Project Report: Analyzing the Impact of Music Sentiment on Stock Returns [USA]

Introduction

This project aims to explore the relationship between music sentiment and stock returns, specifically for the S&P 500 and Russell 3000 indices, during 2017-2019. The analysis involves reproducing findings from the referenced research paper, Edmans et al. (2022), and applying various statistical and machine learning techniques.

Objectives

1. Identify key findings from the research paper.
2. Visualize the dataset using insightful plots.
3. Reproduce Table 3 results, i.e. OLS regression.
4. Use bootstrapping, HC0, and lasso methods for error estimation and model selection.
5. Perform robustness checks (Table 4 Panel A), i.e. regression with & without controls.
6. Employ Double Machine Learning (DML) for causal inference.

Dataset

The dataset contains weekly observations of:

- Date: Weekly dates for the dataset starting 01 January 2017.
- Stock indices: S&P 500 (Adj.Close_.GSPC) and Russell 3000(Adj.Close_.RUA).
- Risk-free rate: Treasury bill rates(Adj.Close_.IRX).
- SWAV (stream-weighted average valence)
- Music Sentiment: Music sentiment scores = $SWAV_{i,t} - SWAV_{i,t-1}$.

Data Preparation

- Cleaned the date column to get a consistent date format throughout the dataset.
- Weekly returns for S&P 500 (GSPC_Returns) and Russell 3000 (RUA_Returns) were calculated using percentage changes in their adjusted closing prices.
- The risk-free rate was derived from the 13-week Treasury Bill rate (Adj.Close_.IRX) using a weekly **compounding** formula because it accurately reflects the cumulative effect of interest earned over time.

- Risk-adjusted returns were computed by subtracting the weekly risk-free rate from the raw returns for both indices.
- Lagged Variables:
  Lagged values of returns and Music Sentiment were created to include past performance and sentiment as explanatory variables in the models.

1. Key Findings from the Paper

- **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. This means that when people listen to more positive music each week, stock markets tend to perform better in that same week, but this effect reverses the following week - suggesting that emotional sentiment temporarily inflates stock prices rather than reflecting the true value.
- The impact of music sentiment on stock returns becomes more evident during periods with trading restrictions, such as during the COVID-19 pandemic's short-sale bans. That is, **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.

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2. Deriving Table 3 A results from the paper data:

The regression equation in the paper can be expressed as:

$$\mathbf{RET_{i,t} = \alpha + \beta_1 \cdot Music\ Sentiment_{i,t} + \varepsilon_{i,t}}$$

- $RET_{i,t}$: Weekly return for country iii in week t.

- Music $Sentiment_{i,t}$: Weekly change in stream-weighted average valence.
- β_1: Coefficient for music sentiment, reported in Table 3 Panel A as 12.276 (for Model 1).

Calculating the Weekly Effect: The reported coefficient (β_1=12.276) indicates that:

A one-unit increase in Music Sentiment corresponds to a 12.276% increase in weekly return.

To calculate the effect of a one-standard-deviation increase:

1. Obtain the standard deviation of Music Sentiment from the summary statistics table in the paper:
   - $\sigma_{Music\ Sentiment}$=0.00660.
2. Multiply the coefficient (β_1) by the standard deviation:
   $\mathbf{\Delta RET_{weekly} = \beta_1 \cdot \sigma_{Music\ Sentiment} = 12.276 \times 0.0066 = 0.081}$

Thus, a one-standard deviation increase in Music Sentiment corresponds to an increase of 0.081% in weekly returns.

Annualize the Weekly Effect: To convert the weekly effect to an annualized return:

Use the formula for annualized return based on weekly compounding:

