**Abstract (250-300 words):**

### This study examines the relationship between music-based sentiment, captured through Spotify’s Stream-Weighted Average Valence (SWAV), and stock market performance in the UK from 2017 to 2023. The analysis focuses on the FTSE 100, FTSE 250, and FTSE Small Cap indices, exploring how music sentiment correlates with stock returns across varying conditions of market capitalization, liquidity constraints, and seasonality.

### Regression models are applied with key controls, including the TED spread, COVID-19 Stringency Index, and Economic Policy Uncertainty (EPU). The results show a negative relationship between SWAV and FTSE 100 returns, but this significance disappears once COVID-related controls are added. In contrast, the FTSE Small Cap exhibits a consistent positive relationship with music sentiment, particularly during festive periods and times of market stress. The FTSE 250 also shows sensitivity to sentiment shifts, with varying significance depending on the control factors.

### This study introduces music sentiment as a novel proxy for mood, offering new insights into how external sentiment factors influence different segments of the stock market, contributing to the behavioral finance literature.

### **Introduction**

**Background and Context**

This paper investigates the relationship between music-based sentiment and financial market behavior, specifically within the UK stock market. Investor sentiment is widely recognized as an important factor influencing short-term market movements, and its impact has been thoroughly explored in the field of behavioral finance. Traditionally, sentiment has been measured through news headlines, social media activity, or macroeconomic indicators. However, this study introduces music sentiment, derived from Spotify data, as a novel and real-time proxy for public mood. Music’s emotional tone offers a unique perspective on collective sentiment, providing a new approach to understanding how mood may be associated with market behavior.

The analysis focuses on how music sentiment, represented by the Stream-Weighted Average Valence (SWAV), correlates with stock returns across different market indices, including the FTSE 100, FTSE 250, and FTSE Small Cap. By examining these relationships, the study contributes to the growing body of literature that connects external sentiment factors with market outcomes, particularly in the context of seasonality, market capitalization, and liquidity constraints. The research also considers the influence of external macroeconomic factors, such as the TED spread (an indicator of liquidity risk) and the COVID-19 Stringency Index, which reflect broader market conditions during the study period.

**Research Question**

This research seeks to address the following key questions:

* How does music-based sentiment (SWAV) correlate with stock returns in the UK market across different indices (FTSE 100, FTSE 250, and FTSE Small Cap)?
* How do liquidity constraints and external factors, such as the TED spread and COVID-19 stringency index, influence the relationship between sentiment and stock returns?

**Objectives**

The primary objectives of this study are as follows:

* Quantify the association between music sentiment (SWAV) and UK stock market returns across various indices, including large-cap, mid-cap, and small-cap stocks.
* Examine how sentiment impacts market indices differently, with a particular focus on variations in response between small-cap, mid-cap, and large-cap stocks.
* Investigate the role of seasonality in market behavior, particularly holiday effects such as the Christmas period, and how these periods might amplify or reduce sentiment-related market movements.
* Analyze the moderating effects of liquidity constraints and macroeconomic conditions, such as the TED spread and COVID-19 Stringency Index, on the sentiment-return relationship.
* Evaluate the consistency of sentiment effects over different time horizons, assessing how market behavior changes in response to sentiment over short-term (1 day) and medium-term (up to 10 days) periods.

**Contribution**

This research contributes to the behavioral finance literature by introducing a novel sentiment measure—SWAV, which is derived from music data and offers a fresh proxy for public mood. By analyzing music sentiment as a real-time indicator, the study expands the scope of sentiment analysis beyond traditional measures such as news media and social media. The study’s focus on market segmentation also adds depth to the understanding of how different types of stocks—particularly small-cap and less liquid assets—may exhibit heightened sensitivity to external sentiment factors.

Additionally, the study addresses the impact of liquidity constraints and macroeconomic conditions by incorporating controls for the TED spread and COVID-19 Stringency Index, providing a more comprehensive view of how these external factors interact with sentiment in times of financial uncertainty. The analysis of seasonality also offers insights into how mood, particularly during festive periods, is reflected in market behavior, contributing to broader discussions on the cyclical nature of investor sentiment and market performance.

In summary, this research explores the associations between music sentiment and stock market performance across various indices, while also considering the effects of broader economic and market conditions. The study’s innovative use of Spotify data as a proxy for mood provides a new tool for understanding sentiment and its potential role in financial markets.

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### **Literature Review (1,600-2,000 words)**

### **Efficient Market Hypothesis (EMH) and Its Challenges**

The Efficient Market Hypothesis (EMH), introduced by Fama (1970), posits that financial markets are informationally efficient, meaning that stock prices reflect all available information at any given time. This idea makes it difficult for investors to consistently achieve returns that exceed the market average without taking on more risk. Fama (1965) earlier demonstrated that stock prices follow a random walk, supporting the weak form of EMH, which asserts that historical prices cannot predict future movements. Fama (1991) expanded on the semi-strong form of EMH, stating that prices adjust quickly to new public information, though he acknowledged anomalies such as the size and value effects, which challenge market efficiency.

Jensen (1978) affirmed EMH's robustness, stating it had more empirical support than most other financial theories, though he conceded the existence of some anomalies. However, critics such as Thaler (1985) explores how interactions between rational and quasi-rational agents in markets can lead to inefficiencies, arguing that competition may not always eliminate irrational behavior and can sometimes exacerbate it. Jegadeesh and Titman (1993) also identified momentum effects, where past winners continue to perform well, challenging the notion of market efficiency. Shiller (2000) documented how behavioral biases can lead to market inefficiencies, such as overreactions to news. Grossman and Stiglitz (1980) argued that perfectly efficient markets are unattainable because there would be no incentive to gather information. Lo (2004) introduced the Adaptive Markets Hypothesis, proposing that market efficiency evolves over time as investors adapt to changing conditions. These critiques suggest that external sentiment measures might expose temporary inefficiencies in markets.

