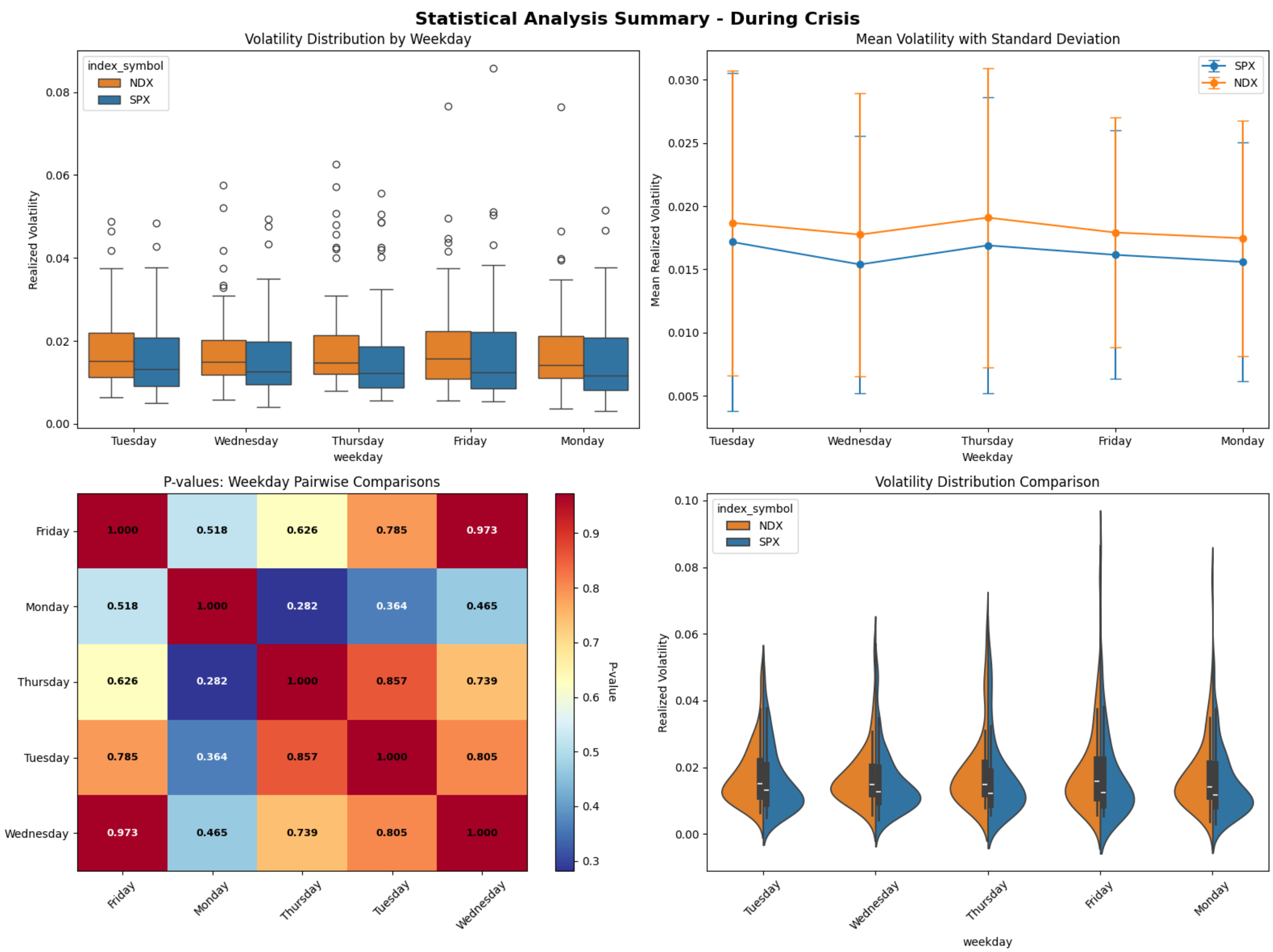

Figure 4 Statistical Analysis of Weekday Realized Volatility - During Crisis

Table 12 Pairwise Weekday Comparisons of Volatility – Recovery Phase

Index	Comparison	p-value	α = 0.1	α = 0.05	α = 0.01
SPX	Tuesday vs Wednesday	0.603573	No	No	No
SPX	Tuesday vs Thursday	0.321934	No	No	No
SPX	Tuesday vs Friday	0.918515	No	No	No
SPX	Tuesday vs Monday	0.089399	Yes	No	No
SPX	Wednesday vs Thursday	0.653257	No	No	No
SPX	Wednesday vs Friday	0.670532	No	No	No
SPX	Wednesday vs Monday	0.022530	Yes	Yes	No
SPX	Thursday vs Friday	0.388025	No	No	No
SPX	Thursday vs Monday	0.006171	Yes	Yes	No
SPX	Friday vs Monday	0.067482	Yes	No	No
NDX	Tuesday vs Wednesday	0.794744	No	No	No
NDX	Tuesday vs Thursday	0.757053	No	No	No
NDX	Tuesday vs Friday	0.446441	No	No	No
NDX	Tuesday vs Monday	0.121213	No	No	No
NDX	Wednesday vs Thursday	0.896248	No	No	No
NDX	Wednesday vs Friday	0.301960	No	No	No
NDX	Wednesday vs Monday	0.061213	Yes	No	No
NDX	Thursday vs Friday	0.263131	No	No	No
NDX	Thursday vs Monday	0.057879	Yes	No	No
NDX	Friday vs Monday	0.457094	No	No	No

