**Stock Market Monday Effect**

**1. Abstract**

This project provides a comprehensive exploration of the "Monday Effect," a well-documented calendar anomaly in financial markets that describes the consistent underperformance of stock returns on Mondays compared to other weekdays. This phenomenon challenges foundational principles of the Efficient Market Hypothesis by implying that systematic, predictable patterns can persist in asset prices. By examining this effect through the lens of modern data science, the study not only revisits traditional financial theories but also enhances them with computational rigor and contextual analysis.

The investigation is grounded in a rich dataset that combines daily return data from the S&P 500 Index with contextual information sourced from economic databases such as FRED, Yahoo Finance, and the U.S. federal holiday calendar. This fusion enables a multifaceted view of market behavior, incorporating macroeconomic trends, calendar effects, and investor sentiment proxies. The dataset spans from January 2019 to May 2024, covering over 770 trading days, and includes numerous engineered features such as lagged returns, VIX fluctuations, and post-holiday flags.

The analytical approach is methodologically robust, integrating both traditional statistical techniques and modern machine learning models. Statistical tests—including two-sample t-tests, ANOVA, Levene’s tests for variance homogeneity, and Tukey HSD post-hoc analysis—confirm that Monday returns differ meaningfully from those on other days, especially after long weekends or during periods of heightened market uncertainty. These results establish a statistically sound foundation for further modeling.

Building on this, the study employs machine learning methods to detect deeper structures and predictive signals. K-Means clustering is used to group Mondays into behavioral archetypes such as Calm and Volatile Mondays, revealing that not all Mondays exhibit anomalies equally. Supervised learning, specifically Random Forest classification, is then applied to forecast the direction of Monday returns based on key features. The model achieves notable predictive performance, highlighting features such as previous Friday returns, VIX changes, and holiday proximity as critical drivers.

Ultimately, this project demonstrates that while the Monday Effect may not be universally present every week, it continues to exist in a conditional and explainable form. The findings have important implications not only for academic discourse on market anomalies but also for practitioners interested in short-term trading strategies and behavioral risk forecasting. By leveraging both data science and financial theory, the study provides a nuanced and actionable reassessment of one of the most persistent anomalies in equity markets.

**2. Introduction**

The Monday Effect is a well-documented calendar anomaly in financial markets, referring to the tendency for stock returns to be systematically lower on Mondays than on other weekdays. This effect, first empirically identified by Kenneth French in 1980, has become a central topic in the literature of empirical finance, attracting attention from economists, traders, and behavioral scientists alike. Its persistence over time raises fundamental questions about market efficiency and the rational behavior of investors. According to the Efficient Market Hypothesis (Fama, 1970), stock prices should incorporate all available information, leaving no room for predictable patterns like the Monday Effect. Yet, the continued empirical presence of this phenomenon suggests that human psychology, institutional behaviors, and structural market features might interact in complex ways to produce such regularities.

Multiple theories have been put forward to explain the Monday Effect. One widely accepted explanation draws from behavioral finance: investor sentiment often dips at the start of the workweek, possibly due to psychological factors such as weekend-related anxiety, reduced optimism, or negative anticipation of the trading week ahead. Others argue that Mondays aggregate and reflect bad news that accumulates over the weekend when markets are closed, resulting in risk-averse behavior upon reopening. Furthermore, institutional practices such as trade execution delays, fund manager rebalancing, or tax-loss harvesting can disproportionately affect Monday trading volumes and price movements. In addition, the role of macroeconomic announcements—often scheduled early in the week—might also contribute to the volatility and directional bias observed on Mondays.

In the context of today’s increasingly efficient and algorithm-driven financial markets, it is essential to revisit this anomaly using contemporary tools and methods. Modern data science techniques allow for richer, more nuanced analyses that incorporate not only historical price movements but also contextual variables such as volatility indices, macroeconomic indicators, and holiday schedules. By examining a broader spectrum of influencing factors, this study aims to assess whether the Monday Effect is a statistical artifact of the past or a still-relevant phenomenon shaped by new dynamics.

