Popular Music and the U.S. Economy: How Consumer Preferences in Music Change as the U.S. Economy Shifts

Kohta Asakura

Department of Economics, Keio University

Fujiwara Ippei Seminar

February 2, 2023

Abstract

Music has been an integral part of human culture for thousands of years. However, little is known regarding the relationship between popular music and socioeconomic circumstances. In this research, I investigated the relationship between the U.S. unemployment rate and popular music's audio features, such as acousticness, danceability, energy, instrumentality, key, liveliness, loudness, mode, speechiness, tempo, and valence, using regression analyses. The results illustrated that, in times of economic decline, people are likely to listen to songs with faster tempos, major chords, higher levels of acoustics and energy, as well as lower levels of danceability and speechiness. These findings imply that consumers seek comfort and positivity through music during periods of economic insecurity.

Keywords: music, musical preferences, song, unemployment, economic fluctuations

1. Introduction

Popular music has always been a reflection of the society it is produced in. It reflects the emotions, experiences, and cultural values of the people who create and consume it. Throughout history, popular music has played a significant role in shaping the cultural and social landscape, and it continues to influence society in various ways. The development of different musical genres, the rise and fall of different artists, and the changes in how music is produced and consumed reflect the economic, social, and cultural changes of a particular period. Rentfrow and Gosling (2003) reported that people in the United States dedicate a significant portion of their lives, approximately 14%, to listening to music. Today, access to music has dramatically improved due to the proliferation of music streaming services, leading to an even more significant amount of time consumers in the United States have spent listening to music.

The way of consuming music has undergone significant changes over the years. Introducing new technology has played a significant role in shaping how music is consumed. In the past, record players and radio were the primary music sources, followed by cassette tapes and CDs and the current era of streaming technology (see Appendix Figure A1). The release of the iPod in 2001 and the launch of iTunes, the online music store, in 2003 by Apple revolutionized how people listened to and purchased music (Apple, 2001, 2003). The iPod allowed people to carry their entire music library with them wherever they went, and iTunes made it easy for people to purchase and download music.

With the advent of digital technology, music streaming services such as Spotify and Apple Music have made it easier for people to access music and listen to it anytime and anywhere. This has greatly increased the convenience and accessibility of music for consumers and has led to a shift in how people consume music, with streaming becoming the primary method of listening. According to a survey conducted by the International Federation of the Phonographic Industry (IFPI), 74% of people listen to music through licensed audio streaming services, including paid subscriptions and ad-supported streaming (IFPI, 2022). The survey also estimated that 69% of people state that music is important to their mental health and physical well-being (IFPI, 2022). With the increased accessibility of music, popular music reflects people's moods and tastes more accurately than before. This is because, in the past, the physical format, such as CDs, was only available at stores. The music labels and CD stores' marketing efforts greatly affected popular music charts, limiting the exposure of different genres and independent artists. With a more accurate reflection of people's moods and tastes, popular music has the potential to be used to investigate the economic atmosphere of a country.

As music has been an integral part of human culture for thousands of years, many researchers have studied the relationship between popular music and socioeconomic environments. Hobara (2010) has studied the relationship between the pitch, tone range, and ictus of Japanese hit songs and economic conditions in the Showa and Heisei eras. He has found that the economic situation at the time reflects Japanese hit songs. Pettijohn et al. (2012) have indicated that songs with higher beats per minute and more standard key signatures were favored during times of social and economic prosperity. Whereas, during periods of social and economic decline, songs with lower beats per minute ad less common key signatures were more popular.

Although the majority of previous study has concentrated on specific characteristics of songs, such as tempo, pitch, and key signatures, there have been few studies concerning three or more characteristics of songs. Therefore, this paper aims to provide a greater understanding of the relationship between the U.S. economy and the characteristics of popular music. I conduct regression analysis to investigate the correlations between the unemployment rate and audio features of popular songs, including acousticness, danceability, energy, instrumentalness, key, liveness, loudness, mode, speechiness, tempo, and valence.

This paper is organized as follows. I will first provide an overview of literature studying music sentiment and the relationship between music and the economic state. Then, I present an empirical analysis and results. Finally, the core conclusions of this study are stated.

2. Literature Review

Economists, psychologists, and music industry professionals have studied trends in popular music and the relationship between popular music and economic conditions for decades. The Billboard Hot 100 is a widely recognized chart that ranks the most popular songs in the United States. It is published weekly by Billboard Publications Inc. and is based on a combination of factors, including physical and digital music sales, radio airplay, and streaming data (Billboard, n.d.). The Hot 100 chart was first introduced in August 1958 and has since provided a clear and objective method for measuring the success of songs in the music industry.

The Billboard Hot 100 chart is an important measure not only for music industry professionals but also for economists as it provides insight into music preferences in the United States. Rentfrow and Gosling (2003) found that through their analysis of two groups of college students and 500 individuals across the U.S., music preferences are linked to a person's personality, self-view, emotional state, and cognitive ability. They also noted that while personality and cognitive ability tend to remain consistent throughout a person's life, an individual's emotional state and self-view can change daily due to external factors. Given that individuals tend to choose music that aligns with their emotional state and concerns (Qiu et al., 2019; Schwartz & Fouts, 2003), it is likely that popular songs of a country reflect the economic and social environment of a country.