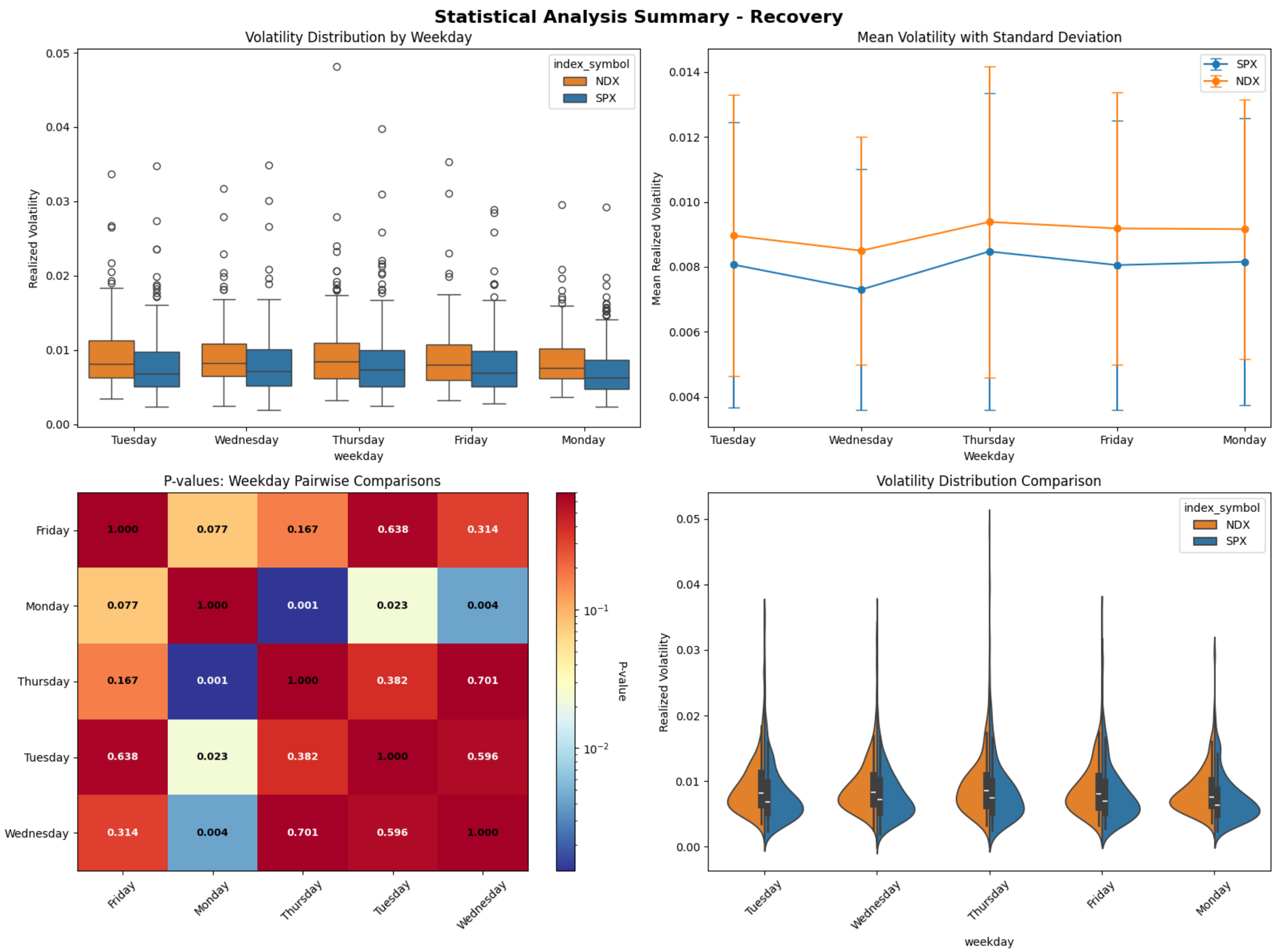

Figure 5 Statistical Analysis of Weekday Realized Volatility - Recovery

Table 13 Pairwise Weekday Comparisons of Volatility – Post Crisis

Index	Comparison	p-value	α = 0.1	α = 0.05	α = 0.01
SPX	Monday vs Tuesday	0.054175	Yes	No	No
SPX	Monday vs Wednesday	8.1e-05	Yes	Yes	Yes
SPX	Monday vs Thursday	0.000155	Yes	Yes	Yes
SPX	Monday vs Friday	0.062937	Yes	No	No
SPX	Tuesday vs Wednesday	0.028749	Yes	Yes	No
SPX	Tuesday vs Thursday	0.053951	Yes	No	No
SPX	Tuesday vs Friday	0.981859	No	No	No
SPX	Wednesday vs Thursday	0.779988	No	No	No
SPX	Wednesday vs Friday	0.037938	Yes	Yes	No
SPX	Thursday vs Friday	0.006403	Yes	Yes	No
NDX	Monday vs Tuesday	0.146918	No	No	No
NDX	Monday vs Wednesday	6.3e-05	Yes	Yes	Yes
NDX	Monday vs Thursday	0.00821	Yes	Yes	No
NDX	Monday vs Friday	0.460767	No	No	No
NDX	Tuesday vs Wednesday	0.035154	Yes	Yes	No
NDX	Tuesday vs Thursday	0.227471	No	No	No
NDX	Tuesday vs Friday	0.462451	No	No	No
NDX	Wednesday vs Thursday	0.354860	No	No	No
NDX	Wednesday vs Friday	0.005890	Yes	Yes	No
NDX	Thursday vs Friday	0.054703	Yes	No	No