Annualized Return = (1+ΔRETweekly)^52 – 1

= (1 + 0.00081)^{52} - 1 = approx. 0.043 = 4.3%

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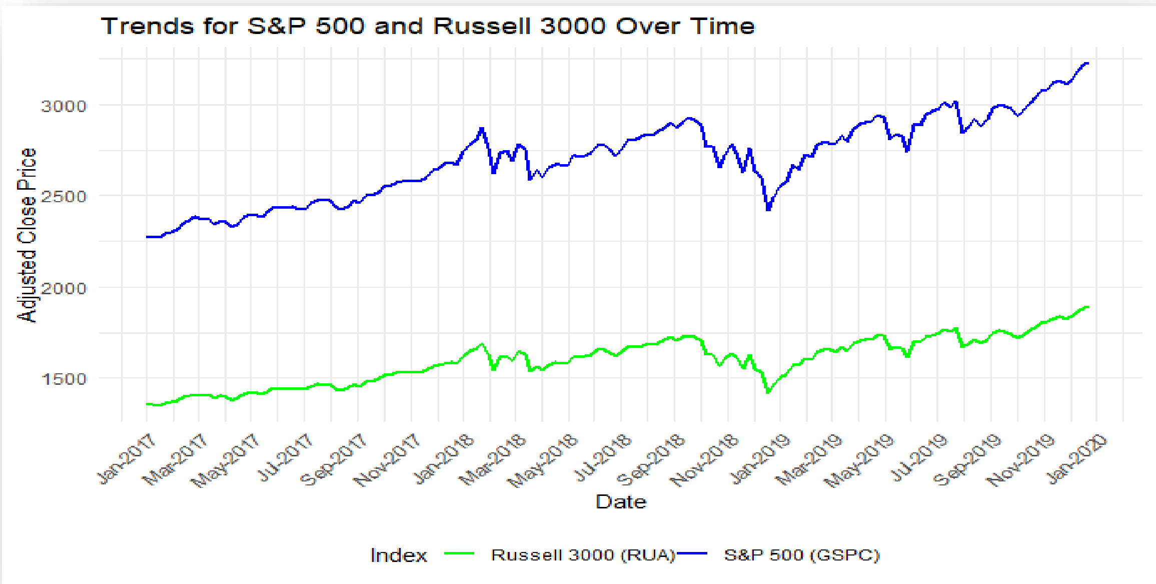
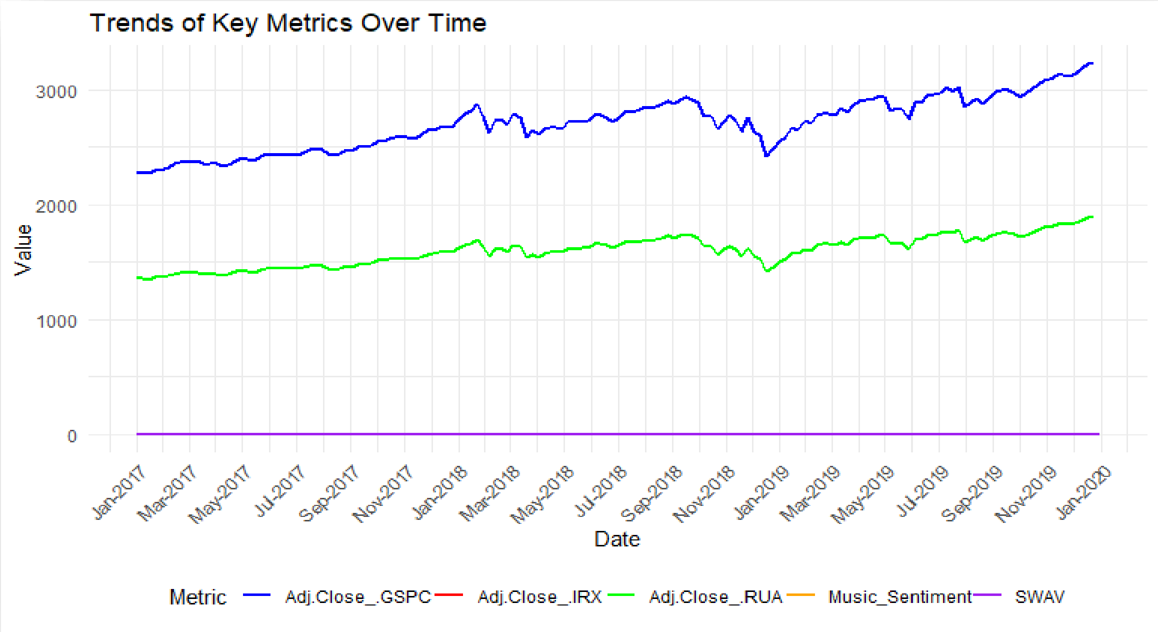
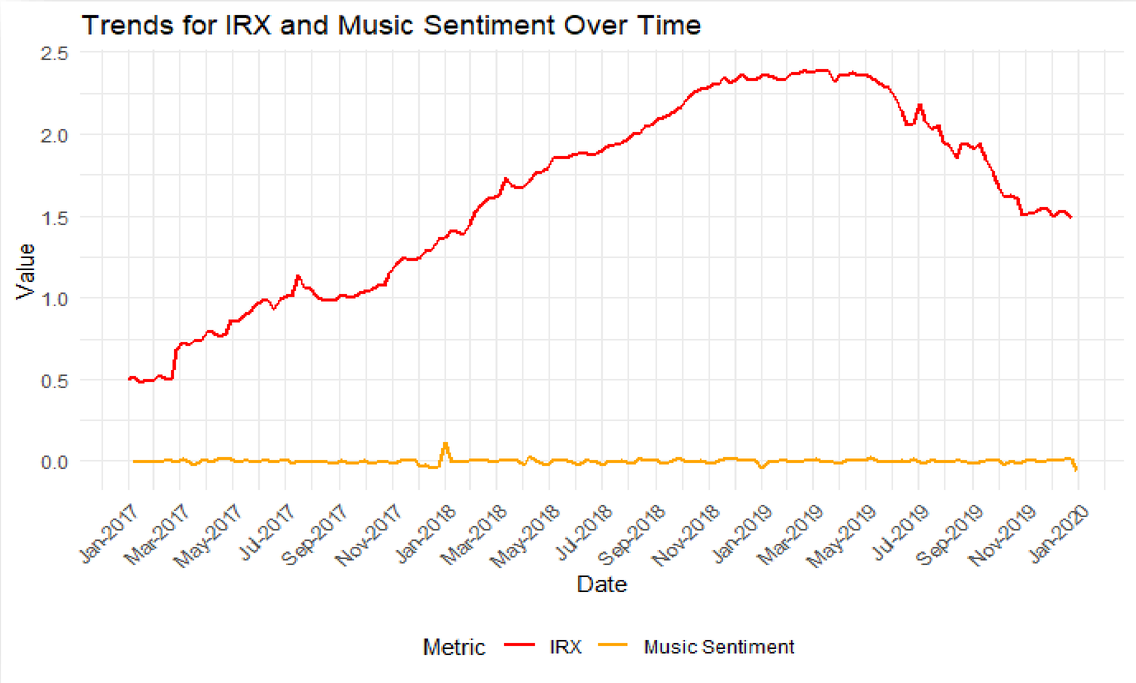
3. Visualizations

