--- title: "Emotional Trends in Popular Music and U.S. Economic Conditions" author: "Jeremy Han, Tianyu Zhao, Junyi (Daniel Tang), Hillary Metcheka, Bryce Grover" format: pdf number-sections: true ---

Abstract

Introduction

Related Work

Data

Data Collection

This project explores the change in emotional traits of popular music and the market performance of a leading streaming company before, during and after COVID-19. The project focuses on the 2017-2021 period, providing a unique viewpoint for interpreting shifts in cultural attitudes and financial turbulence associated with the pandemic. Although earlier iterations of the project considered unemployment data as a macroeconomic indicator, the final analysis excluded unemployment data due to limited incremental insight and redundancy with other economic measures. Instead, the final dataset emphasizes **Spotify streaming behavior, song-level audio features, and Spotify stock price data**, which together provide a more direct connection between music consumption, emotional sentiment, and economic performance.

The final analysis uses three primary datasets:

Dataset 1: Spotify Top 200 Chart Data

- We used Spotify's Top 200 global chart data to map out large-scale listening behavior and preference. All these features were recorded in the dataset, which represents the daily rankings of the most consumed songs found in the world. To decrease background noise and focus on the broad trends, we organized daily observations into monthly values which facilitate an accurate and consistent temporal comparison between pre-COVID, COVID, and post-COVID periods.

Dataset 2: Spotify Audio Features

- Spotify Audio Features Data was combined with the chart data in order to estimate the emotional and acoustic properties of popular songs. Important features such as valence, energy, danceability, liveness, loudness, tempo and duration, are identified. These machine-learned features act as a quantitative indicator of musical sentiment and allow for formally perform statistical testing on such changes in emotional tone over time.

Dataset 3: Spotify Stock Price Data

- We also incorporated monthly Spotify (SPOT) stock price data, to model firm market performance and sentiment within the market. This dataset enables comparison of music consumption patterns with financial market behavior, particularly during the COVID-19 period when abnormal volatility and structural shifts were observed If the data sources changed from previous study stages, our merging approach was identical. All datasets were aligned using standardized time variables, ensuring that results are driven by substantive changes in data rather than methodological differences.

Data Preprocessing/Cleaning

Data cleaning focused on resolving inconsistencies across sources and preparing the data for time-series, hypothesis testing, and comparative analysis.

Standardization of Song Metadata

The Spotify Top 200 and audio feature datasets came from diverse entities where the naming conventions were not consistent. To prevent overlap between different datasets, titles and the names of the songs were standardized before merging them. For each of the song periods, duplicate entries of songs based on repeated appearances in the charts were aggregated into one observation per song.

Numeric Variable Cleaning

Several numeric variables (e.g. streaming counts, audio feature values) were stored as strings or formatted fields with commas. The non-numeric characters were removed and converted into numeric numbers in these variables. Invalid entries are given by their missing values to avoid bias or computational errors.

Date Processing and Temporal Alignment

Chart data contained a “week of highest charting” variable as a date range. This variable was processed into start and end dates and using the starting date to act as the main temporal reference. All date variables had been changed to datetime objects and been reformatted into a year-month pattern to achieve uniformities of aggregation and to support monthly stock price data.

Aggregation and Merging

In order to see the bigger picture and diminish short-term volatility, daily chart data was consolidated to the monthly level. The month-to-month Spotify stock prices were then combined with the music dataset using the same year-month key. Data integrity was ensured by excluding records where irreconcilable missing time values were present.