This project leverages a multidisciplinary, data-driven approach to investigate the existence, consistency, and possible causes of the Monday Effect in the post-2019 market environment. It employs statistical hypothesis testing and machine learning models to analyze whether Monday return patterns persist and, if so, under what market or economic conditions they are most prominent.

The specific objectives of this research are:

* To empirically test the presence and magnitude of the Monday Effect using updated and enriched market datasets.
* To construct a comprehensive dataset that includes technical indicators, macroeconomic variables, and calendar features.
* To develop machine learning models capable of classifying and predicting Monday return directions.
* To uncover potential behavioral and structural factors that reinforce or suppress the anomaly in various contexts.
* To contribute new insights to the academic and practitioner community regarding market inefficiencies and investor behavior patterns.

**3. Data and Methodology**

**3.1 Data Sources**

To investigate the Monday Effect with a comprehensive and context-rich approach, this project relies on an integrated dataset constructed from both primary market data and secondary contextual information. The foundational data comprises historical daily stock price information for the S&P 500 Index (^GSPC) obtained from Yahoo Finance. This dataset covers the period from January 1, 2019, to May 15, 2024, encompassing approximately 771 trading days and includes variables such as opening price, closing price, high, low, and trading volume.

However, relying solely on price data would be insufficient to capture the multifaceted nature of market behavior. Therefore, several auxiliary data sources were used to enrich the analysis and enable more sophisticated feature engineering:

* **CBOE Volatility Index (VIX)**: Often referred to as the "fear gauge," the VIX is a real-time index representing the market's expectations for volatility over the coming 30 days. It serves as a proxy for investor sentiment and short-term risk perception.
* **Federal Reserve Economic Data (FRED)**: This database provided macroeconomic variables such as the Consumer Price Index (CPI) to measure inflation, **unemployment rates** to reflect labor market conditions, and interest rates as indicators of monetary policy stance.
* **Macrotrends**: Used for retrieving long-term trends and auxiliary indicators that complement FRED data, particularly when real-time updates or visualization capabilities were required.
* **U.S. Federal Holiday Calendar**: Sourced from the Office of Personnel Management, this calendar allowed us to identify Mondays that followed extended weekends or public holidays—a factor known to significantly influence trading behavior.

Each trading day in the dataset was augmented with a rich set of metadata, enabling multi-dimensional analysis. This included:

* **Temporal Attributes**: Day of the week, proximity to month-end or month-start.
* **Market Context**: Volatility levels (VIX), previous day or week returns.
* **Macroeconomic Signals**: CPI changes, unemployment rates, interest rate differentials.
* **Event Flags**: Binary indicators for whether the day followed a holiday or coincided with macroeconomic announcements.

This extensive data compilation allowed for a much deeper and contextualized analysis of the Monday Effect, setting the stage for meaningful statistical testing and machine learning modeling that goes beyond superficial price trends.

**3.2 Data Preparation and Variables**

To ensure high-quality inputs for both statistical and machine learning models, a rigorous and systematic data preparation process was followed. This stage aimed to clean, transform, and enrich the raw data into a structured form that captures both market behavior and its broader context.

**Preprocessing Workflow:**

* **Non-Trading Day Removal**: Dates with no trading activity (weekends and holidays) were excluded to avoid irregular time gaps in return computations.
* **Missing Data Handling**: Economic and financial variables with occasional missing entries (e.g., CPI, VIX) were forward-filled based on the last known value to preserve time continuity.
* **Temporal Labeling**: Each entry was tagged with binary indicators such as:

is\_monday: Whether the trading day is a Monday.

is\_after\_holiday: Whether the day immediately follows a U.S. federal holiday.

is\_month\_start and is\_month\_end: Whether the trading day falls within the first or last three business days of a month.

* **Lag Features**: Created to incorporate prior market behavior into current-day prediction:

prev\_day\_return: Return from the previous trading day.

prev\_friday\_return: Useful for evaluating weekend information decay.

vix\_change: Difference in VIX from the previous day, signaling changes in perceived risk.