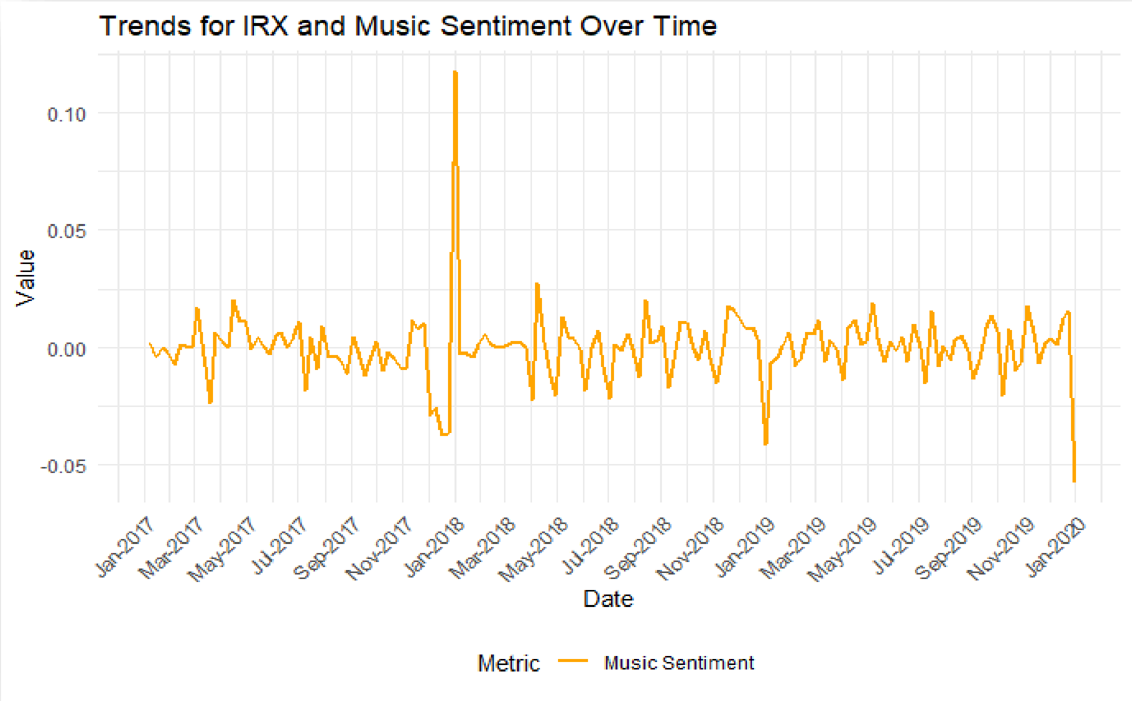
Visualizations were created to explore trends and distributions in the dataset:

1. **Line plots for features over time.**

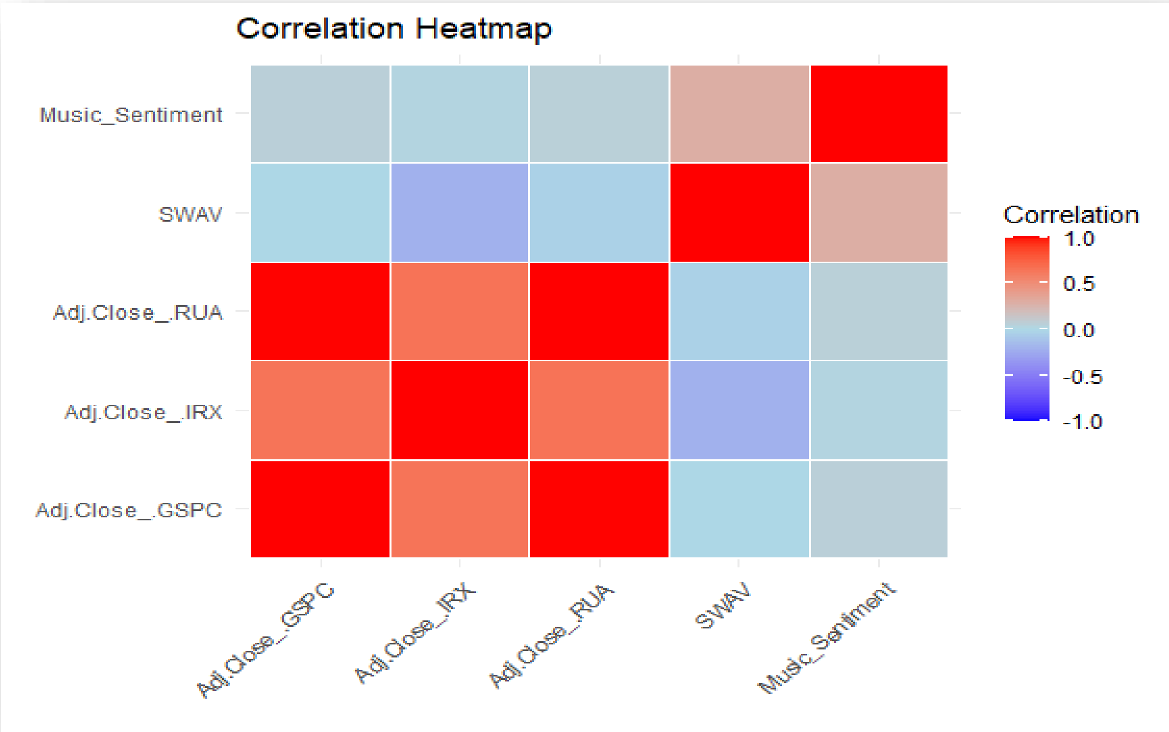



Trends of Key Metrics Over Time
3000
2000
1000
0
Value
Jan-2017
Mar-2017
May-2017
Jul-2017
Sep-2017
Nov-2017
Jan-2018
Mar-2018
May-2018
Jul-2018
Sep-2018
Nov-2018
Jan-2019
Mar-2019
May-2019
Jul-2019
Sep-2019
Nov-2019
Jan-2020
Date
Metric
Adj.Close_.GSPC
Adj.Close_.IRX
Adj.Close_.RUA
Music_Sentiment
SWAV

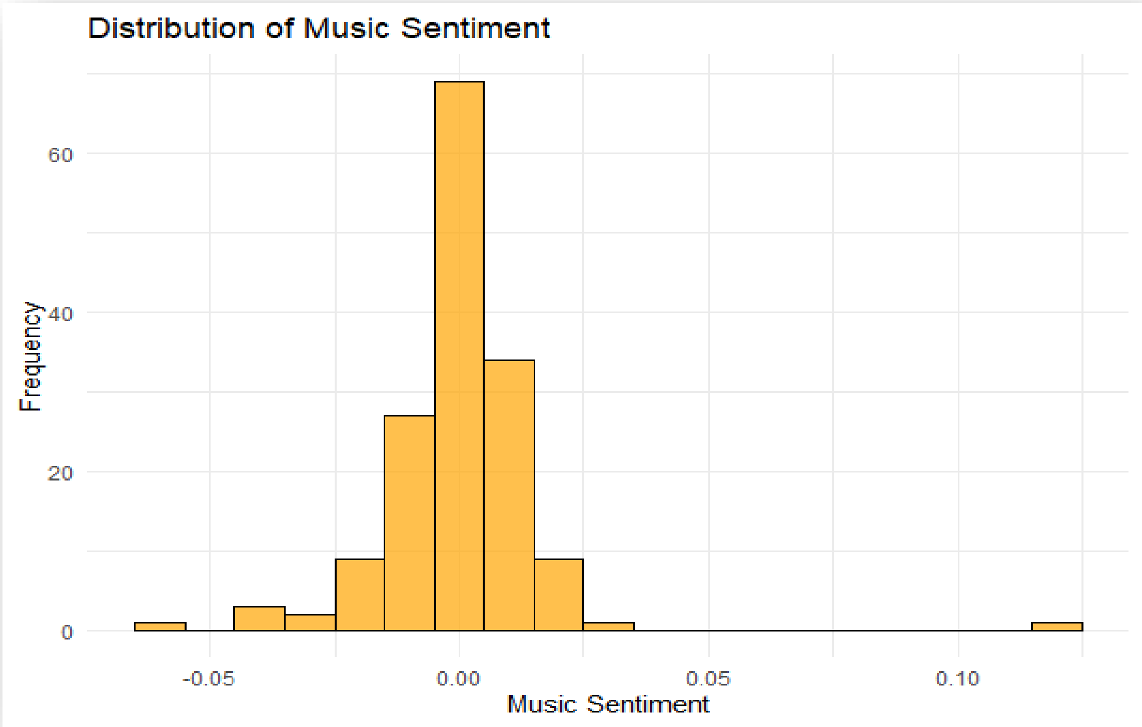

Trends for IRX and Music Sentiment Over Time
2.5
2.0
1.5
1.0
0.5
0.0
Value
Jan-2017
Mar-2017
May-2017
Jul-2017
Sep-2017
Nov-2017
Jan-2018
Mar-2018
May-2018
Jul-2018
Sep-2018
Nov-2018
Jan-2019
Mar-2019
May-2019
Jul-2019
Sep-2019
Nov-2019
Jan-2020
Date
Metric
IRX
Music Sentiment