### **Sentiment and Stock Market Behavior**

The influence of sentiment on stock market behavior has been extensively studied, with evidence showing that both internal and external sentiment drive market movements. **Bollen et al. (2011)** hypothesized Twitter sentiment as a predictor of stock market trends, demonstrating how social media sentiment correlates with short-term market fluctuations. Similarly, **Sprenger et al. (2014)** also explored the role of Twitter sentiment in financial markets and found more evidence validating the association between tweet sentiment and stock returns**. Edmans et al. (2007)** examined how national mood, influenced by international soccer match outcomes, significantly affected stock returns, their study revealed that soccer losses led to stock return declines in the losing country.

**Tetlock (2007)** provided compelling evidence that media sentiment, particularly pessimistic news, can predict declines in stock prices, while optimistic news correlates with rising prices. **Da et al. (2015)** took a different approach by using internet search volume data to measure fear-related sentiment, finding that increased fear correlates with lower stock prices. These studies underscore the significant role that various forms of sentiment play in shaping short-term market movements.

Additionally, **Hirshleifer and Shumway (2003)** examined how external factors, such as weather, affect sentiment and stock returns. They found that sunny days, associated with improved mood, lead to positive stock returns. **Baker and Wurgler (2006)** and **Schmeling (2009)** highlighted that sentiment-driven mispricing is more prevalent in small-cap and volatile stocks. Collectively, these studies lay a foundation for investigating how music sentiment, as an external sentiment indicator, can be associated with stock market behavior.

### **Music and Mood**

Research on the connection between music and mood reveals that music is a powerful tool for influencing and reflecting emotions. **North and Hargreaves (1996)** found that background music in public spaces affects collective moods, demonstrating its potential to shape social behavior and public sentiment. **DeNora (2000)** emphasized that music serves as an emotional regulator in daily life, helping individuals manage their emotional states and, in turn, reflecting broader societal moods. **Juslin and Västfjäll (2008)** explored the mechanisms behind music-induced emotions, identifying emotional contagion, episodic memory, and musical expectancy as key processes through which music evokes emotional responses.

**Koelsch (2010)** linked music-induced emotions to neurological activity, showing that music activates brain regions associated with emotional processing, thereby highlighting the biological basis for music’s influence on mood. **Rentfrow and Gosling (2003)** found that music preferences are linked to personality traits and emotional states, suggesting that societal emotional climates can be mirrored in musical trends.

These findings indicate that music not only affects individual emotions but also serves as a reflection of broader public sentiment, making it a valuable tool for analysing how mood influences societal trends, including financial markets. \*Spotify Proxy for mood Edmans study

**Music Sentiment and Market Behavior**

Recent studies have investigated the link between music sentiment and stock market behavior, proposing that music-based sentiment provides a novel proxy for investor mood. **Edmans et al. (2021)** introduced a real-time music-based sentiment measure using Spotify data, demonstrating that positive music sentiment correlates with higher same-week stock returns but leads to declines in the following week, likely due to sentiment-driven mispricing. This study highlights the value of music sentiment as an alternative sentiment indicator that captures public mood in real time, going beyond traditional measures like news or social media sentiment.

Building on this**, Nguyen et al. (2022)** analysed the impact of music sentiment on the Vietnamese stock market, revealing that music sentiment affects both stock returns and volatility. Notably, foreign music sentiment, such as that from the U.S. and Hong Kong, also had a measurable impact on Vietnam's stock market performance, demonstrating the global reach of music sentiment’s influence on market behavior. These studies suggest that music sentiment offers a unique lens for understanding investor mood and its effect on financial markets, particularly during periods of heightened uncertainty or volatility.

### **Seasonality and Stock Market Behavior**

Seasonality in stock market behavior has been documented extensively, with a focus on anomalies like the **holiday effect** and the **January effect**. **Ariel (1990)** found that stock returns are significantly higher before holidays, while **Kim and Park (1994)** confirmed the holiday effect, showing stock return anomalies around public holidays in the US, UK and Japan. **Keim (1983)** explored the **January effect,** where small-cap stocks outperform larger ones, revealing a key seasonal pattern. **Haugen and Jorion (1996)** showed the persistence of these effects over time, reinforcing the idea that seasonality plays a critical role in market behavior. **Meneu and Pardo (2004)** added that small investors' optimism drives the pre-holiday effect. These studies provide a backdrop for examining how music sentiment might interact with seasonality in stock markets.

### **Market Capitalization, Index Type, and Returns**

The relationship between market capitalization and returns has been a focus in sentiment studies, with small-cap stocks often exhibiting stronger sentiment-driven movements. **Fama and French (1992)** introduced the three-factor model, which links small-cap stocks to higher returns due to their size-related risk premium. **Brown and Cliff (2004)** and **Kumar and Lee (2006)** found that sentiment has a more significant effect on small-cap stocks, as these stocks are more speculative and volatile. As mentioned previously, **Baker and Wurgler (2006)** showed that small-cap stocks are more prone to mispricing due to their higher idiosyncratic risk and lower liquidity. **Schmeling (2009)** confirmed that investor sentiment has a stronger predictive power in small-cap stocks internationally. Finally, **Gromb and Vayanos (2010)** highlighted how limits to arbitrage exacerbate the impact of sentiment on smaller, less liquid stocks, which is particularly relevant when analyzing how music sentiment correlates the UK market across different indices.