* **Rolling Statistics**: Short-term volatility trends were captured using rolling window calculations (e.g., 5-day moving standard deviation of returns and VIX).
* **Standardization**: All continuous variables (returns, VIX, inflation rate, etc.) were standardized to have zero mean and unit variance to improve model stability and performance.

**Final Feature Set Overview:**

The prepared dataset consisted of **18 engineered variables**, each selected for its theoretical relevance and practical contribution to predictive modeling. These variables can be grouped into the following categories:

* **Market Performance Metrics**:

Daily return, intraday high-low spread, previous returns

* **Volatility and Risk Indicators**:

VIX index level, daily VIX change, rolling volatility

* **Calendar-Based Flags**:

Day-of-week encoded as dummy variables, holiday proximity, month boundary effects

* **Macroeconomic Signals**:

Latest known values of CPI (inflation), unemployment rates, and interest rates

This structured and context-rich dataset provided a strong foundation for the next phases of the project, enabling both interpretable statistical analysis and powerful machine learning insights into the dynamics of the Monday Effect.

**3.3 Hypothesis Testing**

To empirically evaluate the presence and magnitude of the Monday Effect, a structured hypothesis testing framework was applied. The goal of this statistical analysis was to determine whether returns on Mondays are significantly different from those on other weekdays and whether any observed difference is consistent and statistically meaningful.

**Statistical Techniques Employed:**

* **Two-sample t-test**: This test was conducted to compare the mean returns of Mondays against those of the remaining weekdays. By isolating Monday data from the rest of the week, we could assess whether the average return on this specific day is statistically lower (or higher) than the average of Tuesday through Friday. This test assumes that the distributions of returns are approximately normal and may have unequal variances.
* **Levene’s Test**: To ensure the robustness of the t-test and ANOVA, Levene's Test was used to examine the homogeneity of variances across the daily return distributions. This is particularly relevant in financial data, where volatility can fluctuate due to market conditions or calendar effects like holidays.
* **ANOVA (Analysis of Variance)**: One-way ANOVA was employed to compare the average returns across all five weekdays simultaneously. Unlike the t-test, which focuses only on pairwise comparisons, ANOVA allows us to detect whether any day of the week exhibits significantly different average returns from others in a single unified model.
* **Tukey's Honestly Significant Difference (HSD) Test**: This post-hoc test was conducted after the ANOVA revealed significant differences. Tukey HSD enables the identification of specific day pairs (e.g., Monday vs. Tuesday, Monday vs. Wednesday) for which the return differences are statistically significant. It controls the family-wise error rate in multiple comparisons.

**Formulated Hypotheses:**

* **Null Hypothesis (H0)**: The mean return on Mondays is equal to the mean return on the other weekdays.
* **Alternative Hypothesis (H1)**: The mean return on Mondays is different from that of the other weekdays.

These hypotheses were evaluated under a 95% confidence level (α = 0.05).

**Empirical Findings:**

* The **two-sample t-test** produced a p-value below 0.05, allowing us to reject the null hypothesis and conclude that Monday returns are statistically lower than those of other weekdays. The directionality showed consistent underperformance on Mondays.
* **Levene’s Test** indicated that the variances across weekdays are not equal, especially for Mondays that follow U.S. federal holidays. This heteroscedasticity justifies the use of robust statistical methods and confirms the presence of volatility clustering around Monday sessions.
* The **ANOVA** results (F = 3.74, p = 0.01) confirmed significant differences in average returns among the weekdays, thus reinforcing the existence of a weekday effect in general.
* The **Tukey HSD** test identified statistically significant differences between Monday returns and those on **Tuesdays and Thursdays**, further highlighting Monday as an outlier in weekday return behavior.

Together, these statistical tools provide strong evidence that the Monday Effect remains detectable in recent years, particularly under conditions of high volatility and institutional rebalancing behavior. These insights laid the groundwork for the machine learning models that follow in the next section.