Study I: Longitudinal Analysis of Musical Sentiment

Study II: Economic Volatility and the Decoupling of Cultural Sentiment

Structural Instability in the Streaming Economy: A Time Series Approach

Motivation and Research Questions

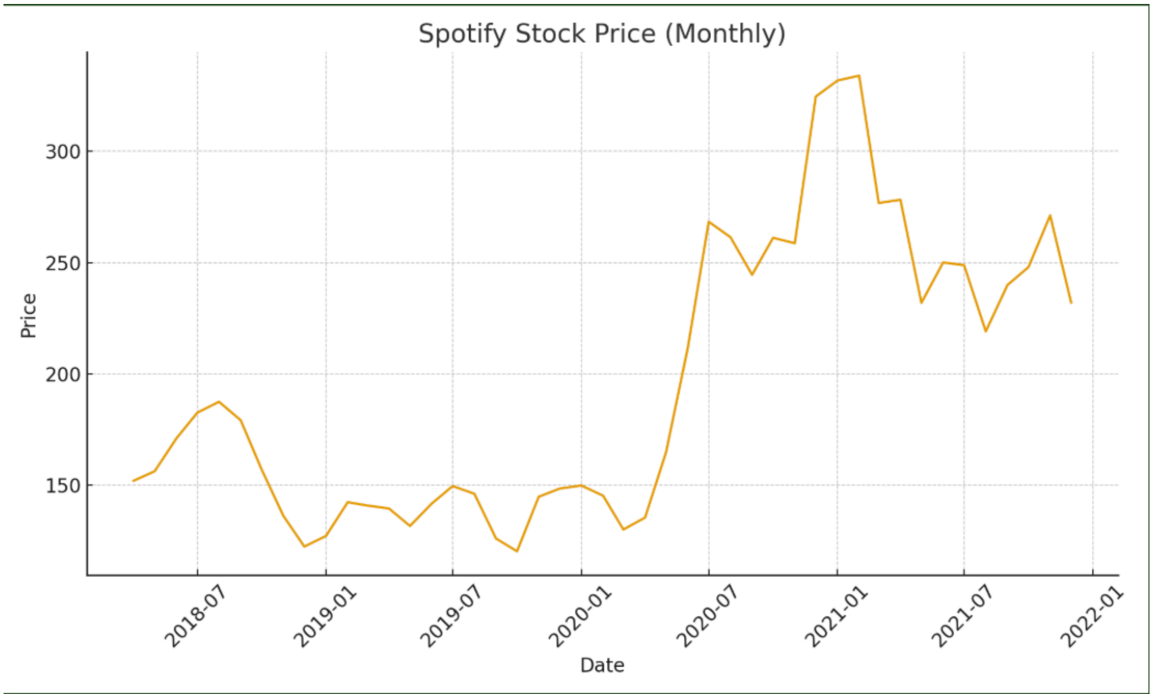
While Study I focused on how music changed, this section shifts to the economic side of the music industry. The COVID-19 pandemic was a health crisis, but it also caused a major shock to the economy. We wanted to investigate two main questions regarding the financial performance of the sector:

- How were the stock prices of music streaming companies affected during the COVID-19 period?
- Did Spotify's stock exhibit abnormal volatility or structural changes during the pandemic compared to before?

We hypothesized that even if the content of the music (sentiment) stayed stable, the market valuation (stock price) would show distinct signs of instability and "abnormal volatility" due to the pandemic.

Closing Stock Price Inspection

We first plotted Spotify’s monthly closing stock prices from 2018 to 2021 to get a general sense of how the market behaved over time.



{#fig-spotify width=80% fig-align="center"}

From the figure @fig-spotify, it is clear that the price does not follow a smooth or consistent linear trend.