### **Liquidity Constraints and Limits to Arbitrage**

Liquidity plays a crucial role in determining stock returns, especially for less liquid stocks. **Amihud and Mendelson (1986)** demonstrated that stocks with lower liquidity require higher returns to compensate for higher trading costs. **Datar (1998)** and **Amihud (2002)** extended this by examining how illiquidity affects stock returns in both cross-sectional and time-series contexts, showing that liquidity is a key determinant of the liquidity premium. **Pastor and Stambaugh (2001)** introduced liquidity risk into asset pricing models, finding that stocks with higher liquidity risk have higher expected returns. **As mentioned previously, Gromb and Vayanos (2010)** explained how liquidity constraints and limits to arbitrage lead to more pronounced mispricing, particularly in small-cap stocks. **Shleifer and Vishny (1997)** emphasized the importance of liquidity in maintaining market efficiency, showing how illiquidity leads to persistent market inefficiencies. These findings are crucial for understanding how liquidity constraints might amplify the impact of music sentiment on UK stock returns.

### **COVID-19 Stringency Index**

The COVID-19 pandemic introduced unprecedented volatility in financial markets, influenced by global lockdowns and restrictions. The **COVID-19 stringency index** captures the severity of these restrictions and their impact on market behavior. **Al-Awadhi et al. (2020)** found that rising COVID-19 cases and stringent lockdowns led to significant negative stock returns, driven by uncertainty. **Baker et al. (2020)** documented the unprecedented volatility in global stock markets, showing that sentiment and fear of the pandemic significantly impacted market behavior. **Zhang et al. (2020)** highlighted the role of investor sentiment in driving market volatility during the pandemic, showing that markets responded strongly to pandemic-related news. **Cevik (2022)** found that sentiment-driven market fluctuations were more pronounced in the early stages of the pandemic, with negative news having a greater impact than positive news. The inclusion of the stringency index helps to isolate the effects of music sentiment from broader economic disruptions caused by the pandemic, providing clearer insights into how sentiment impacts stock returns in periods of extreme uncertainty.

### **Data and Methodology 1,200-1,600 words**

**Data Sources**

This study relies on a combination of sentiment data, stock market performance data, and control variables to analyse the relationship between music sentiment and stock market returns.

Data on Top UK music rankings was retrieved from the Spotify Charts website (Spotify Charts, 2024). Music sentiment is derived from Spotify’s API (Spotify API, 2024), which provides access to song metadata, the specific variables is valence—a measure of a song's emotional positivity. The Spotify Web API allows for the retrieval of content metadata and popularity rankings. For this study, music sentiment is aggregated using data from the Spotify Charts for the Top 200 streamed songs in the UK, collected daily. This real-time sentiment measure serves as a unique proxy of collective mood, with valence scores from the top songs aggregated into a sentiment index reflective of the emotional tone in the UK.

Stock market data for various UK indices, including the FTSE 100, FTSE 250, and FTSE Small Cap, representing large-cap, mid-cap, and small-cap companies respectively, were all sourced from Investing.com (Investing.com, 2024). Comparative data from the MSCI World Stock Market Indices were also obtained from the same platform.

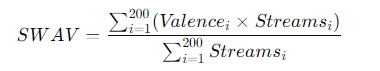
To control for external factors that may influence stock market returns, several variables are incorporated. Weather data, particularly cloud cover, is sourced from the Open-Meteo weather forecast API, helping to account for mood changes linked to weather variations (Open-Meteo, 2024). The EPU, Economic Policy Uncertainty index, sourced from the website policyuncertainty.com, captures weekly news-based uncertainty in economic policy (Baker, Bloom & Davis, 2024). The ADS, Aruoba-Diebold-Scotti Business Conditions Index, from the Federal Reserve Bank of Philadelphia, provides macroeconomic activity data (Federal Reserve Bank of Philadelphia, 2024). The VIX index, sourced from the Chicago Board Options Exchange, tracks volatility expectations, offering insights into global market risk sentiment (CBOE, 2024). The TED Spread, sourced from FRED, measures the difference between interbank loan rates and U.S. Treasury bills, indicating liquidity risk (FRED, 2024). Finally, the COVID-19 Stringency Index, from the University of Oxford’s COVID-19 Government Response Tracker, captures the severity of government-imposed pandemic restrictions, controlling for the effects of the pandemic on market behavior (Hale et al., 2024).

### Variables

This study investigates the relationship between music sentiment and stock market performance in the UK from **January 1, 2017, to December 31, 2023**, with some models covering **January 1, 2017, to December 31, 2022**, due to data limitations on the TED Spread. The key variables include the dependent variable, the independent variable, and several control variables to account for external factors influencing stock returns.

The dependent variable is the Percentage Change in FTSE Price across three indices: FTSE 100, FTSE 250, and FTSE Small Cap. In all models, the price change is initially measured using a 5-business-day window. However, for the final model, the price change is also examined over different time horizons—1-business-day, 3-business-day, and 10-business-day periods. This allows the study to capture both short- and medium-term impacts of sentiment on stock returns, offering insights into immediate and prolonged market reactions to shifts in music sentiment.

The **independent variable** is the **Change in SWAV, Stream-Weighted Average Valence**, which is a measure of national music sentiment. SWAV aggregates the emotional positivity/valence of the top 200 songs streamed in the UK, weighted by the number of streams for each song. Higher SWAV values indicate a more positive overall emotional tone, reflecting the collective mood of the population. This measure is crucial as it serves as a proxy for national sentiment. SWAV is calculated as follows:



Where Valence represents the emotional positivity of a song, and Streams represent the number of times the song was played.

Changes in SWAV are observed over the same time periods as the percentage changes in FTSE prices, aligning the independent and dependent variables for direct comparison.

Several control variables are included to ensure that other factors are not confounding the relationship between music sentiment and stock returns. The change in Economic Policy Uncertainty (EPU) captures variations in economic policy uncertainty as reflected in news coverage, providing insight into political and economic instability that could influence market behavior. Similarly, the Change in Aruoba-Diebold-Scotti Business Conditions Index (ADS) is included as a weekly measure of macroeconomic activity, accounting for broader economic trends that might impact stock prices. To ensure consistency, the changes in both EPU and ADS follow the same time periods as the change in FTSE prices—1-business-day, 3-business-day, 5-business-day, and 10-business-day windows—allowing for better comparison between economic indicators and stock market movements. Additionally, the VIX (Implied Volatility Index), commonly referred to as the "fear gauge," is used to measure market volatility expectations, serving as a proxy for global investor risk aversion.