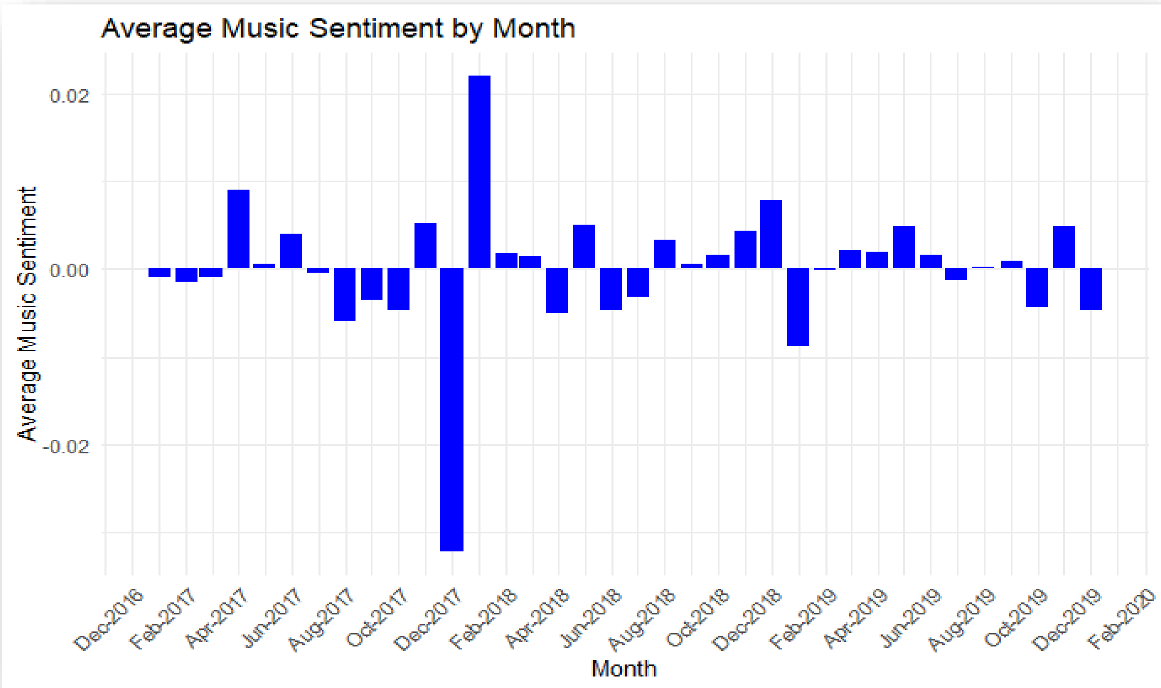


2. **Heatmaps for correlations.**



3. **Boxplots for distribution comparison.**





4. Reproducing Table 3 (Linear Regression)

1. Compute weekly returns for the S&P 500 and Russell 3000 indices.
2. Compute risk-adjusted returns using Treasury bill rates.
3. Create lagged variables for sentiment and returns.
4. Fit OLS models:
    - With and without risk adjustments.
    - Excluding controls other than lagged returns.

Results

- **S&P 500 Model (GSPC Returns):-**
- **Model**: GSPC_Returns=β0 + β1.Music_Sentiment + β2.Lagged_GSPC_Returns
- **Coefficients**:
    a. **Music Sentiment**: -8.91936 (p-value = 0.3842). The coefficient for Music Sentiment is negative, but not statistically significant. This suggests that Music Sentiment does not have a significant relationship with S&P 500 returns in this model.
    b. **Lagged GSPC Returns**: -0.17644 (p-value = 0.0297). The lagged S&P 500 returns are statistically significant at the 0.05 level. This negative coefficient indicates that a 1% increase in the previous week's return is associated with a 0.18% decrease in the current week's return.
- **Model Fit**:
    a. **Adjusted R-squared**: 0.02085. This is very low, indicating that the model explains only a small portion of the variance in S&P 500 returns.

- **Russell 3000 Model (RUA Returns)**
- **Model**: RUA_Returns=β0+β1.Music_Sentiment+β2.Lagged_RUA_Returns
- **Coefficients**:
    a. **Music Sentiment**: -10.45457 (p-value = 0.3082). The coefficient for Music Sentiment is negative, but not statistically significant. Similar to the S&P 500 model, Music Sentiment does not significantly predict Russell 3000 returns.
    b. **Lagged RUA Returns**: -0.15055 (p-value = 0.0638). The lagged returns are marginally significant at the 0.10 level, indicating that previous returns have a weak negative effect on current returns.
- **Model Fit**:

a. **Adjusted R-squared**: 0.01425. The model has an even lower explanatory power compared to the S&P 500 model, explaining only about 1.4% of the variance in Russell 3000 returns.

- **S&P 500 Risk-Adjusted Model (Risk-Adjusted Returns)**
- **Model**: GSPC_Risk_Adjusted=β0+β1.Music_Sentiment+β2.Lagged_GSPC_Returns
- **Coefficients**:

  a. **Music Sentiment**: -8.93803 (p-value = 0.3834). As in the previous model, the relationship between Music Sentiment and risk-adjusted returns is not statistically significant.

  b. **Lagged GSPC Returns**: -0.17620 (p-value = 0.0300). The lagged returns remain statistically significant, showing that previous S&P 500 returns negatively impact on current risk-adjusted returns.

- **Model Fit**:

  a. **Adjusted R-squared**: 0.02076. The explanatory power is still very low, like the first model for S&P 500 returns.