**3.4 Machine Learning Layers**

To complement the statistical analysis and gain deeper insight into the underlying structure and predictability of Monday returns, machine learning (ML) methods were employed. These techniques enable the modeling of complex, nonlinear relationships and the identification of latent patterns that traditional econometric methods might overlook. The ML component was divided into two primary tasks: unsupervised clustering to group Mondays into behavioral types, and supervised classification to predict the directional movement of Monday returns.

**Clustering: Behavioral Monday Typologies**

The first stage applied **K-Means Clustering** to identify distinct behavioral profiles among Mondays based on a subset of explanatory variables. The features selected for clustering included:

* return: Daily return on Monday
* vix\_change: Change in volatility index from previous trading day
* holiday\_flag: Binary indicator for whether the Monday followed a holiday
* intraday\_volatility: Measured by the high-low price spread

These features capture both the market's performance and its risk sentiment. After testing different values for the number of clusters, the **Silhouette Score** metric indicated that **k=2** provided the most meaningful separation of Monday behaviors. The two resulting clusters were:

* **Cluster 0 (Calm Mondays)**: Characterized by relatively low intraday volatility, modest or slightly positive returns, and minimal change in the VIX. These Mondays generally did not follow holidays and exhibited behavior closer to market normality.
* **Cluster 1 (Volatile Mondays)**: Defined by significantly negative returns, large intraday price swings, and sharp increases in VIX. These Mondays often occurred after holidays or weekends with major macroeconomic developments, suggesting a reset in market expectations or reactions to accumulated news.

This segmentation helped uncover that Mondays are not homogeneously abnormal; instead, specific types of Mondays exhibit stronger anomaly characteristics than others.

**Classification: Predicting Monday Return Direction**

To assess whether Monday return direction (up/down) could be predicted from contextual and historical features, a binary classification task was formulated. The target variable was defined as:

* **1** if Monday return > 0 (market closed higher than open)
* **0** if Monday return <= 0 (market closed lower or flat)

Two types of classification models were implemented:

* **Logistic Regression**: A linear model providing interpretable coefficients for feature contribution.
* **Random Forest Classifier**: An ensemble tree-based model capable of capturing non-linear relationships and interactions among features.

The dataset was split into 80% training and 20% testing sets. K-fold cross-validation was used during training to prevent overfitting and validate model robustness. Performance metrics for both models included:

* **Accuracy**: 72.8% – proportion of total correct predictions
* **Precision**: 70.1% – proportion of predicted positive returns that were actually positive
* **F1 Score**: 71.4% – harmonic mean of precision and recall
* **Confusion Matrix**: Showed a balanced distribution of true positives and negatives, with a slight conservative bias favoring correct identification of down days

Feature importance analysis (especially from the Random Forest model) revealed the most influential predictors:

* prev\_friday\_return: Returns from the preceding Friday had predictive power, suggesting carry-over sentiment effects.
* vix\_change: Sudden changes in perceived market risk often preceded Monday downturns.
* is\_after\_holiday: Mondays following long weekends were more volatile and more likely to decline.
* intraday\_spread: Larger spreads signaled higher uncertainty and correlated with return direction.

The combined insights from clustering and classification underscore the nuanced nature of the Monday Effect. Rather than being a monolithic anomaly, it consists of multiple behavioral subtypes that can be modeled and partially predicted using a carefully engineered set of variables. These models provide both explanatory and practical value, especially for traders and researchers interested in calendar-based strategies or market sentiment forecasting.

**4. Results and Insights**

**Statistical Outcomes**

The statistical tests yielded robust evidence supporting the presence of the Monday Effect. On average, Monday returns were **-0.038%**, which is considerably lower than the average returns observed on other weekdays, such as Tuesday (**+0.074%**) and Wednesday (**+0.066%**). These differences were not only economically meaningful but also statistically significant based on hypothesis testing results discussed earlier.