The study also includes Rolling Average Change in Deseasonalised Cloud Cover (DCC). DCC controls for the effect of weather on investor mood and behavior by adjusting for the typical seasonality of cloud cover and capturing any deviation from normal patterns. This allows the model to account for how weather conditions, particularly cloud cover, influence sentiment and stock returns. Rolling Average Change in DCC is calculated as follows:

**1. Deseasonalizing Cloud Cover**

Since the seasonal component is the average cloud cover over the same time period as the FTSE price change (let's call this period n business days), deseasonalizing would involve subtracting the average cloud cover for each n-day window from the observed value for that period.

**Deseasonalized Cloud Cover** for each period t:



where:

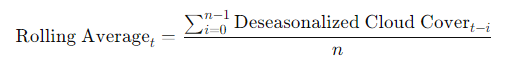
* *t* is the current time period.
* *n* is the number of business days corresponding to the time period used in the FTSE price change (1-day, 3-day, 5-day, 10-day).

The **Average Cloud Cover for the Last** *n* **days** is calculated by averaging the cloud cover data for the previous ***n*** days.

**2. Rolling Average of Deseasonalized Cloud Cover**

Once you’ve deseasonalized the cloud cover data, you can calculate the rolling average of the deseasonalized values over the same time period as the FTSE price changes.

**Rolling Average** for each period t:



**3. Change in Rolling Average of Deseasonalized Cloud Cover**

Finally, to get the change in the rolling average, you would compare the rolling averages for two consecutive periods (e.g., the current period and the previous one).

**Change in Rolling Average:**



where:

* k is the lag (e.g., 1, 5, or 10 days depending on your time frame).

Furthermore, the Previous Period’s FTSE Performance Percentage Change is included to control for momentum and autoregressive effects, ensuring that the influence of past stock performance is properly captured. This variable uses the same time period as the current FTSE price change (1-business-day, 3-business-day, 5-business-day, or 10-business-day). The Percentage Change in MSCI World Index, representing global stock market trends, is also used as a control, providing a broader international context for understanding the UK market's movements. This variable is measured over the same period as the FTSE price change, allowing for consistent comparison across both domestic and global market trends.

In addition to these basic controls, several extra control variables are included to capture specific market conditions and seasonal effects. A Festivity Dummy is used to account for the potential sentiment shifts that occur during the holiday period from December 24 to January 8, commonly associated with the "Santa Claus Rally." This variable is set to 1 during this period and 0 otherwise. Exploratory analysis of music sentiment data reveals extreme fluctuations in SWAV during the festive period, with sharp jumps and drops in music-based sentiment (see Appendix A for supporting charts).

Although similar patterns have not yet been clearly observed in the stock market data, the Festivity Dummy is still included in the model due to the relevance of the Santa Claus Rally effect, where stock returns are typically influenced by year-end portfolio adjustments and holiday-related optimism.

Additionally, the Change in COVID-19 Stringency Index is incorporated as a continuous variable. This index measures the severity of government-imposed restrictions during the pandemic, with higher values indicating more stringent lockdown measures. The inclusion of the COVID-19 Stringency Index helps control for the impact of pandemic-related restrictions on stock market behavior, ensuring that the effects of music sentiment are isolated from broader economic disruptions caused by the pandemic.

Lastly, the TED Spread Dummy is introduced to capture periods of heightened liquidity risk, with a value of 1 if the TED Spread (the difference between the interest rates on interbank loans and U.S. Treasury bills) is in the top 10th percentile, and 0 otherwise. An interaction term between SWAV and the TED Spread Dummy is also included to explore how music sentiment interacts with periods of market stress. (see Appendix A for supporting charts).

**Methodology**

The first step in this study is to assess the direct relationship between Change in SWAV (Stream-Weighted Average Valence) and Percentage Change FTSE stock price over a 5-business-day window, using Ordinary Least Squares (OLS) regression, without incorporating any control variables. This initial OLS analysis provides a baseline understanding of whether there is an unadjusted, direct correlation between music sentiment and stock market performance. By examining the raw relationship between SWAV and the changes in the FTSE indices (FTSE 100, FTSE 250, and FTSE Small Cap), we aim to capture the influence of sentiment on stock returns within this 5-business-day period. This baseline model allows us to explore whether sentiment, as captured by music preferences, has a standalone correlation on stock market behavior, serving as a comparison point for the more complex models that follow.

(\*Edmans reasoning for these variable) After this initial step, we proceed to estimate a basic OLS regression model (Model 1) that includes core variables to examine the relationship between music sentiment and stock market returns in greater detail. The dependent variable in this model is the percentage change in FTSE price for the FTSE 100, FTSE 250, and FTSE Small Cap indices, specifically over a 5-business-day window. The independent variable is the Change in SWAV, which captures national music sentiment based on the valence and streaming volume of the top 200 songs in the UK. To account for other factors that might influence stock returns, several control variables are introduced. These include the Change in the Aruoba-Diebold-Scotti Business Conditions Index (ADS), reflecting overall economic activity, and the Change in Economic Policy Uncertainty (EPU), which captures uncertainty related to economic policy. The model also controls for Previous FTSE performance, which accounts for momentum effects, the MSCI World Index to adjust for global market trends, Rolling Average Change in Deseasonalised Cloud Cover (DCC) to control for weather effects on investor behavior, and the VIX (Implied Volatility Index) as a proxy for global risk sentiment. By focusing on a 5-business-day window, this OLS model provides a more refined understanding of how music sentiment impacts stock market performance while accounting for key economic, global, and environmental factors during this time frame.

