# Music and Markets: Exploring the Impact of Public Mood on Stock Performance

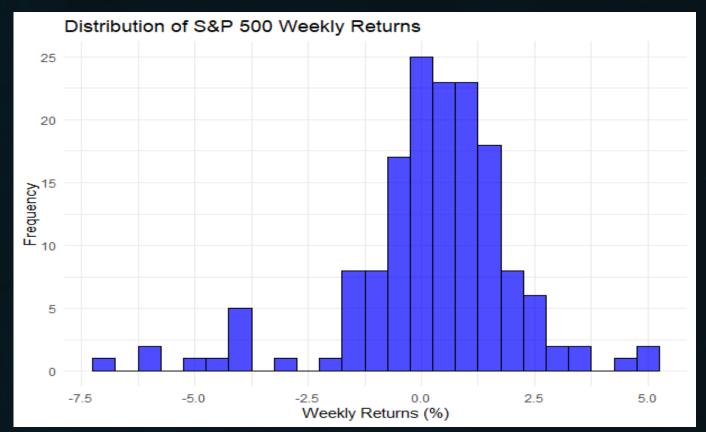
This project investigates the potential connection between public sentiment (music) and stock market performance. By analyzing music sentiment and their impact on stock returns, we shed light on the possible role of it in financial markets. Our analysis encompasses major indices like the S&P 500 and Russell 3000.

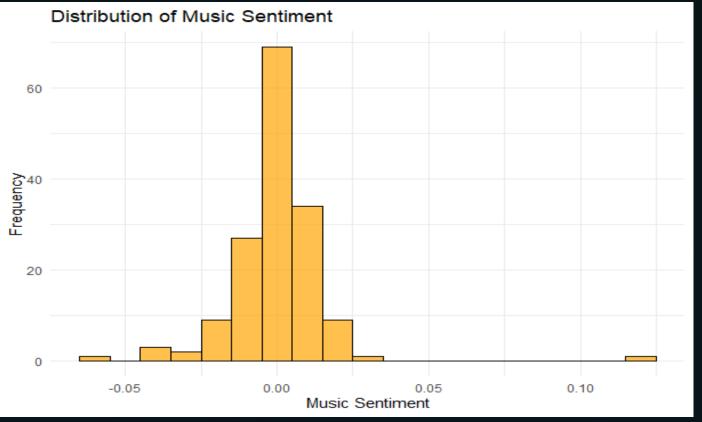
by ABHISHEK KUMAR SINGH

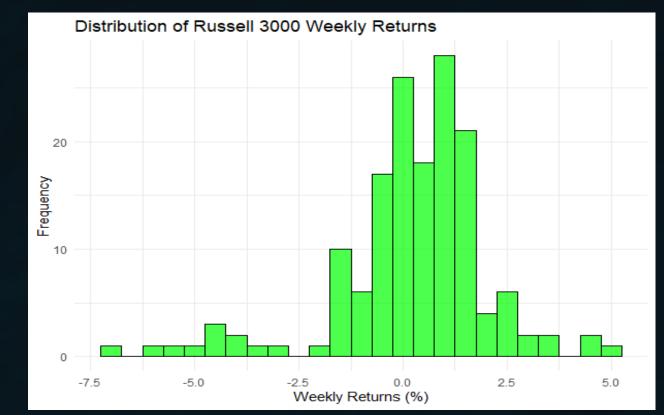


# <u>Article Insights</u>

- 1. Music sentiment shows a positive correlation with same-week stock market returns and a negative correlation with next week's returns, suggesting sentiment-driven mispricing.
- 2. During times when certain trading activities were restricted (like during COVID-19 when some countries banned short-selling), the relationship between the music sentiment and stock prices became stronger, likely because these restrictions made it harder for markets to correct sentiment-driven price movements







# Data Pre-processing

# Feature engineering & Data Cleaning

- Calculated columns for weekly returns for S&P 500 and Russell 3000 markets, with & without risk-adjustment, Lagged returns & Lagged sentiments.
- After Pre-processing, there were **154 rows** and **16 columns** in the dataset.