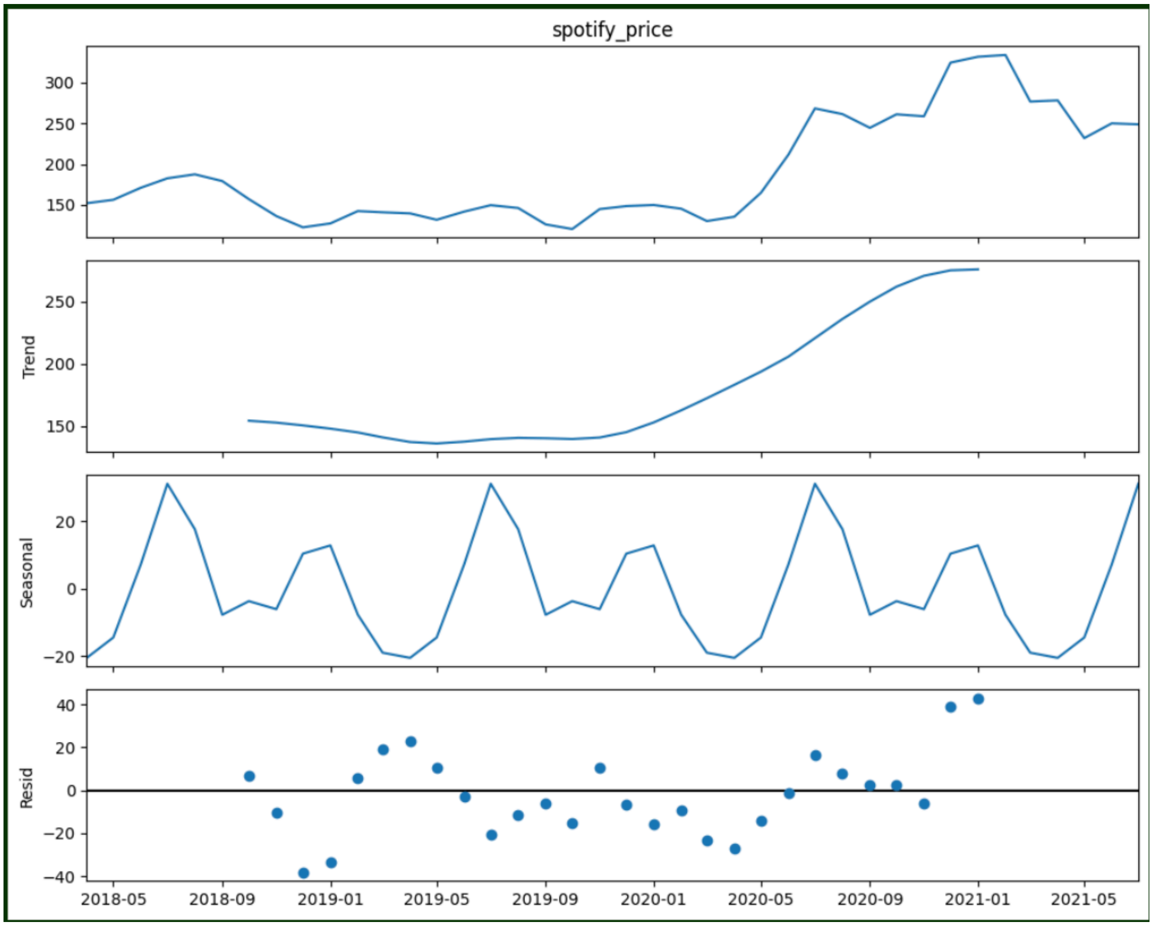
1. We first plotted Spotify's monthly closing stock prices from 2018 to 2021 to get a general sense of how the market behaved over time. From the figure, it is clear that the price does not follow a smooth or consistent linear trend.

2. Around the start of the pandemic in early 2020, the pattern changes noticeably. The stock price increases rapidly and in a non-linear way, rising from roughly $150 to above 300$ within about a year. This sharp shift suggests a structural break rather than a continuation of the earlier trend.

That said, a line chart alone cannot tell us whether this growth was smooth or whether it came with increased instability or volatility.

Decomposition

After examining the trend, we knew the price had increased, but we needed to know how it went up. Was it just a normal seasonal thing? Or was something broken? To figure this out, we used decomposition.



{#fig-decomp width=80% fig-align="center"}

We plotted these components in Figure @fig-decomp, and here is what we discovered:

- Trend: This part of the decomposition merely illustrates the general direction. It confirms what we already knew—the price started skyrocketing in 2020. It was not a straight line, instead, it curved upwards very fast.

- Seasonality: We thought maybe there would be a pattern, like sales going up every Christmas. However, if you examine the y-axis, the numbers are relatively small compared to the trend. The waves are present, but they do not significantly impact the price. This indicates that the substantial price jump was not due to the time of year.

- Residuals: In a healthy market, residual should be small and randomly scattered around zero. However, upon inspecting the bottom panel, we see a distinct cluster of huge spikes starting in 2020.