In the next stage, additional controls are introduced to further refine the OLS model and account for specific market conditions that may influence sentiment and stock returns, again over the 5-business-day window. Model 2 incorporates the Festivity Dummy to control for the period between December 24 and January 8, which is often associated with the "Santa Claus Rally." This period typically exhibits deviations in both SWAV and stock market behavior, with stock returns generally increasing due to year-end portfolio adjustments and holiday-related optimism. Adding the Festivity Dummy ensures that any observed relationship between SWAV and FTSE changes during this period is not confounded by seasonal effects.

In Model 3, the Change in COVID-19 Stringency Index is introduced as a control to account for the significant disruptions caused by the pandemic. The COVID-19 pandemic led to changes in both sentiment and stock market behavior due to strict lockdown measures and government-imposed restrictions. By adding the Change in COVID-19 Stringency Index, the OLS model controls for these pandemic-related disruptions, ensuring that the impact of music sentiment on stock returns is captured accurately. An interaction term between Change in SWAV and the Change in COVID-19 Stringency Index is also included to explore whether the relationship between music sentiment and stock performance was stronger during periods of stricter lockdown measures, when music consumption patterns and investor mood were more closely linked.

Finally, in Model 4, the TED Spread Dummy is introduced to account for periods of heightened liquidity risk and market stress, again using the 5-business-day window. The TED Spread, which measures the difference between interbank lending rates and U.S. Treasury rates, saw significant increases during times of financial uncertainty, particularly in 2020. The TED Spread Dummy takes the value of 1 during periods when the spread is in the top 10th percentile, indicating high market stress, and 0 otherwise. An interaction term between SWAV and the TED Spread is included to investigate whether music sentiment has a stronger influence on stock returns during periods of high market stress, when external sentiment factors like music may play a larger role in market behavior. This final OLS model, focused on the 5-business-day window, allows the study to explore how the relationship between sentiment and stock returns changes during periods of heightened financial instability.

The window period analysis is conducted exclusively using Model 4, testing the OLS model across different time windows: 1-business-day, 3-business-day, 5-business-day, and 10-business-day periods. While the earlier models use a 5-business-day window, this step explores how the OLS model behaves across shorter and longer time horizons. The 1-business-day window captures the immediate reaction of the stock market to changes in music sentiment, which is useful for understanding short-term volatility. The 3-business-day and 5-business-day windows explore medium-term effects, where sentiment may have a more sustained impact on investor behavior and stock performance. Finally, the 10-business-day window captures the longer-term impact of music sentiment on stock returns, providing insights into how mood-driven behaviours accumulate over a longer period. This multi-window approach ensures that the temporal dynamics of the sentiment-stock return relationship are thoroughly examined, allowing the study to identify whether the effects of music sentiment on stock market returns are short-lived or persist over time.

### **Empirical Results**

#### **Direct Relationship Results**

### The initial analysis tested the direct relationship between Change SWAV (Stream-Weighted Average Valence) and Percentage Change in FTSE Index Prices for the 5-business-day window, without including any control variables. The results show a significant negative relationship between SWAV change and FTSE 100 returns over the 5-day period. No significant relationship was found between SWAV change and FTSE 250 or FTSE Small Cap price changes in this initial model.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | **-9.0466\*\*\*** | **-5.8649** | **-1.5308** |
| Constant | 0.0277 | 0.0463 | 0.0722 |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV = Stream Weighted Average Valence | | | |

### **Basic Regression Results**

### The basic regression model was estimated next, including the core control variables (ADS, EPU, previous FTSE performance, MSCI World Index, DCC, and VIX) over the same 5-business-day window. The results showed a significant negative relationship between SWAV change and FTSE 100 price changes for the 5-day period, similar to the direct relationship analysis. However, there was still no significant relationship between SWAV change and FTSE 250 or FTSE Small Cap returns.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | **-5.3631\*\*** | **-1.2951** | **2.0933** |
| ADS Change | 0.1533\*\*\* | 0.1892\*\*\* | 0.1715\*\*\* |
| EPU Change | 0.000035 | -0.0002 | -0.0003\*\* |
| Prev. FTSE % Change | -0.0641\*\*\* | -0.0467\*\*\* | 0.0805\*\*\* |
| % MSCI World Change | 0.6799\*\*\* | 0.9012\*\*\* | 0.7175\*\*\* |
| VIX | -0.0072 | -0.0132\*\* | -0.0093\*\* |
| DCC Rolling Avg. Change | 0.0047 | 0.0035 | 0.0038 |
| Constant | 0.0479 | 0.1427 | 0.1186 |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV | | | |

### **Festivity Dummy Analysis**

### In Model 2, the Festivity Dummy was introduced to account for the period between December 24 and January 8. The results for the FTSE 100 continued to show a negative relationship between SWAV change and returns. For the FTSE Small Cap, a significant positive relationship emerged between SWAV change and returns over the 5-business-day period, while no significant relationship was found for the FTSE 250.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | **-3.3553\*** | **2.0844** | **5.6265\*\*\*** |
| ADS Change | 0.1561\*\*\* | 0.1948\*\*\* | 0.1787\*\*\* |
| EPU Change | 0.00001291 | -0.0003 | -0.0004\*\* |
| Prev. FTSE % Change | -0.0672\*\*\* | -0.0524\*\*\* | 0.0721\*\*\* |
| % MSCI World Change | 0.6782\*\*\* | 0.8981\*\*\* | 0.7139\*\*\* |
| VIX | -0.0074 | -0.0137\*\*\* | -0.0100\*\* |
| DCC Rolling Avg. Change | 0.0056 | 0.005 | 0.0054 |
| Festive Dummy | 0.6073\*\*\* | 1.0252\*\*\* | 1.0710\*\*\* |
| Constant | 0.035 | 0.124 | 0.1015 |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV | | | |