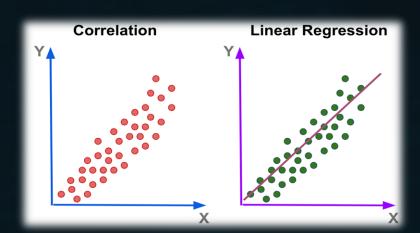
- Since, there were very less NA values, Removed "NA" values because they could interfere with the modeling results
- Converted IRX rates using compounding interest formula to replicate real world analysis.

| Date       | Adj.CloseGSPC Adj. | .CloseIRX A | dj.CloseRUA S | WAV       | Music_Sentiment ( | GSPC_Returns | RUA_Returns | Weekly_Risk_Free_Rate | GSPC_Risk_Adjusted | RUA_Risk_Adjusted | Lagged_GSPC_Returns | Lagged_RUA_Returns | Lagged_Music_Sentiment | Lagged_GSPC_RA | Lagged_RUA_RA |
|------------|--------------------|-------------|---------------|-----------|-------------------|--------------|-------------|-----------------------|--------------------|-------------------|---------------------|--------------------|------------------------|----------------|---------------|
| 01-15-2017 | 2271.310059 0.4    | 479999989   | 1350.099976   | 0.4469045 | -0.003949192      | -0.1463895   | -0.2806742  | 0.00920911            | -0.155598611       | -0.289883305      | -0.102771523        | -0.011079723       | 0.002033302            | -0.112612173   | -0.020920374  |
| 01-22-2017 | 2294.689941 0.4    | 497999996   | 1364.48999    | 0.4469491 | 0.0000446         | 1.029356688  | 1.06584803  | 0.009553612           | 1.019803076        | 1.056294419       | -0.146389501        | -0.280674195       | -0.003949192           | -0.155598611   | -0.289883305  |
| 01-29-2017 | 2297.419922 0.4    | 488000005   | 1367.290039   | 0.4446552 | -0.002293891      | 0.118969493  | 0.205208468 | 0.009362229           | 0.109607264        | 0.195846238       | 1.029356688         | 1.06584803         | 0.0000446              | 1.019803076    | 1.056294419   |
| 02-05-2017 | 2316.100098 0.5    | 523000002   | 1378.579956   | 0.4372419 | -0.007413329      | 0.813093672  | 0.825714858 | 0.010031986           | 0.803061686        | 0.815682872       | 0.118969493         | 0.205208468        | -0.002293891           | 0.109607264    | 0.195846238   |
| 02-12-2017 | 2351.159912 0.5    | 508000016   | 1398.040039   | 0.4382885 | 0.001046627       | 1.51374347   | 1.411603507 | 0.009744976           | 1.503998495        | 1.401858531       | 0.813093672         | 0.825714858        | -0.007413329           | 0.803061686    | 0.815682872   |
| 02-19-2017 | 2367.340088 0.4    | 497999996   | 1405.599976   | 0.4390204 | 0.000731866       | 0.688178457  | 0.540752538 | 0.009553612           | 0.678624845        | 0.531198927       | 1.51374347          | 1.411603507        | 0.001046627            | 1.503998495    | 1.401858531   |
| 02-26-2017 | 2383.120117 0.6    | 683000028   | 1413.550049   | 0.4388264 | -0.000193966      | 0.666572119  | 0.565599967 | 0.013090821           | 0.653481298        | 0.552509146       | 0.688178457         | 0.540752538        | 0.000731866            | 0.678624845    | 0.531198927   |
| 03-05-2017 | 2372.600098 0.7    | 725000024   | 1404.040039   | 0.4559315 | 0.017105104       | -0.44143889  | -0.67277491 | 0.013892975           | -0.455331866       | -0.68666788       | 0.666572119         | 0.565599967        | -0.000193966           | 0.653481298    | 0.552509146   |
| 03-12-2017 | 2378.25 0.7        | 708000004   | 1410.380005   | 0.4523829 | -0.003548607      | 0.238131239  | 0.451551653 | 0.013568333           | 0.224562906        | 0.43798332        | -0.44143889         | -0.672774905       | 0.017105104            | -0.455331866   | -0.68666788   |
| 03-19-2017 | 2343.97998 0.7     | 748000026   | 1387.959961   | 0.4286518 | -0.023731065      | -1.44097635  | -1.58964562 | 0.014332111           | -1.455308459       | -1.603977733      | 0.238131239         | 0.451551653        | -0.003548607           | 0.224562906    | 0.43798332    |
| 03-26-2017 | 2362.719971 0.7    | 737999976   | 1401.5        | 0.4351395 | 0.006487656       | 0.799494499  | 0.975535273 | 0.014141194           | 0.785353305        | 0.96139408        | -1.440976348        | -1.589645622       | -0.023731065           | -1.455308459   | -1.603977733  |
| 04-02-2017 | 2355.540039 0.7    | 797999978   | 1395.630005   | 0.4376093 | 0.002469836       | -0.30388417  | -0.4188366  | 0.015286414           | -0.319170585       | -0.434123018      | 0.799494499         | 0.975535273        | 0.006487656            | 0.785353305    | 0.96139408    |