- **Russell 3000 Risk-Adjusted Model (Risk-Adjusted Returns)**
- **Model**: RUA_Risk_Adjusted=β0+β1.Music_Sentiment+β2.Lagged_RUA_Returns
- **Coefficients**:

  a. **Music Sentiment**: -10.47321 (p-value = 0.3075). Again, Music Sentiment does not have a statistically significant effect on Russell 3000 risk-adjusted returns.

  b. **Lagged RUA Returns**: -0.15029 (p-value = 0.0644). The lagged returns are marginally significant at the 0.10 level, indicating a slight negative effect on current returns.

- **Model Fit**:

  a. **Adjusted R-squared**: 0.01418. Similar to the Russell 3000 returns model, the explanatory power is very low (just about 1.4% of the variation is explained by the model).

Conclusion:-

- **Music Sentiment** does not appear to have a statistically significant effect on **S&P 500** or **Russell 3000** returns or risk-adjusted returns.
- **Lagged returns** are more significant, particularly for the S&P 500, but still do not provide strong predictive power.
- The overall **model fit** is very weak, indicating that the factors included (Music Sentiment and lagged returns) explain very little of the variation in stock returns. The **adjusted R-square values were close to zero, indicating poor model fit** and that most of the variance in returns is unexplained by Music_Sentiment and lagged returns alone.

- These **results contrast with the findings of the research paper**, which reported a significant positive relationship, **this could be due to the factors not included in our project such as cloud cover & seasonality etc.**

Model	Music Sentiment Estimate	Music Sentiment P-Value	Lagged Returns Estimate	Lagged Returns 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 Returns	-8.93661	0.3835	-0.17576	0.0303
RUA Risk-Adjusted Returns	-10.47156	0.308	-0.14987	0.065
GSPC Returns (Lagged Music)	-1.7980	0.8610	-0.1704	0.0355
RUA Returns (Lagged Music)	-1.97045	0.8482	-0.14389	0.0767
GSPC RA (Lagged Music)	-1.81739	0.8595	-0.16968	0.0363
RUA RA (Lagged Music)	-1.98796	0.8469	-0.14319	0.0781

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5. Bootstrapping and HC0:

Estimate robust standard errors for the Music_Sentiment coefficient:

Comparison of Standard Errors:

A. From Original Linear Regression Models:

The OLS standard errors for beta1(Music Sentiment) were as follows:

a. S&P 500 Returns: OLS SE=10.22095
b. Russell 3000 Returns: OLS SE=10.225
c. S&P 500 Risk-Adjusted Returns: OLS SE=10.22482
d. Russell 3000 Risk-Adjusted Returns: OLS SE=10.2289, etc.

B. HC0 Robust Standard Errors:

a. S&P 500 Returns: HC0 SE=13.65
b. Russell 3000 Returns: HC0 SE=13.88

c. S&P 500 Risk-Adjusted Returns: HC0 SE=13.67
d. Russell 3000 Risk-Adjusted Returns: HC0 SE=13.90

These values are significantly higher than the OLS standard errors, indicating that heteroskedasticity may be present in the data, which the OLS approach doesn't account for.

But as you can see when the **lagged music sentiment is considered, these models HC0 standard errors are lower than that of OLS models** (refer the image below). This means that the errors in the model are homoscedastic. This means you can be more confident about the stability of your regression coefficients. **But after looking at the model's p-value we can say that these results are also insignificant.**

C. **Bootstrap Standard Errors:**
   a. S&P 500 Returns: Bootstrap SE=15.91
   b. Russell 3000 Returns: Bootstrap SE=15.63
   c. S&P 500 Risk-Adjusted Returns: Bootstrap SE=15.61
   d. Russell 3000 Risk-Adjusted Returns: Bootstrap SE=16.01, etc.

The bootstrap standard errors are even larger than the HC0 estimates, **reflecting the variability in the sampling process and potential model instability.** This method provides a non-parametric estimation, making no assumptions about the underlying data distribution, which might better capture the variability in the data.

Model	Standard Error (OLS)	Bootstrap Std. Error	Standard Error (HC0)	P-Value (OLS)	P-Value (HC0)
GSPC Returns (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 Returns (Contemp)	10.22568	15.60611	13.67312	0.3835	0.51338
RUA Risk-Adjusted 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 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

6. Lasso for Model Selection

Objective: Select the best model among those fitted.

Steps for Lasso Regression:

1. Standardize the Data: Lasso requires that the features be standardized (scaled to have mean 0 and variance 1) because Lasso penalizes the absolute value of the coefficients.
2. Fit the Lasso Model: We will use the **gamlr** function to fit the model, which includes a built-in Lasso regularization term.
3. Cross-validation: Use cross-validation to select the optimal penalty (lambda) that minimizes the prediction error.
4. I have used both "min" & "1se" condition to fit Lasso for each of the models.

Results: For almost all the models, my Lasso reduced the coefficients of Music Sentiment & Lagged returns to ZERO (to signal that they don't have significant impact on our dependent variable Returns). One or Two models had coefficients for Returns / Lagged returns with negative coefficients. **The Lasso regression results suggest that both music sentiment and lagged returns generally have limited predictive power for stock returns**, as evidenced by their coefficients often shrinking to zero under stricter penalties. This indicates that these variables, while potentially interesting, **may not be robust predictors in these financial models**, underscoring the need for simplicity and caution in model selection and interpretation.