### **COVID Stringency Controls**

### In Model 3, the COVID-19 Stringency Index and its interaction with SWAV were added to the model. The results showed no significant relationship between SWAV change and returns for both the FTSE 100 and FTSE 250. However, for the FTSE Small Cap, a significant positive relationship remained between SWAV change and returns over the 5-business-day period in the presence of the COVID-19 Stringency control.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | **-2.7914** | **2.4721** | **5.8888\*\*\*** |
| ADS Change | 0.1782\*\*\* | 0.1947\*\*\* | 0.1619\*\*\* |
| EPU Change | -0.00002707 | -0.0003 | -0.0004\*\* |
| Prev. FTSE % Change | -0.0566\*\*\* | -0.0522\*\*\* | 0.0580\*\*\* |
| % MSCI World Change | 0.6800\*\*\* | 0.9017\*\*\* | 0.7181\*\*\* |
| VIX | -0.009 | -0.0131\*\*\* | -0.0077\* |
| DCC Rolling Avg. Change | 0.0068 | 0.0057 | 0.0056 |
| Festive Dummy | 0.5450\*\* | 0.9925\*\*\* | 1.0751\*\*\* |
| Covid Stringency Change | 0.0970\* | -0.0171 | -0.1223\*\* |
| Covid Stringency\* SWAV | -10.0539\*\*\* | -8.2345\*\*\* | -6.8823\*\*\* |
| Constant | 0.0638 | 0.1098 | 0.0566 |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV | | | |

### **TED Spread Controls**

### In Model 4, the TED Spread Dummy and its interaction with SWAV were included. The results indicated no significant relationship between SWAV change and returns for the FTSE 100. For the FTSE Small Cap and FTSE 250, a significant positive relationship between SWAV change and returns over the 5-business-day period was found.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | **0.7918** | **4.7561\*** | **6.1773\*\*\*** |
| ADS Change | 0.1628\*\*\* | 0.1840\*\*\* | 0.1424\*\*\* |
| EPU Change | 0.00009176 | -0.0003 | -0.0004 |
| Prev. FTSE % Change | -0.0847\*\*\* | -0.0535\*\*\* | 0.0516\*\*\* |
| % MSCI World Change | 0.7663\*\*\* | 0.9538\*\*\* | 0.8062\*\*\* |
| VIX | -0.0171\*\*\* | -0.0169\*\*\* | -0.0033 |
| DCC Rolling Avg Change | 0.011 | 0.0057 | 0.0087 |
| Fesitve Dummy | 0.5967\*\* | 0.8601\*\*\* | 0.8532\*\*\* |
| Covid Stringency Change | 0.1301\*\* | 0.0131 | -0.1413\*\* |
| Covid Stringency\* SWAV | -11.4793\*\*\* | -9.9871\*\*\* | -9.6100\*\*\* |
| TED Spread | 0.4881\*\*\* | 0.3151\*\* | 0.1373 |
| TED Spread\*SWAV | -17.8105\*\* | -6.3381 | 6.6415 |
| Constant | 0.0894 | 0.1388 | -0.0263 |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV | | | |

### **Window Period Analysis**

### The window period analysis was conducted using Model 4 across 1-business-day, 3-business-day, 5-business-day, and 10-businss-day windows. For the FTSE 250, there was a significant positive relationship between SWAV change and returns for the 5-day and 10-day periods. For the FTSE Small Cap, a significant positive relationship between SWAV change and returns was observed across all time windows: 1-day, 3-day, 5-day, and 10-day periods.

|  |  |  |  |
| --- | --- | --- | --- |
| 1 Business Day | | | |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | 0.548 | 1.623 | 2.913 |
| … | … | … | .. |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV | | | |
| 3 Business Days | | | |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | 1.387 | 2.532 | 4.265 |
| … | … | … | .. |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV | | | |
| 5 Business Days | | | |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | 0.792 | 4.756\* | 6.177\*\* |
| … | … | … | .. |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV | | | |
|  |  |  |  |
| 10 Business Days | | | |
|  | **Dependent Variables (% Change in Price)** | | |
|  | **FTSE 100** | **FTSE 250** | **FTSE Small Cap** |
| **SWAV Change** | 3.310 | 8.372\*\*\* | 6.890\*\*\* |
| … | … | … | .. |
| \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.10; SWAV | | | |

### **Discussion**

#### **Comparison of Models**

The analysis across the various models provides nuanced insights into how music sentiment (SWAV) impacts stock market returns across the FTSE 100, FTSE 250, and FTSE Small Cap indices, particularly when control variables are introduced. Certain core economic controls become significant at different stages, adding complexity to the analysis.

#### **Direct Relationship Model**

In the initial direct relationship model, no control variables are included. A **significant negative relationship** is observed between SWAV change and FTSE 100 returns, while no significant relationships are found for the FTSE 250 or FTSE Small Cap indices.

#### Basic Regression Model

When core economic controls are introduced, including **ADS (Aruoba-Diebold-Scotti Business Conditions Index), Economic Policy Uncertainty (EPU), previous FTSE performance, MSCI World Index, VIX (Volatility Index), and DCC (Dynamic Conditional Correlation)**, several of these controls show significance:

* **Previous FTSE Performance**: This variable is consistently **significant** across all indices and models. For the FTSE 100, its negative coefficient indicates a **mean-reverting behavior** where past positive returns tend to result in subsequent negative returns. The same pattern is observed for the FTSE 250 and FTSE Small Cap indices, reflecting how momentum dissipates in the short term.
* **% MSCI Change**: This control is consistently **highly significant** across all models for all indices, particularly for the FTSE 100. The **positive relationship** between the MSCI World Index and FTSE returns suggests that broader global equity market movements heavily influence returns in all three indices. For the FTSE 100, this global exposure is particularly pronounced, reinforcing the idea that the large-cap index is more susceptible to international market trends than sentiment-driven volatility alone.
* **VIX (Volatility Index)**: The VIX is another **significant control** in multiple models, especially for the FTSE 100. Its negative coefficient suggests that periods of increased market volatility are associated with declining returns, reflecting risk-off behavior by investors. This is particularly relevant for the FTSE 100, where larger, more stable companies may be more affected by market-wide risk sentiment.