# Ordinary Least Squares (OLS)

## OLS Regression:

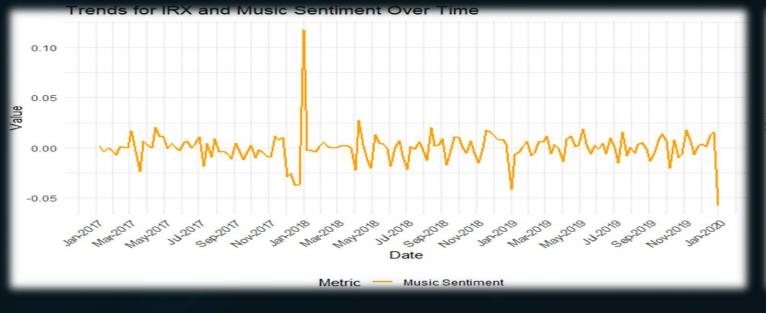
OLS regression is a fundamental technique for estimating relationships between variables. It finds the line that best fits a set of data points, minimizing the sum of squared errors between predicted and actual values.



# OLS regression models:

### 8 OLS models

4 Models related to S&P500 returns & 4 related to Rusell 3000 returns. These 4 models include each model with simple returns, risk-adjusted returns for the same week and then 2 models for sentiment from the previous weeks (lagged music sentiments).





# OLS Model Results: Music Sentiment and Stock Returns

### S&P 500

The analysis shows that music sentiment has a coefficient of -8.919 with a standard error of 13.649 and a p-value of 0.513. These results indicate that music sentiment does not significantly predict S&P 500 returns for both the normal returns & risk-adjusted returns.

### Russell 3000

Similarly, here, we found a music sentiment coefficient of – 10.13, a standard error of 10.44, and a p-value of 0.333. These findings reinforce the conclusion that music sentiment lacks a significant predictive power on Russell 3000 returns for both the normal returns & risk-adjusted returns.

If we don't consider the p-values, for a moment. We can see that returns are this week's music sentiment has more profound effect on the stock returns than the sentiment last week, i.e. Lagged Music sentiment.

| Model                          | Music Sentiment<br>Estimate | Music Sentiment<br>P-Value | Lagged Returns<br>Estimate | Lagged Returns<br>P-Value |
|--------------------------------|-----------------------------|----------------------------|----------------------------|---------------------------|
| GSPC Returns                   | -8.91936                    | 0.3842                     | -0.17644                   | 0.0297                    |
| RUA Returns                    | -10.45457                   | 0.3082                     | -0.15055                   | 0.0638                    |
| GSPC Risk-Adjusted<br>Returns  | -8.93661                    | 0.3835                     | -0.17576                   | 0.0303                    |
| RUA Risk-Adjusted<br>Returns   | -10.47156                   | 0.308                      | -0.14987                   | 0.065                     |
| GSPC Returns<br>(Lagged Music) | -1.7980                     | 0.8610                     | -0.1704                    | 0.0355                    |
| RUA Returns<br>(Lagged Music)  | -1.97045                    | 0.8482                     | -0.14389                   | 0.0767                    |
| GSPC RA (Lagged<br>Music)      | -1.81739                    | 0.8595                     | -0.16968                   | 0.0363                    |
| RUA RA (Lagged<br>Music)       | -1.98796                    | 0.8469                     | -0.14319                   | 0.0781                    |