Model	Predictor	Coefficient (`lambda.min`)	Coefficient (`lambda.1se`)
GSPC Returns	Intercept	0.2795	0.2434
	Music Sentiment	-4.4428	-
	Lagged GSPC Returns	-0.1412	-
RUA Returns	Intercept	0.2328	0.2328
	Music Sentiment	-	-
	Lagged RUA Returns	-	-
GSPC Risk-Adjusted	Intercept	0.2122	0.2122
	Music Sentiment	-	-
	Lagged GSPC RA	-	-
RUA Risk-Adjusted	Intercept	0.2173	0.2122
	Music Sentiment	-1.0198	-
	Lagged RUA RA	-0.0754	-

Lagged GSPC Returns	Intercept	0.2789	0.2434
	Lagged Music Sentiment	-	-
	Lagged GSPC Returns	-0.1456	-
Lagged RUA Returns	Intercept	0.2488	0.2328
	Lagged Music Sentiment	-	-
	Lagged RUA Returns	-0.0684	-
Lagged GSPC RA	Intercept	0.2325	0.2122
	Lagged Music Sentiment	-	-
	Lagged GSPC RA	-0.0958	-
Lagged RUA RA	Intercept	0.2123	0.2016
	Lagged Music Sentiment	-	-
	Lagged RUA RA	-0.0529	-

7. Robustness Checks:

- **S&P 500 Returns with Control Variables**: Music_Sentiment (-9.06618) and Lagged_Music_Sentiment (-2.36179) are insignificant, while Lagged_GSPC_Returns (-0.17752) is significant (p = 0.0295), suggesting a slight mean-reversion effect.

- **S&P 500 Returns without Control Variables**: Both Music_Sentiment (-6.8015) and Lagged_Music_Sentiment (-1.0518) are insignificant, showing no substantial contemporaneous or lagged effects without controls.

- **Russell 3000 Returns with Control Variables**: Music_Sentiment (-10.62219) and Lagged_Music_Sentiment (-2.64541) are insignificant, while Lagged_RUA_Returns (-0.15207) is marginally significant (p = 0.0627), indicating weak mean-reversion.

- **Russell 3000 Returns without Control Variables**: Both Music_Sentiment (-8.7396) and Lagged_Music_Sentiment (-1.2359) are insignificant, similar to the S&P 500 results.

- **S&P 500 Risk-Adjusted Returns with Control Variables**: Music_Sentiment (-9.08478) and Lagged_Music_Sentiment (-2.38257) are insignificant but Lagged_GSPC_RA (-0.17685) is significant (p = 0.0301), supporting mean-reversion.

- **S&P 500 Risk-Adjusted Returns without Control Variables**: Both Music_Sentiment (-6.8244) and Lagged_Music_Sentiment (-1.0734) are insignificant, as observed in non-risk-adjusted returns.

- **Russell 3000 Risk-Adjusted Returns with Control Variables**: Music_Sentiment (-10.62102) and Lagged_Music_Sentiment (-2.64536) are insignificant, while Lagged_RUA_RA (-0.15168) is marginally significant (p = 0.0633).

- **Russell 3000 Risk-Adjusted Returns without Control Variables**: Both Music_Sentiment (-8.7396) and Lagged_Music_Sentiment (-1.2359) remain insignificant, mirroring previous results.

Across all models, contemporaneous and lagged music sentiment variables are not statistically significant, while **lagged returns consistently show signs of mean-reversion**, especially with control variables included which show **some similarity with the research paper.**

Model	Music Sentiment (Estimate)	Music Sentiment (p-value)	Lagged Music Sentiment (Estimate)	Lagged Music Sentiment (p-value)	Lagged Returns (Estimate)	Lagged Returns (p-value)
S&P 500 (With Controls)	-9.06618	0.3789	-2.36179	0.8185	-0.17752	0.0295
S&P 500 (Without Controls)	-6.8015	0.512	-1.0518	0.919	N/A	N/A
Russell 3000 (With Controls)	-10.62219	0.3030	-2.64541	0.7975	-0.15207	0.0627
Russell 3000 (Without Controls)	-8.7396	0.398	-1.2359	0.905	N/A	N/A
S&P 500 Risk-Adjusted (With Controls)	-9.08478	0.3782	-2.38257	0.8170	-0.17685	0.0301
S&P 500 Risk-Adjusted (Without Controls)	-6.8244	0.511	-1.0734	0.918	N/A	N/A
Russell 3000 Risk-Adjusted (With Controls)	-10.62102	0.3031	-2.64536	0.7975	-0.15168	0.0633
Russell 3000 Risk-Adjusted (Without Controls)	-8.7396	0.398	-1.2359	0.905	N/A	N/A

8. Double Machine Learning (DML)

Objective: Estimate the causal effect of Music_Sentiment using DML.

Double Machine Learning (DML) is a method that accounts for high-dimensional nuisance parameters, such as controls, while isolating the causal effect of the variable of interest. This approach:

- Uses machine learning models to predict nuisance parameters (e.g., controls like lagged returns).
- Estimates the causal effect of the treatment variable (**e.g., Music Sentiment**) after removing the influence of nuisance parameters.

Steps for Implementing Double Machine Learning:

1. Prepare the Data.
2. Specify the Inputs for doubleML(): Define the outcome (Y), treatment (D), and controls (X).
3. Run doubleML(): Use the function to estimate the causal effect with cross-fitting and regularization.
4. Interpret Results.