However, despite the presence of these controls, the **negative relationship** between SWAV change and FTSE 100 returns remains significant, suggesting that music sentiment independently affects the stock returns of large-cap companies, even when accounting for core economic factors.

The introduction of the **Festivity Dummy** in **Model 2** added complexity to the results. The FTSE 100 continued to show a negative relationship with SWAV change, while the FTSE Small Cap exhibited a significant positive relationship. This shift suggests that smaller companies may benefit from the optimism and trading activity during festive periods, such as the "Santa Claus Rally." By contrast, the FTSE 250 remained largely unaffected, reflecting its position as a middle-ground between the larger, more stable FTSE 100 and the volatile, sentiment-driven FTSE Small Cap.

The addition of the **COVID-19 Stringency Index** and interaction terms in **Model 3** resulted in no significant relationship for both the FTSE 100 and FTSE 250. However, a significant positive relationship between SWAV and FTSE Small Cap returns emerged. This indicates that smaller companies, perhaps driven by retail investor sentiment, are more susceptible to sentiment shifts during periods of heightened restrictions and uncertainty, such as the COVID-19 pandemic. In this context, SWAV appears to capture a unique dimension of sentiment that impacts smaller, more volatile stocks during periods of economic instability.

The **TED Spread Dummy** introduced in **Model 4** yielded a notable change in the relationship between SWAV and market returns. While there was no significant relationship between SWAV and FTSE 100 returns, the FTSE Small Cap and FTSE 250 both showed significant positive relationships. This finding suggests that smaller companies and mid-cap firms are more influenced by sentiment during periods of heightened market stress, as reflected by the TED Spread, possibly due to increased investor speculation or liquidity constraints that amplify sentiment-driven volatility.

The **window period analysis** further demonstrated that the relationship between SWAV and stock returns varies by time horizon and index. The FTSE 250 displayed a significant positive relationship over the **5-day and 10-day periods**, suggesting that sentiment effects on mid-cap stocks may take longer to materialize. On the other hand, the FTSE Small Cap consistently showed a significant positive relationship with SWAV change across **1-day, 3-day, 5-day, and 10-day periods**, indicating that smaller, more volatile stocks are highly sensitive to sentiment shifts regardless of the time frame.

#### Interpretation of Results

The negative relationship between **SWAV change** and **FTSE 100** returns observed across multiple models suggests that positive music sentiment may drive initial over-optimism in larger companies, leading to subsequent market corrections. The FTSE 100, composed of well-established and widely traded companies, tends to react more strongly to sentiment shifts that are quickly corrected by institutional investors, who may see sentiment-driven spikes as unsustainable. This is particularly true when no significant external factors like financial stress or festive periods are in play, as shown in the basic regression model and direct relationship results.

The positive relationship between **SWAV change** and **FTSE Small Cap** returns during festive periods and under the influence of **COVID-19 Stringency** and **TED Spread** suggests that smaller companies, which are often more volatile and less liquid, are more sensitive to sentiment-driven behavior. Retail investors, who tend to dominate trading in small-cap stocks, may be more influenced by sentiment, particularly during periods of market uncertainty or optimism. This is consistent with the idea that small-cap stocks are more speculative, and investor sentiment—especially in the absence of strong fundamental drivers—can play a larger role in driving stock prices.

The lack of a significant relationship between SWAV change and **FTSE 250** returns in most models highlights the distinct characteristics of mid-cap stocks. The FTSE 250, representing mid-sized companies, occupies a middle ground where sentiment may not have as immediate or clear an impact as in large-cap or small-cap indices. However, in the **TED Spread** model and **window period analysis**, the FTSE 250 did exhibit a positive relationship with SWAV over longer time windows, indicating that sentiment effects may take longer to manifest in mid-cap stocks, possibly due to their more stable nature compared to small caps.

The **TED Spread Dummy** and its interaction with SWAV reveal the role of market stress in amplifying sentiment effects, particularly for smaller and mid-sized companies. During periods of heightened liquidity risk, smaller firms, which typically have less access to capital and higher volatility, become more prone to sentiment-driven trading behavior. This may be due to increased speculation or liquidity concerns that make these stocks more sensitive to external factors like sentiment. The lack of a significant relationship with the FTSE 100 suggests that large-cap stocks are less affected by sentiment in times of financial stress, possibly because these firms have greater access to capital and are viewed as safer investments during periods of uncertainty.

#### Implications for Theory and Practice

The findings of this study have important implications for both behavioral finance theory and market practice, particularly in understanding the role of sentiment in stock market behavior. The consistent negative relationship between SWAV change and FTSE 100 returns supports the notion that sentiment-driven over-optimism can lead to corrections in larger, more liquid stocks. This aligns with the **behavioral finance theory** that investor sentiment can drive temporary mispricings, particularly in markets dominated by institutional investors who quickly correct for sentiment-induced distortions.

For **smaller companies** (FTSE Small Cap), the positive relationship with SWAV change suggests that sentiment can drive stock returns, particularly during periods of market stress or festive optimism. This highlights the vulnerability of smaller, less liquid firms to sentiment-driven trading behavior, where investor mood, as captured by music sentiment, can influence stock performance in the absence of strong fundamental drivers. This has practical implications for investors and market participants, especially retail investors who may be more prone to trading based on sentiment rather than fundamentals.