# Robust standard errors: Bootstrapping and HCo Standard Errors



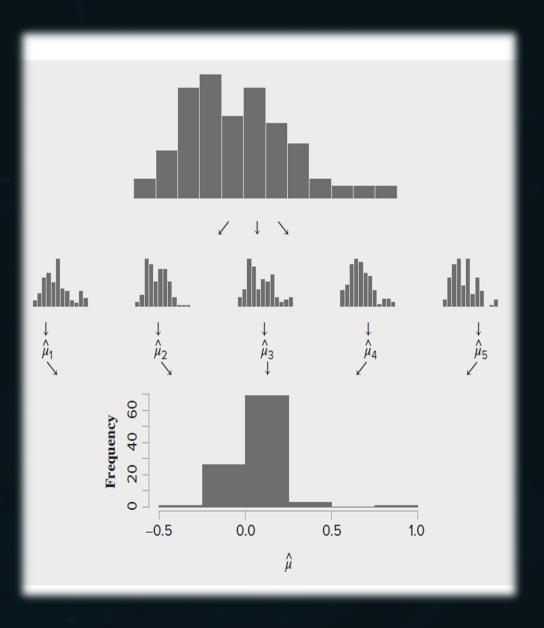
## Bootstrapping

Bootstrapping is a resampling technique that generates multiple datasets by randomly sampling with replacement from the original dataset.



### HCo

HCo standard errors address heteroscedasticity, a condition where the variance of the errors is not constant across all observations.



# Comparing Standard Errors: OLS, Bootstrap, and HCo

10.2257

OLS

The standard error for music sentiment in the OLS model is 10.2257.

15.52354

Bootstrap

The bootstrap method produces a higher standard error of 15.52354, indicating greater uncertainty in the estimate.

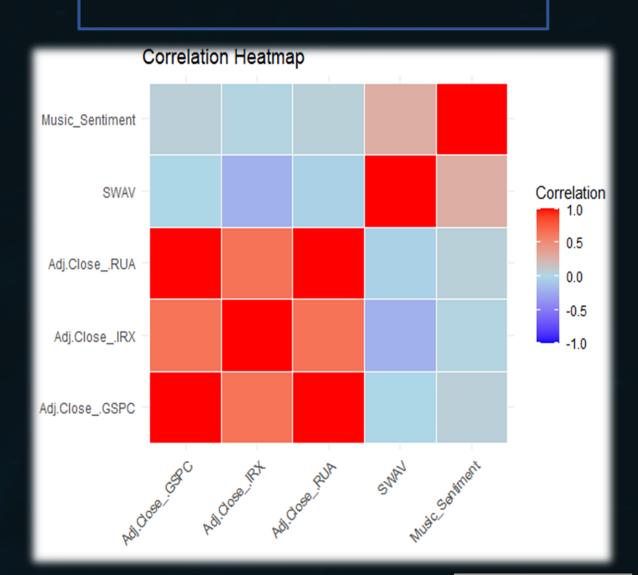
13.67312

**HCo** 

The HCo method provides a standard error of 13.67312, which is also higher than OLS, suggesting potential underestimation of standard errors by the original OLS model.

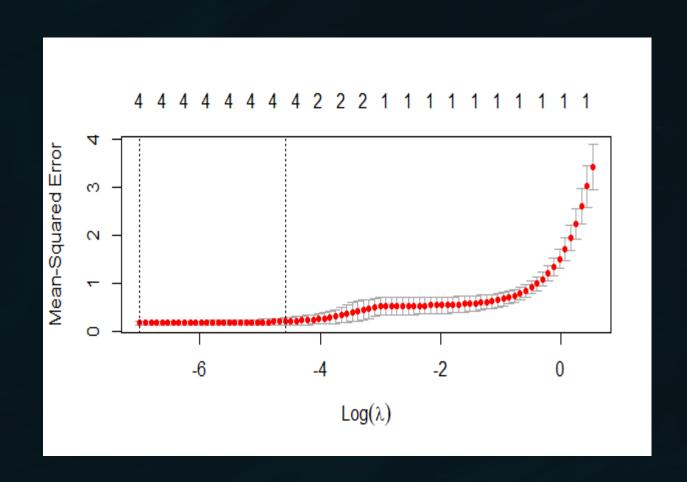
Reasons why OLS could have underestimated the standard errors:

- . Small sample size.
- 2. Autocorrelation.



| Model                                   | Standard Error<br>(OLS) | Bootstrap Std.<br>Error | Standard Error<br>(HC0) | P-Value<br>(OLS) | P-Value<br>(HC0) |
|---|-------------------------|-------------------------|-------------------------|------------------|------------------|
| GSPC Returns<br>(Contemp)               | 10.22095                | 15.91051                | 13.64994                | 0.3842           | 0.51348          |
| RUA Returns (Contemp)                   | 10.22519                | 15.63012                | 13.87782                | 0.3082           | 0.45125          |
| GSPC Risk-Adjusted<br>Returns (Contemp) | 10.22568                | 15.60611                | 13.67312                | 0.3835           | 0.51338          |
| RUA Risk-Adjusted<br>Returns (Contemp)  | 10.22971                | 16.00841                | 13.90015                | 0.3080           | 0.45124          |
| GSPC Returns (Lagged)                   | 10.2475                 | 11.32415                | 9.43220                 | 0.8610           | 0.84882          |
| RUA Returns (Lagged)                    | 10.27400                | 11.07718                | 9.40695                 | 0.8482           | 0.83408          |
| GSPC Risk-Adjusted<br>Returns (Lagged)  | 10.25226                | 11.20277                | 9.44853                 | 0.8595           | 0.84747          |
| RUA Risk-Adjusted Returns (Lagged)      | 10.27855                | 11.27499                | 9.42257                 | 0.8469           | 0.83290          |

# Lasso Model Selection Results:



### 1 <u>S&P 500</u>

Lasso analysis resulted in a lambda.min value of **0.313**, which led to the music sentiment coefficient being shrunk to zero. This indicates that music sentiment is not a significant predictor of S&P 500 returns.

### 2 Russell 3000

Similar results were observed, with a lambda.min of <u>0.262</u>. The Lasso algorithm reduced the music sentiment coefficient to zero, confirming the insignificance of music sentiment in explaining Russell 3000 stock returns.

# Robustness Checks: Impact of Control Variables

### **Control Variables**

1

We conducted robustness checks by adding control variables ( lagged Music sentiment )to the same model, which account for previous week's sentiment that may influence stock returns.

### S&P 500 with Controls

5

The S&P 500 model with control variables yielded a music sentiment coefficient of -9.066, while the model without controls had a coefficient of -6.8015. This difference is not statistically significant, suggesting that the inclusion of control variables does not substantially alter the results.



# Double Machine Learning: Causal Inference

#### Causal Inference

Double Machine Learning is a powerful framework for causal inference, allowing for robust estimation of treatment effects while controlling for potential confounding variables. It utilizes machine learning algorithms to estimate the treatment and control groups, reducing bias and improving accuracy.

#### Robustness Across Models

In the S&P 500 model, Double Machine Learning produced a music sentiment coefficient of **-9.096**, with a standard error of **10.340** and a **p-value of 0.38**. This result further supports the conclusion that music sentiment has a non-significant impact on stock returns.

1

2

Variables

Treatment variable: Music Sentiment

Outcome variable: Returns

Confounders: Lagged Returns, Lagged Music Sentiment.



# Conclusion: Music Sentiment's Negligible Predictive Power

This analysis using multiple methods, including OLS, Lasso, and Double Machine Learning, consistently demonstrates that **music sentiment has negligible predictive power** regarding stock returns across the indices, S&P 500 and Russell 3000.

Our findings does not align with the results for same week in the research paper. Although the coefficient being negative for previous week aligns with the paper, the p-values in our analysis clearly shows that our results are clearly insignificant. Maybe due to small sample size, autocorrelation and due to various factors not being in our dataset, the results do not significantly match with the results from the paper except for a miniscule similarity in previous weeks returns findings.

# Thank you

Prof. Hongwei (Harry) Zhu – Fall 2024