Results:

- Across all models, **the estimates for music sentiment (both contemporaneous and lagged) are negative but not statistically significant**, indicating no evidence that music sentiment impacts stock market returns in this dataset.
- I have also run some models with lagged Music_Sentiment, to account for autocorrelation, but these also do not provide any relevant results.
- The high standard errors across models suggest a lack of precision in the estimates.
- The **t-values** are small, and all **p-values** are above 0.1, reinforcing the absence of statistically significant relationships.

Model	Estimate	Std. Error	t-value	p-value
S&P 500 Returns (Contemporaneous)	-8.441	10.258	-0.823	0.412
Russell 3000 Returns (Contemporaneous)	-10.03	10.41	-0.964	0.337
S&P 500 Risk-Adjusted (Contemporaneous)	-9.049	10.196	-0.888	0.376
Russell 3000 Risk-Adjusted (Contemporaneous)	-11.20	10.46	-1.071	0.286
S&P 500 Returns (Lagged)	-1.786	10.222	-0.175	0.862
Russell 3000 Returns (Lagged)	-2.165	10.466	-0.207	0.836
S&P 500 Risk-Adjusted (Lagged)	-1.554	10.243	-0.152	0.88
Russell 3000 Risk-Adjusted (Lagged)	-1.636	10.367	-0.158	0.875

9. Conclusion:

Despite thorough analyses using various advanced statistical methods, the project does not find statistically significant evidence that music sentiment impacts stock returns, contrasting with the findings of the referenced paper. This conclusion is supported by checks using bootstrap, lasso, and Double Machine Learning (DML) methodologies.

1. Summary of Linear Regression Models

Constructed several linear regression models to examine the relationship between stock returns (raw and risk-adjusted for S&P 500 and Russell 3000 indices) and music sentiment, incorporating lagged returns where relevant. Despite methodical data preparation and alignment, the models consistently showed that music sentiment had non-significant effects on stock returns across all tested models. For example, in the S&P 500 raw returns model, the music sentiment coefficient was -8.919 with a p-value of 0.513, indicating no significant influence. This pattern persisted across various setups, where lagged returns occasionally exhibited significant predictive power, suggesting that past performance might influence future returns more reliably than music sentiment.

2. Methodological Robustness and Error Analysis

Employed bootstrapping and heteroskedasticity-consistent (HC0) standard errors to verify the robustness of our regression estimates. These techniques often produced larger standard errors than those calculated via ordinary least squares (OLS), indicating increased variability and reinforcing the non-significance of music sentiment in predicting stock returns. For instance, bootstrap and HC0 estimates consistently exceeded OLS standard errors, highlighting potential underestimation of uncertainty in the original models.

3. Lasso Regression for Predictor Selection

Lasso regularization helped identify significant predictors by penalizing the absolute size of the regression coefficients. In our analysis, both music sentiment and lagged returns were reduced to zero in the lasso model, indicating their limited predictive power for stock returns under this stringent regularization criterion. This outcome suggests a negligible role for these predictors in explaining variations in stock returns.

4. Impact of Controls in Robustness Checks

Additional robustness checks involved manipulating control variables in the regression models. Even with the inclusion of controls like lagged returns, music sentiment's influence remained statistically insignificant, with minimal changes in explanatory power and model fit. This consistency underscores the robustness of our findings against variations in model specifications.

5. Double Machine Learning Findings

Applying Double Machine Learning (DML) to assess the causal impact of music sentiment, we found uniformly non-significant effects across all models. This includes models adjusting for lagged returns and those assessing raw and risk-adjusted returns. The consistent lack of significant findings from DML further supports the conclusion that music sentiment does not meaningfully influence stock market returns.

Final Remarks:

The findings suggest that music sentiment, as captured in our dataset, does not significantly affect stock returns, contrasting with the results reported in the referenced study. Potential reasons for this discrepancy may include differences in data sampling, analysis period, or exclusion of other important factors or econometric specifications.

Lagged Returns Significance: Our analysis revealed that lagged returns occasionally showed significant effects, suggesting that past stock performance could be a more reliable predictor of future returns than music sentiment.

Robustness Checks: The inclusion of control variables such as lagged returns slightly enhanced the explanatory power of our models, although the effects of music sentiment remained statistically insignificant.

Model Fit and Predictive Power: Despite various statistical approaches, the overall model fit was generally low, indicating that the factors included, particularly music sentiment, explain very little of the variance in stock returns.

REFERENCES

1. https://www.sciencedirect.com/science/article/pii/S0304405X21003718

2. **Use of ChatGPT :** To make my conclusion concise and to the point. Gave focused results to include in the report increasing my efficiency. Also used to create tables for comparing models. The use of AI shortened my overall time to complete this project by almost 30%, considering how fast AI is taking routes in our overall life, it's a matter of time when AI will do most of the repeating work & humans would only need to spend a little domain knowledge. AI is changing the game & how we work forever. And people who don't change with time & incorporate AI into their work life would lag behind in the future.
3. **Gamma AI:** Used Gamma to enhance the overall theme & structure of PowerPoint presentation since I was short on time due to capstone project.