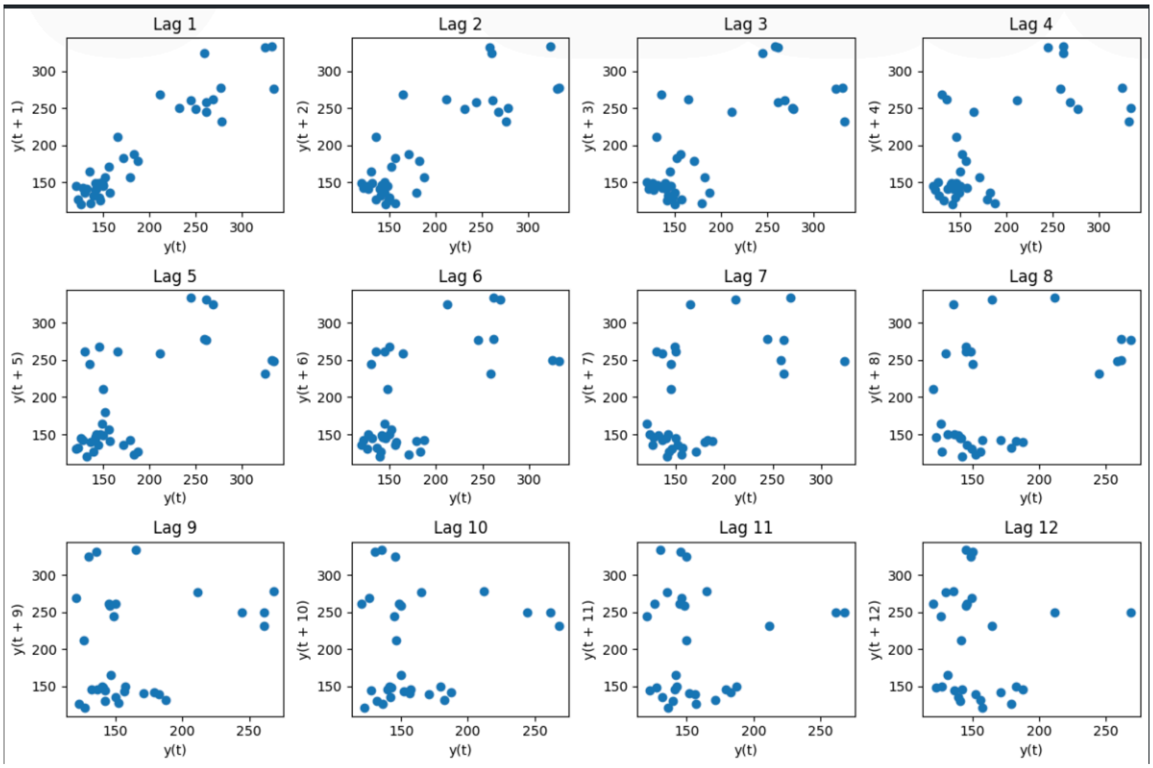
Seeing those big, clustered spikes in the bottom graph proves that the market was not stable. This gave us the proof we needed to say that the volatility was abnormal during COVID.

Data Transformation

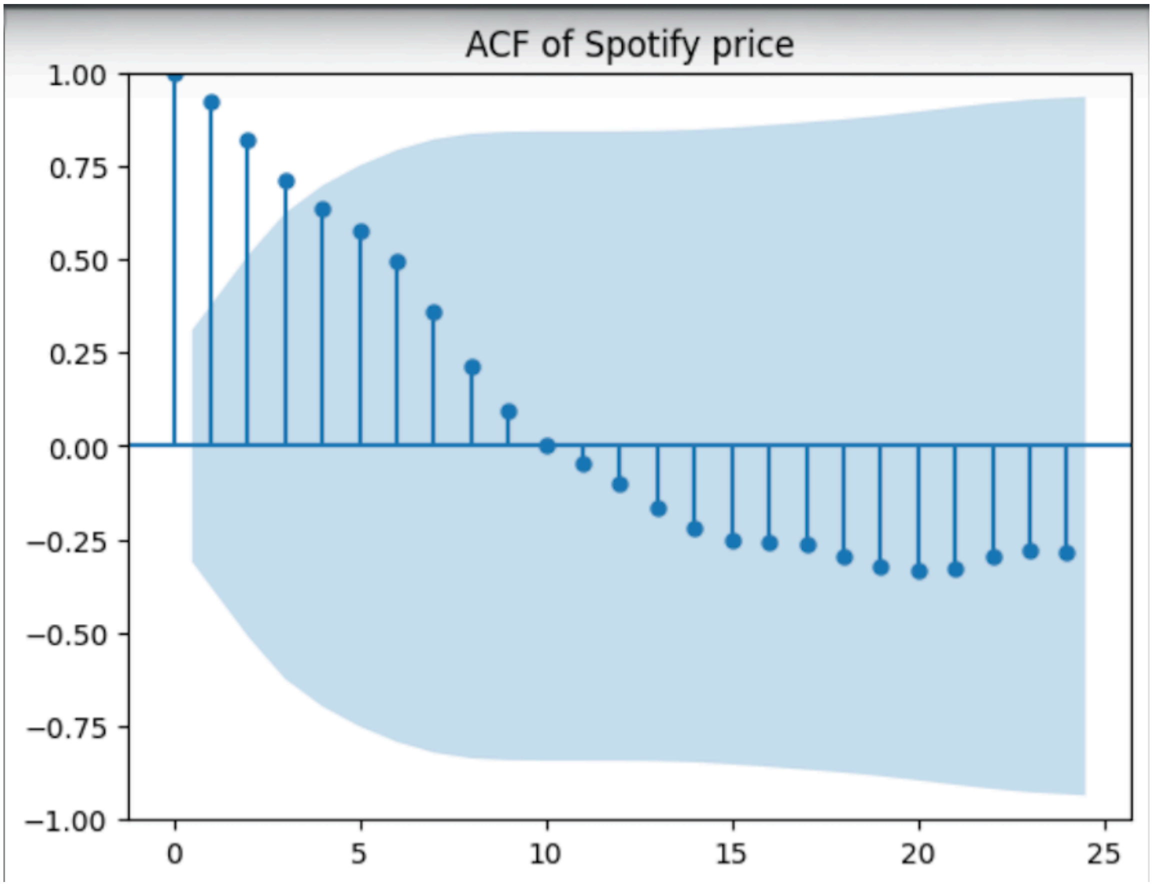
We noticed that in the decomposition section, it creates a problem for our modeling. Models like ARIMA assume the data is stationary, which basically means the average and the spread of the data shouldn't change over time. However, looking at our stock price charts, the data clearly breaks this rule. It goes up and down wildly. So, we need to conduct a preprocessing step to make it stationary