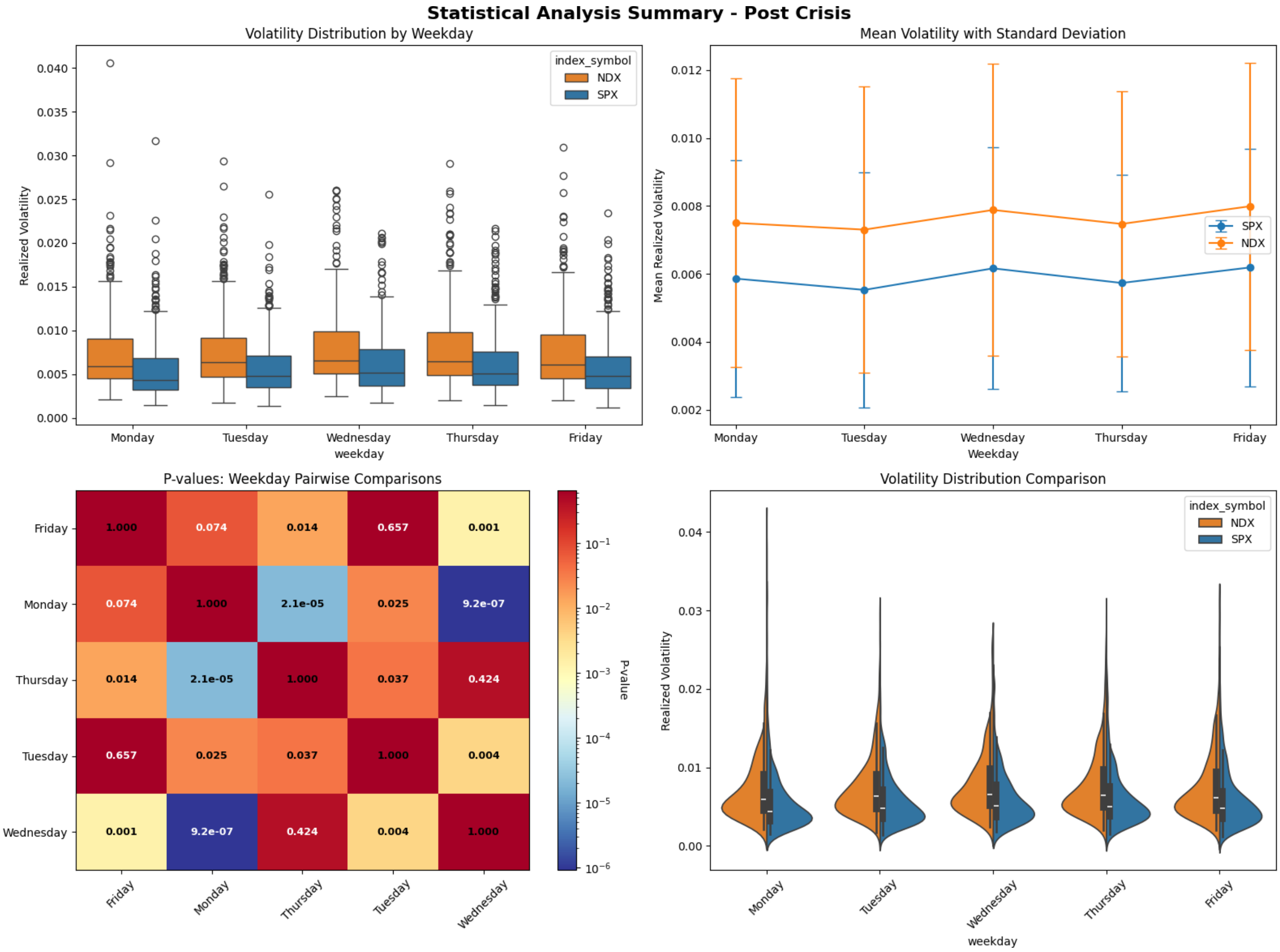

Figure 6 Statistical Analysis of Weekday Realized Volatility - Post Crises

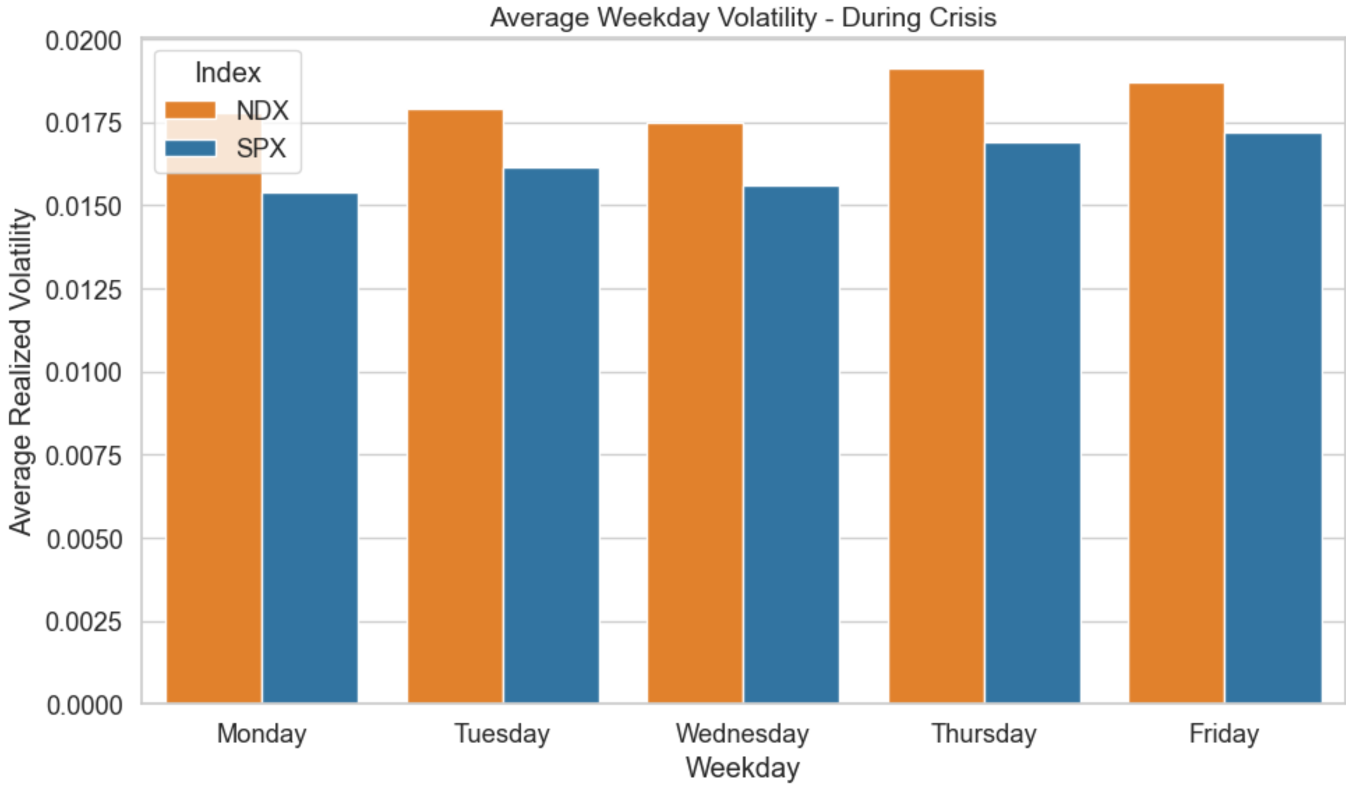

Figure 7 Average Weekday Volatility