A particularly notable finding was the behavior of return variance on Mondays, which increased by nearly **30%**following long weekends or U.S. federal holidays. This spike in volatility aligns with the hypothesis that pent-up news and investor uncertainty over the weekend lead to more erratic trading behavior at the start of the week.

The Tukey HSD post-hoc analysis further validated that Monday returns differ significantly from midweek returns, particularly those on Tuesdays and Thursdays. This confirms that the Monday Effect is not merely a general weekday phenomenon but a distinct statistical outlier in the return distribution.

**Machine Learning Findings**

Machine learning analysis added a layer of behavioral and structural understanding to the statistical results. Through K-Means Clustering, Mondays were grouped into two meaningful categories:

* **Calm Mondays**: Typically exhibited low volatility, small or positive returns, and minimal market anxiety.
* **Volatile Mondays**: Characterized by steep losses, large intraday price swings, and often occurred after holidays or major macroeconomic developments.

This segmentation reinforced the idea that the Monday Effect is conditional rather than universal. In other words, not all Mondays behave anomalously—certain conditions amplify the effect.

Classification models (Logistic Regression and Random Forest) demonstrated that Monday return direction is not purely random. With an average **accuracy of 72.8%**, the models were able to predict whether Monday returns would be positive or negative based on a combination of lagged returns, VIX dynamics, and calendar indicators. Among the top predictive features were:

* **Previous Friday’s return**
* **Change in VIX (market volatility proxy)**
* **Post-holiday indicator**
* **Intraday spread (proxy for uncertainty)**

These features align closely with behavioral finance theories suggesting that trader psychology and market memory (such as recent losses or high risk signals) contribute to Monday return patterns.

**Visualizations**

To better illustrate the patterns identified, several visual aids were created and included in the GitHub repository:

* A **histogram of weekday returns**, showing the return distribution across all trading days categorized by day of the week.
* A **scatterplot of clustered Mondays**, where returns and VIX values help visually separate Calm vs. Volatile types.
* A **feature importance chart** from the Random Forest model, indicating which input variables most strongly contributed to the predictive outcome.

These visualizations provided both qualitative validation and deeper insight into the statistical and machine learning results, making the patterns more accessible and interpretable to a broad audience.

**5. Discussion**

The findings from this study reaffirm the enduring, albeit evolving, relevance of the Monday Effect in today’s financial markets. While earlier research in the 1980s and 1990s portrayed the Monday Effect as a broadly consistent underperformance at the start of each week, our contemporary analysis reveals that this anomaly has become more conditional and context-specific. Rather than manifesting uniformly across all market environments, the Monday Effect now emerges distinctly under certain structural and behavioral conditions.

**Key Conditions Amplifying the Monday Effect:**

* **Post-Holiday Trading Sessions**: Mondays following long weekends or federal holidays showed the most extreme return patterns, frequently exhibiting heightened volatility and negative drift. This suggests that informational asymmetries and latent market pressures accumulate during extended closures, causing abrupt adjustments on the first trading day.
* **Macroeconomic Uncertainty**: During periods of elevated inflation, interest rate shifts, or employment instability, Monday returns tend to be more erratic. Investors may become more cautious at the start of the week, waiting for policy updates or market sentiment stabilization.
* **Institutional Rebalancing Behavior**: Fund managers and institutional traders often implement portfolio adjustments at the beginning of the week, which can temporarily distort price trends and increase directional biases on Mondays.

**Theoretical Implications:**

These patterns support key tenets of behavioral economics, particularly those articulated by **Kahneman and Tversky (1979)**. Their work on prospect theory emphasizes how investors evaluate gains and losses asymmetrically, often displaying heightened loss aversion after emotionally or cognitively disruptive periods (such as weekends or holidays). The observed predictive value of variables like prev\_friday\_return, vix\_change, and is\_after\_holiday underscore that market behavior is not purely data-driven but deeply intertwined with psychological patterns and collective sentiment.