Lag & ACF

We fisrt plotted the Lag Plots and the Autocorrelation Function to look at the internal patterns.



{#fig-lag width=80% fig-align="center"}



{#fig-acf_lag width=80% fig-align="center"}

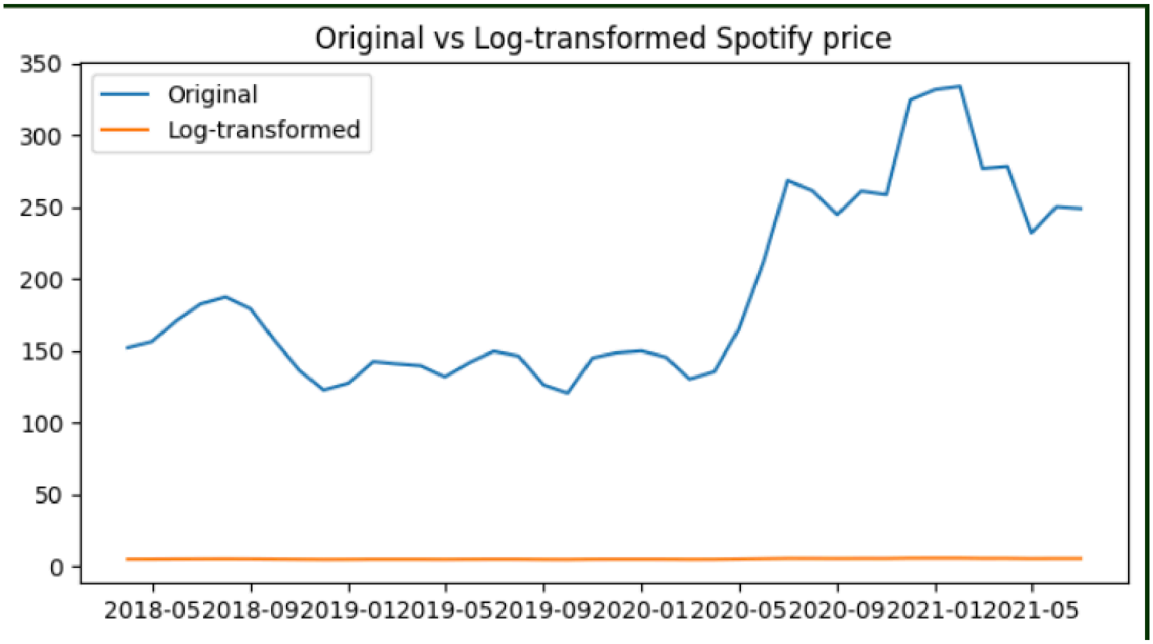
Base on the figures we notices:

- Lag Plots: Strong positive relationship is observed at lag 1 and lag 2. This means today's price is almost perfectly predicted by yesterday's price.
- ACF: The autocorrelation bars decay very slowly and stay outside the confidence bounds for many lags. This usually happens when the data is not stationary and shows strong persistence. In this case, the slow decay likely means that the overall trend is very strong and is affecting the series, making the short-term changes harder to see.

Step 1: Log-Transformation

The first thing we noticed was the variance. There was a strange pattern here. When the stock price was low in 2018, the movements were pretty small. But once the price became much higher around 2020, the fluctuations also became much bigger.