During Crisis

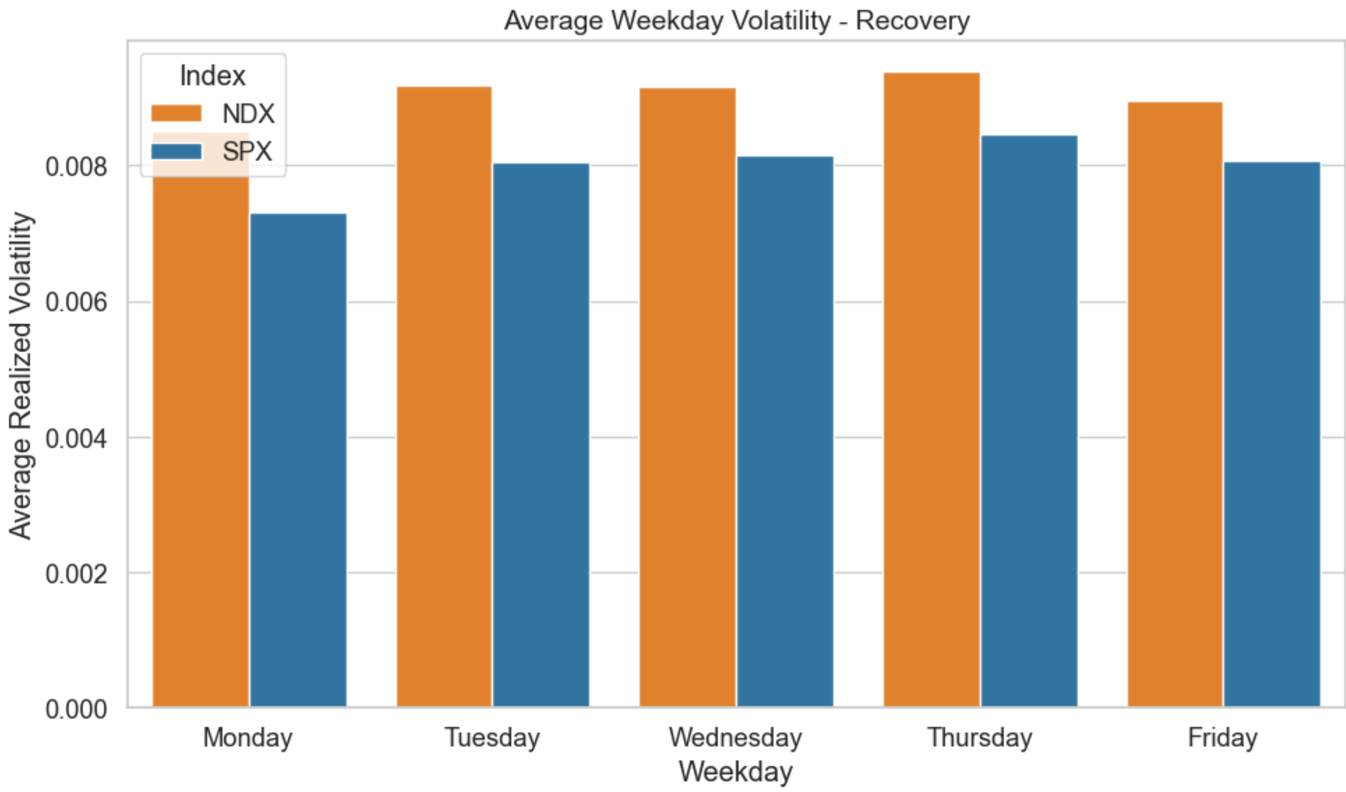

Figure 8 Average Weekday Volatility - Recovery