The **COVID-19 Stringency Index** results demonstrate that in times of significant economic or social disruption, sentiment can still play a crucial role in influencing market behavior, particularly for smaller firms. This suggests that sentiment-based trading may become more prevalent during periods of uncertainty, where traditional market signals may be less reliable, and sentiment-driven trading could dominate.

The **TED Spread findings** further emphasize the role of market stress in amplifying sentiment effects. In times of liquidity risk, smaller and mid-cap companies are more susceptible to external sentiment-driven volatility, which suggests that market participants should be cautious about sentiment effects during periods of financial instability. This finding could inform **risk management strategies**, where investors may need to account for sentiment indicators, such as SWAV, when evaluating smaller stocks during times of heightened liquidity risk.

Finally, the results from the **window period analysis** offer insights into the **temporal dynamics** of sentiment-driven stock returns. The immediate impact on small-cap stocks across all time horizons suggests that sentiment-based strategies may be particularly effective in shorter-term trading of volatile, less liquid stocks. However, the delayed response observed in the FTSE 250 over longer windows indicates that sentiment effects can accumulate over time, providing opportunities for sentiment-based strategies in mid-cap stocks over longer horizons.

In conclusion, the study provides strong evidence that sentiment, particularly music-based sentiment as captured by SWAV, plays a significant role in driving stock market behavior across different indices and market conditions. The implications for both theory and practice suggest that sentiment should not be overlooked, especially in times of market stress, festive periods, and when considering smaller, more volatile stocks.

### 6. Conclusion

### Summary of Key Findings

### This study examined the relationship between music sentiment, as measured by the Stream-Weighted Average Valence (SWAV), and stock market returns across different FTSE indices (FTSE 100, FTSE 250, and FTSE Small Cap) in the UK. Using a series of regression models with various controls, the results highlight several important findings.

### First, a negative relationship between SWAV change and FTSE 100 returns was consistently observed across multiple models. This indicates that positive shifts in music sentiment may drive initial market optimism, particularly among larger companies, which is later followed by a correction in stock prices. On the other hand, no significant relationship was observed between SWAV change and FTSE 250 returns until financial stress factors, such as the TED Spread, were introduced. For the FTSE Small Cap, the results showed a significant positive relationship with SWAV change, particularly in models that accounted for festive periods, the COVID-19 pandemic, and market stress, suggesting that smaller companies are more sensitive to sentiment-driven trading behavior.

### The window period analysis further revealed that sentiment has an immediate impact on FTSE Small Cap returns across all time windows, whereas its effect on FTSE 250 returns only becomes apparent over longer periods, particularly during times of heightened market stress. These findings underline the differentiated impact of sentiment across various indices and time horizons.

### Research Contributions

### This research makes several notable contributions to the literature on behavioral finance and sentiment analysis. One of the key contributions is the introduction of music sentiment (SWAV) as a novel sentiment indicator, expanding beyond traditional measures like news, social media, and economic uncertainty indices. By demonstrating that music sentiment can influence stock market behavior, this study opens up new avenues for examining how public mood, as reflected through cultural consumption patterns, affects financial markets.

### Additionally, this study provides detailed insights into how sentiment impacts different segments of the stock market, highlighting that sentiment-driven effects are more pronounced in small-cap stocks, particularly during periods of financial stress or festive optimism. The findings also offer empirical support for the role of sentiment in mid-cap stocks over longer time horizons, suggesting that sentiment-driven effects accumulate over time in this segment. By testing sentiment across multiple time windows and models, this research provides a robust framework for understanding how sentiment interacts with various economic and market conditions to influence stock returns.

### Limitations and Future Research

### Despite its contributions, this study has several limitations that should be acknowledged. First, the use of Spotify music data to capture national sentiment is innovative but may not fully represent the broader emotional climate of the population, as it primarily reflects the preferences of streaming platform users, who may not be fully representative of all investor demographics. Additionally, the SWAV metric is based on aggregated sentiment from a limited set of top songs, which could overlook the diversity of emotional responses to different genres or less popular music.

### The study also focuses on the UK market and may not fully capture the global dynamics of sentiment and stock market behavior. While controls like the MSCI World Index were included to account for global market trends, future research could expand this analysis to a broader range of international markets to examine whether the relationship between music sentiment and stock market returns holds across different economic and cultural contexts.

### Another limitation lies in the TED Spread and COVID-19 Stringency Index, which, while useful proxies for market stress and pandemic-related disruptions, may not fully capture all forms of market instability or economic uncertainty. Future research could explore alternative measures of financial stress or consider more nuanced pandemic-related variables, such as consumer behavior shifts or changes in corporate performance.

### Finally, future research could extend this study by exploring alternative sentiment measures derived from other cultural or social data sources, such as movie preferences, social media interactions, or even global news sentiment, to further investigate how public mood influences financial markets. Additionally, research could examine whether sentiment-driven effects vary across different asset classes (e.g., bonds, commodities) or within different timeframes to deepen our understanding of sentiment’s role in market behavior.

### In conclusion, this study contributes to the growing body of literature on sentiment and stock market behavior by introducing music sentiment as a novel and effective proxy for public mood. It highlights the differentiated impact of sentiment on stock returns across various market indices and offers important implications for both behavioral finance theory and practical investment strategies. However, the limitations noted suggest further exploration is needed to fully understand the nuances of sentiment-driven market behavior.

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### **8. Appendices**

* **Supplementary Material:** Include any additional tables, figures, or technical details that support your analysis but are not central to the main text.

This structure will help you present your research in a coherent and logical manner, ensuring that each stage of your analysis builds on the previous one and contributes to answering your research question.

**Appendix B**

Festivity SWAV proof

Proof of Running Total also

**Appendix A**

Appendix A presents the detailed regression results for significant variables only. For the full set of results, please refer to tables in the main body:

\*Slowly attach all signficant values here