To fix this heteroscedasticity, we applied a Logarithmic Transformation.



{#fig-log width=80% fig-align="center"}

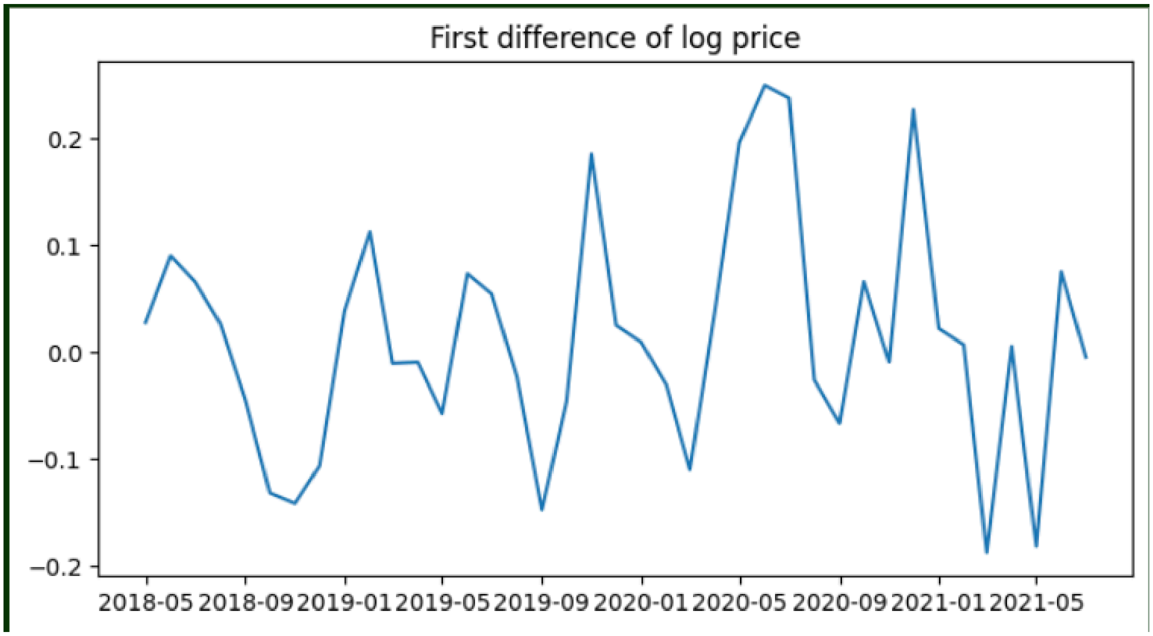
- The blue line is the original price. You can clearly see the huge, messy spike in 2020 where the variance explodes.
- The orange line is the log-transformed price. It looks much smoother and more consistent.

Applying a logarithmic transformation reduces the impact of large values by compressing the scale of the data. Price movements are interpreted in relative terms rather than absolute dollar amounts, making the series more suitable for modeling.

Step 2: First-Order Differencing

At first glance (looking back at log transformation), the log-transformed data (orange line) might appear "flat" enough. However, this is deceptive. While the variance was stabilized, the series still retained a deterministic trend—the mean value was drifting upwards over time as the company grew. For an ARIMA model to be valid, the data must not just be stable in width, but also horizontal in direction (stationary mean).

To rigorously remove this remaining trend, we applied First-Order Differencing.



{#fig-diff width=80% fig-align="center"}

By analyzing the change from one month to the next rather than the raw value, we isolated the stochastic component.

Figure @fig-diff confirms the necessity of this step.

Unlike the log-series which drifted upwards, the differenced series oscillates consistently around zero. This transformation successfully detrended the data, leaving us with a pure "growth rate" metric that satisfies the strict stationarity requirements for autoregressive modeling.