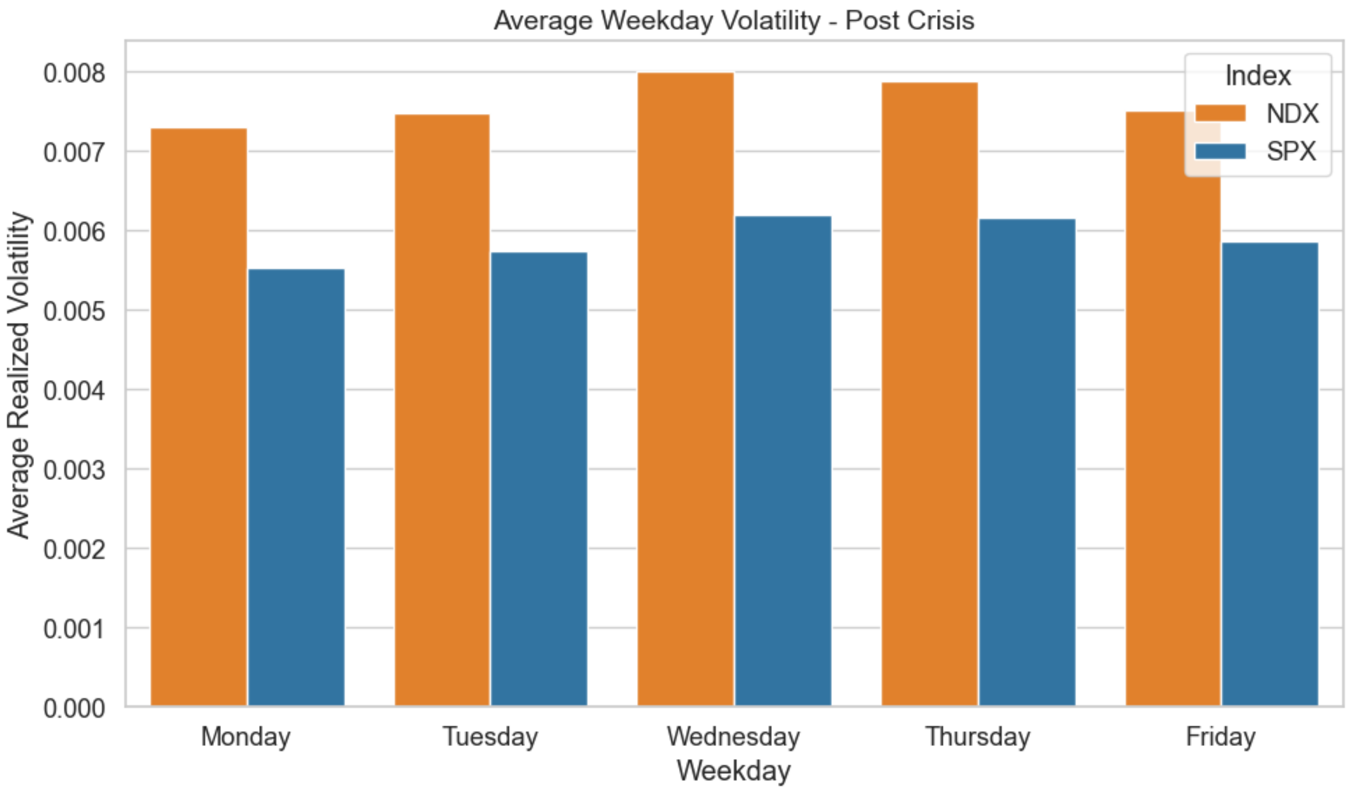

Figure 9 Average Weekday Volatility - Post Crisis