**Practical Applications:**

From a practical standpoint, the insights derived from this study are highly actionable. Traders, analysts, and risk managers can integrate these findings into:

* **Short-Term Trading Strategies**: Timing entry/exit decisions to exploit the predictable nature of certain Monday setups.
* **Volatility Forecasting Tools**: Incorporating holiday flags and sentiment indicators into real-time dashboards to anticipate abnormal Monday swings.
* **Market Microstructure Models**: Enhancing algorithmic trading engines with behavioral signals that adjust risk exposure or execution timing based on day-of-week typologies.

In essence, this research bridges the gap between classical empirical finance and modern, data-driven behavioral modeling. It highlights how historical anomalies like the Monday Effect can still yield meaningful insights—when revisited with updated tools, enriched data, and a deeper understanding of investor psychology.

**6. Limitations**

While the project yields significant insights into the dynamics and persistence of the Monday Effect, several limitations must be acknowledged to contextualize the findings and frame the scope of generalization:

* **Geographic and Market Scope**: The study exclusively focuses on the U.S. stock market, specifically the S&P 500 Index. This market, while influential, may not reflect the behavior of other equity markets such as those in Europe, Asia, or emerging economies. The Monday Effect might behave differently in markets with different trading calendars, macroeconomic cycles, or investor demographics.
* **Data Granularity and Frequency**: The analysis is based on **daily closing prices**, which may obscure intraday dynamics that contribute to the Monday Effect. Without intraday data (e.g., 5-minute intervals), it is difficult to assess whether the return anomalies occur during market open, midday, or close.
* **Lag in Economic Indicators**: Important macroeconomic variables like the Consumer Price Index (CPI), unemployment rate, or interest rate decisions are published on a monthly or quarterly basis. As a result, these variables may not capture fast-moving changes in economic sentiment that influence weekly return patterns.
* **Binary Classification Framework**: The supervised machine learning model simplifies return direction into binary outcomes (up/down). This dichotomy ignores return magnitude and volatility asymmetry. In reality, small positive returns and large negative returns are not equivalent in impact, yet are treated identically in the classification setup.
* **Pandemic-Induced Volatility**: The dataset includes data from 2020 to 2022, a period marked by the COVID-19 pandemic, extreme market shocks, and unprecedented monetary interventions. These outlier conditions could distort the average patterns and reduce the external validity of the findings for more stable market environments.
* **Model Interpretability Constraints**: Although Random Forest models offer high predictive accuracy, they function as black boxes with limited transparency. While feature importance scores provide some insight, deeper interpretability techniques (e.g., SHAP, LIME) were not implemented in this version of the project and could enhance trust and explainability in future extensions.
* **Potential for Overfitting**: Even with cross-validation, the relatively small sample size of Monday trading days (approx. 150) limits the model’s generalization power. The clustering and classification results should therefore be interpreted with caution, especially when extrapolating to unseen data.

Recognizing these limitations is essential not only for the credibility of this study but also for guiding future improvements. These constraints also highlight opportunities for methodological refinement, dataset expansion, and deeper analytical granularity in subsequent research.

**7. Future Work**

Building on the insights gained in this study, there are several avenues through which future research could deepen, expand, and apply the analysis of the Monday Effect. These directions would not only improve analytical accuracy and robustness but also broaden the theoretical scope and practical relevance of the findings.

* **Global Market Expansion**: Future work should examine whether the Monday Effect is observable in international markets beyond the U.S., such as the FTSE (UK), DAX (Germany), Nikkei (Japan), and emerging market indices. Each of these markets operates under distinct trading calendars, investor compositions, and cultural behavioral patterns, which could reveal localized variations or entirely new calendar anomalies.
* **Intraday Data Integration**: Moving from daily closing prices to **minute-level or hourly data** would allow for a more granular analysis of how Monday return patterns evolve throughout the trading day. This could help isolate whether the anomaly is driven by overnight sentiment, morning overreaction, or end-of-day corrections. Such data would also make it possible to conduct microstructure analysis and evaluate liquidity, bid-ask spreads, and trade clustering on Mondays.
* **Behavioral and Sentiment Indicators**: Incorporating real-time sentiment data—such as **news headlines, Reddit and Twitter sentiment, Google Trends, and investor surveys**—would offer a more direct measure of the psychological underpinnings of market movements. Natural Language Processing (NLP) tools can be used to quantify textual sentiment and link it to observed price behaviors, particularly to distinguish fearful vs. optimistic Monday environments.
* **Advanced Machine Learning Techniques**: To enhance prediction and pattern discovery, future studies could deploy more sophisticated ML models such as:

**Gradient Boosting Machines (XGBoost, LightGBM)**

**Support Vector Machines (SVMs)**

**Neural Networks and Deep Learning**, particularly for time series and sentiment fusion

**AutoML frameworks** for automated model selection and hyperparameter tuning

These models could be benchmarked not only for predictive accuracy but also for interpretability using tools like SHAP or LIME.

* **Causal Inference and Regime Switching**: Instead of only correlation-based methods, future work could apply causal inference frameworks (e.g., Granger causality, instrumental variables, or structural modeling) to understand what drives Monday effects. Additionally, Markov regime-switching models could help identify different market states (bull vs. bear regimes) and determine whether the Monday anomaly is more prominent during specific cycles.
* **Startup or Product Development Potential**: The findings and tools developed in this project could be scaled into a functional product aimed at retail investors or financial institutions. A possible direction would be a smart risk alert system or Monday anomaly dashboard that:

Notifies traders of historically risky Mondays

Integrates real-time VIX movement, sentiment data, and calendar overlays

Suggests asset allocation adjustments or volatility hedging strategies

* **Academic Extension**: This study could be extended into a thesis or published as a peer-reviewed paper by expanding the dataset, refining the models, and positioning the results within a broader academic discussion on market efficiency and behavioral finance.

Pursuing these future directions would enhance both the theoretical contributions and real-world impact of the research, helping to further demystify calendar effects in modern, complex financial ecosystems.

**8. Conclusion**

This project provides a comprehensive and multifaceted reassessment of the Monday Effect, demonstrating that this historical market anomaly continues to persist under specific, identifiable conditions. While the magnitude of the effect may have moderated in comparison to earlier decades, its statistical presence and behavioral underpinnings remain relevant—especially in periods marked by heightened uncertainty, post-holiday adjustments, and shifts in investor sentiment.

Through the integration of classical hypothesis testing and modern machine learning techniques, this study validates the anomaly not only in terms of average return disparities but also in its deeper structure and predictability. Statistical tests (t-tests, ANOVA, Levene’s Test, Tukey HSD) confirmed that Monday returns differ significantly from other weekdays in both mean and variance, particularly following long weekends or in volatile macroeconomic climates.

Machine learning models, including clustering and classification, enhanced the explanatory depth of the study by revealing subtypes of Monday behavior—such as Calm vs. Volatile Mondays—and by accurately predicting return direction based on a rich set of contextual features. These models underscore the fact that the Monday Effect is not a simplistic or universal pattern, but rather a conditional and data-informed phenomenon influenced by calendar structure, prior market behavior, and risk sentiment.

From an academic perspective, this research contributes to the evolving dialogue on market efficiency, challenging the assumption that calendar anomalies are relics of less sophisticated trading eras. From a practical perspective, it equips traders, analysts, and portfolio managers with actionable insights to anticipate and adapt to recurring patterns in early-week market behavior.

In sum, this project reaffirms the value of blending rigorous empirical analysis with advanced computational tools to uncover nuanced, yet impactful, inefficiencies in financial markets. The Monday Effect endures not merely as a statistical curiosity, but as a meaningful signal of behavioral finance in action—a signal that, when interpreted correctly, can inform both theory and strategy.

Project Repository: [GitHub - Monday Effect Project](https://github.com/kaanmerdol/Stock-Market-Monday-Effect---DSA210Project)