Verifying the Result

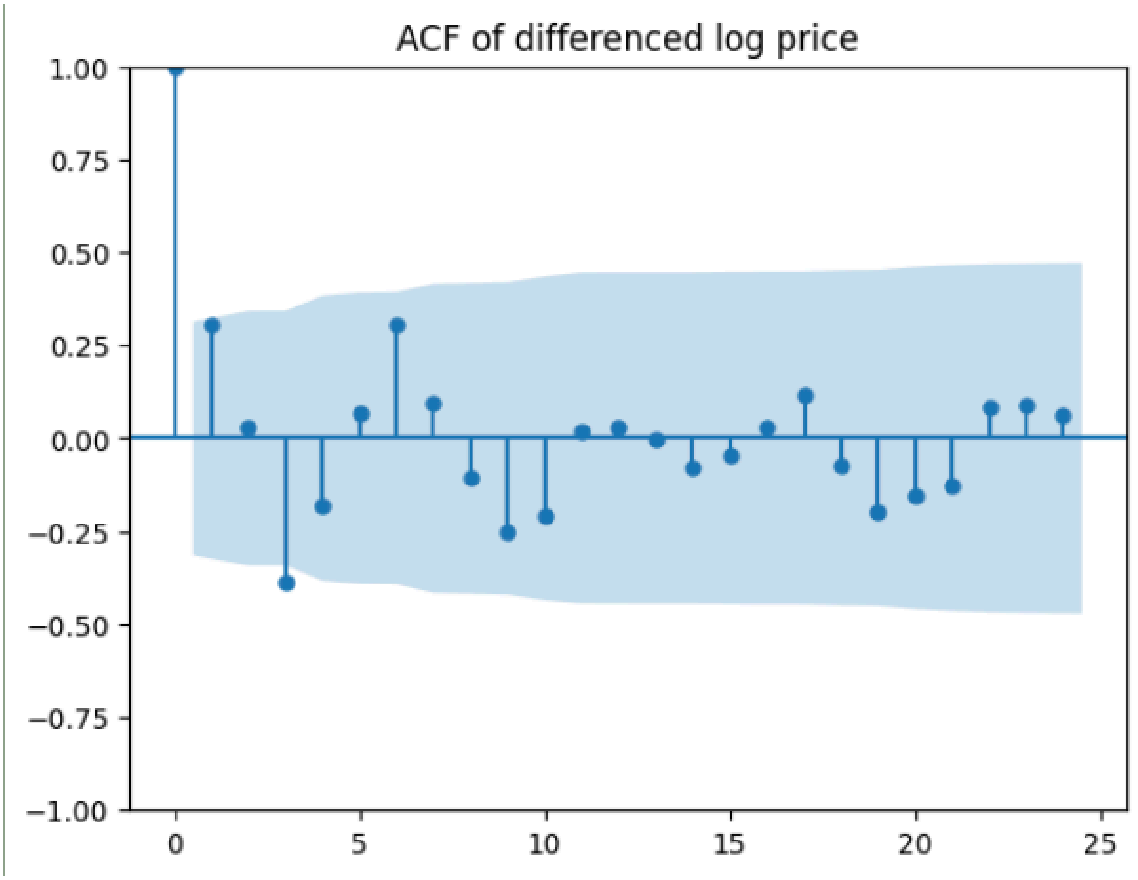
We conduct the Augmented Dickey-Fuller (ADF) test on the before and after transformation series:

Table 1: ADF Stationarity Test Comparison

Series	Test Statistic	p-value	Conclusion
Original Stock Price (P_t)	-1.96	0.304	**Non-Stationary** (Fail to reject H_0)
Transformed Series ($\Delta \ln P_t$)	**-4.91**	**0.00003**	**Stationary** (Reject H_0)

- Before Transformation: The p-value was around 0.30. Since this is way bigger than 0.05, it confirmed that our original data was definitely not stationary.
- After Transformation: After doing the log and the difference, the p-value dropped to 0.00003.

Since 0.00003 is tiny, we can say for sure that the data is stationary now. We also checked the ACF plot one last time.



{#fig-acf_after width=80% fig-align="center"}

In Figure @fig-acf_after, the difference is obvious. Unlike the first ACF plot that dragged on forever, this one cuts off really fast after the first lag. Most of the dots are inside the blue shaded area. This confirms that we successfully removed the trend and the unstable variance, so now we are finally ready to put this data into the ARIMA model.

ARIMA Modeling

Now that the data is stationary, we could finally run the ARIMA model. We didn't know which parameters would be perfect, so we ran a grid search to test different combinations. To pick the winner, we just looked at the AIC score—basically, the lower the number, the better the model.

Table 2: ARIMA Model Comparison

Model	AIC
ARIMA(1, 1, 0)	-60.172188
ARIMA(3, 1, 0)	-59.056107
ARIMA(3, 1, 1)	-57.422914

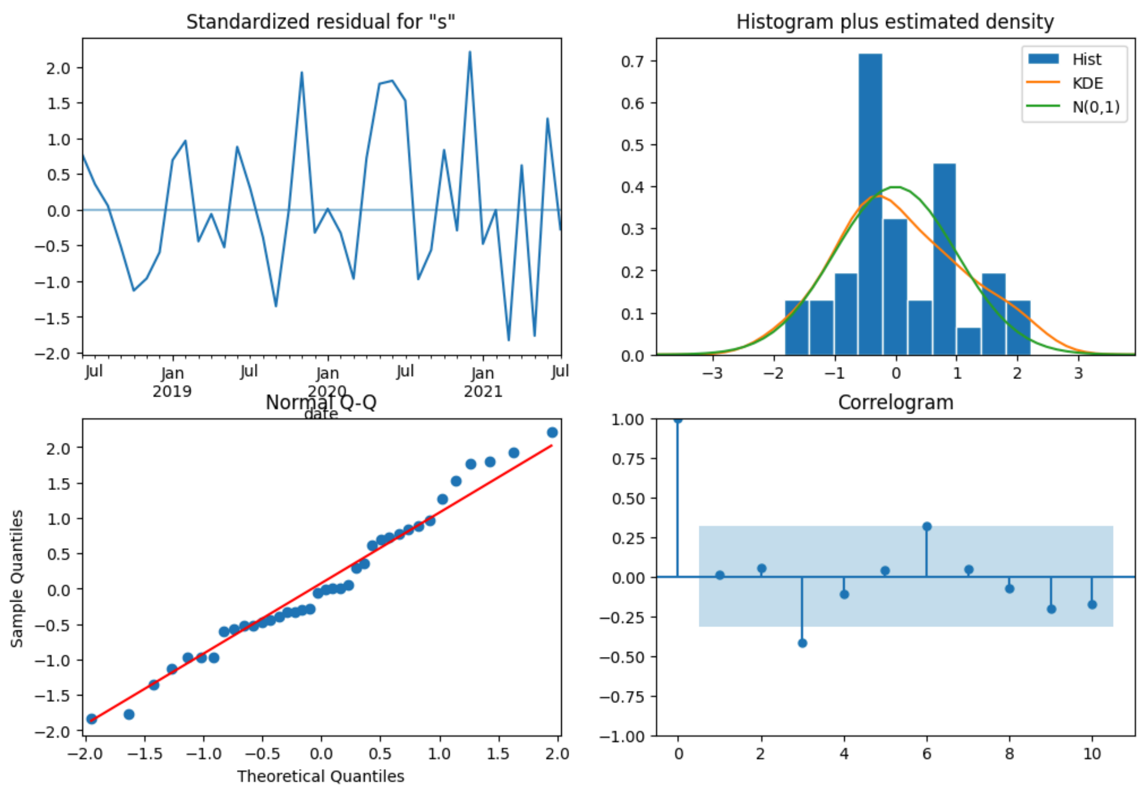
Looking at the table, the ARIMA(1, 1, 0) model gave us the lowest score of -60.17. We tried more complex models like ARIMA(3, 1, 0) and ARIMA(3, 1, 1), but their scores were higher (-59.05 and -57.42), so they weren't worth the extra complexity.

Table 3: SARIMAX Result

Parameter	coef	std err	z	P>\	z\		[0.025
ar.L1	0.3159	0.156	2.026	0.043	0.010	0.621	
sigma2	0.0108	0.003	3.745	0.000	0.005	0.016	

Based on the SARIMAX Result It showed an AR coefficient of 0.3159 with a p-value of 0.043, which means the relationship is statistically significant.

Residual Diagnostics



{#fig-residual width=60% fig-align="center"}

We plotted the residuals to see if the model missed anything.

1. Standardized Residuals: Figure @fig-residual shows the reality. If you look at the top-left graph, the line is messy. You can see huge spikes around 2020 and 2021. This tells us that even with the best model, the variance during the pandemic was just too high to predict perfectly.

2. Q-Q Plot: Next, look at the Q-Q plot. We want the blue dots to sit on the red line. Most of them do, but look at the tails—the dots peel away from the line at both ends.

This confirms "Heavy Tails." It means extreme events happened way more often than a normal statistical model expects.

3. Correlogram: The only good news is in the bottom-right graph. All the dots stay inside the blue shaded area. This means there's no pattern left in the errors, so mathematically, our model did its job correctly.

Cross-Domain Dynamics: The Resilience of Cultural Sentiment

Conclusion

Key Findings

Limitations

Future Directions

References

[1] Dehghani, M., Gouws, S., Vinyals, O., Uszkoreit, J., & Kaiser, Ł. (2018). Universal Transformers. *arXiv preprint arXiv:1807.03819*.