Several studies have examined the relationship between the lyrics of popular songs and the economic and social circumstances both in the United States and worldwide. These studies' findings suggest a correlation between the themes and trends present in top songs and the socioeconomic conditions at a given time. For instance, Qiu et al. (2021) examined the correlation between joblessness and the lyrics of the top 10 songs on the Billboard charts in Germany and the United States from 1980 to 2017. They discovered that when unemployment rates were high in both countries, the lyrics of the top 10 songs reflected a higher level of anger but did not reflect increased anxiety or sadness in either country. Similarly, Pettijohn and Sacco (2009) investigate the lyrics of the Billboard No. 1 songs for each year from 1955 to 2003 concerning changes in social and economic conditions in the United States. Their study found that during times of social and economic insecurity, the lyrics were more fun, meaningful, comforting, and romantic.

Some other studies have examined the musical characteristic of popular songs. For example, Hobara (2010) has studied the relationship between the pitch, tone range, and ictus of Japanese hit songs and economic conditions in the Showa and Heisei eras. He states that the variation in the width of the register and the relative position of the registers, whether a whole song belongs to the higher or lower register, depends on the economic conditions of the previous period. He also discovered that there is a negative correlation between the deviation of each of these and the deviation of the diffusion index.

While previous research has focused on only No. 1 Billboard Hot 100 songs or particular musical characteristics, this paper uses Spotify API data for almost all the song that has appeared on the Billboard Hot 100 weekly chart in the sample period. Spotify API allows developers and data scientists to collect audio features of songs, such as danceability, key, and positiveness. Therefore, with a new and expansive dataset from Spotify API, this paper aims to provide a more comprehensive analysis of the relationship between the musical characteristics of popular songs and the state of the U.S. Economy.

3. Data and Variables

To study the relationship between the attributes of popular music and the U.S economy, music data was collected from the Billboard Hot 100 charts and the Spotify API (Billboard, 2022). The Billboard Hot 100 chart is a weekly chart that ranks the top 100 songs in the United States based on sales, radio airplay, and streaming data (Billboard, n.d.). In addition to the information from the Billboard Hot 100 chart, audio features of the songs were obtained from the Spotify Web API. The Spotify Web API allows developers to access data from Spotify, including track information, playlist information, and audio features. A script was written to match the song titles and artists from the Billboard Hot 100 chart to the corresponding songs on Spotify, and then collect the audio features for those songs. The audio features collected include acousticness, danceability, duration, energy, instrumentalness, key, liveness, loudness, mode, speechiness, tempo, time signature, and valence. Table A1 shows the definition of each audio feature.

As an indicator of the U.S. economy, I select the unemployment rate, and the data was collected from U.S. Bureau of Labor Statistics (2022). Since some of the songs listed on the Billboard Hot 100 charts before 1975 were not available on Spotify, I set the sample period from January 1975 to October 2021. Taking into account Billboard Hot 100 songs not on Spotify, the dataset was narrowed down from 244,387 to 244,367 songs. Table 2 shows the summary statistics for the audio features of hit songs in the sample.

Table 1

Summary Statistics – Billboard Hot 100 Songs

Variable	Mean	Median	Min.	Max.	Std. Dev.	Observations
Acousticness	0.194	0.102	0.000	0.996	0.223	244,367
Danceability	0.638	0.646	0.059	0.988	0.145	244,367
Duration (ms)	242,931	235,767	0.000	1,367,093	56,743	244,367
Energy	0.657	0.667	0.002	0.998	0.186	244,367
Instrumentalness	0.028	0.000	0.000	0.986	0.178	244,367
Key	5.283	5.000	0.000	11.000	3.593	244,367
Liveness	0.179	0.122	0.015	0.997	0.151	244,367
Loudness (dB)	-7.829	-7.087	-42.391	2.291	3.507	244,367
Mode	0.678	1.000	0.000	1.000	0.467	244,367
Speechiness	0.080	0.044	0.022	0.951	0.088	244,367
Tempo	120.318	119.123	36.998	218.179	36.998	244,367
Time Signature	3.969	4.000	1.000	5.000	1.000	244,367
Valence	0.576	0.589	0.000	0.991	0.000	244,367

Note: This table reports the summary statistics of audio features. The sample period is from January 1975 to October 2021. The total number of observations is 244,367.

Figure 1 shows the distribution of each audio feature. While some variables have distributions somewhat close to regular distributions, others have highly skewed distributions. For instance, most values of instrumentalness are distributed near zero. Similarly, it can be said that most songs are in four beats from the time signature histogram. Based on these distributions and whether it is appropriate as a focus of the analysis, I selected nine variables for analysis: acousticness, danceability, energy, liveness, loudness, mode, speechiness, tempo, and valence/positiveness.

The Billboard Hot 100 audio features are averaged monthly to match the monthly unemployment rate data. When conducting regression analysis using time series data, it is important to explore the time trends in variables over time as well as correlations between them. Figure 2 shows the monthly average of Billboard Hot 100 audio features and the unemployment rate over time from January 1975 to October 2021, while Figure A2 illustrates the unemployment and monthly average of Billboard Hot 100 audio features in the same charts. Some audio features have clear trends over time. For instance, loudness is clearly in an uptrend, while valence is in a downtrend. This clear upward trend is due to the trend in the music industry, the so-called “loudness war.” Listeners generally prefer the sound of a piece of music when it is played louder than a lower volume when all other factors are held constant. A phenomenon known as the "loudness war" or "loudness race"—driven by the idea that louder is better—has emerged in music creation over the past few decades (Wykes, 2021).

Figure 3 outlines correlations between each of the monthly averaged audio features over time. Some variables have strong positive and negative correlations with each other. For example, acousticness has negative correlations with energy and loudness. Loudness has positive correlations with energy and speechiness, and negative correlations with acousticness and valence.

Figure 1

Distribution – Billboard Hot 100 Audio Features

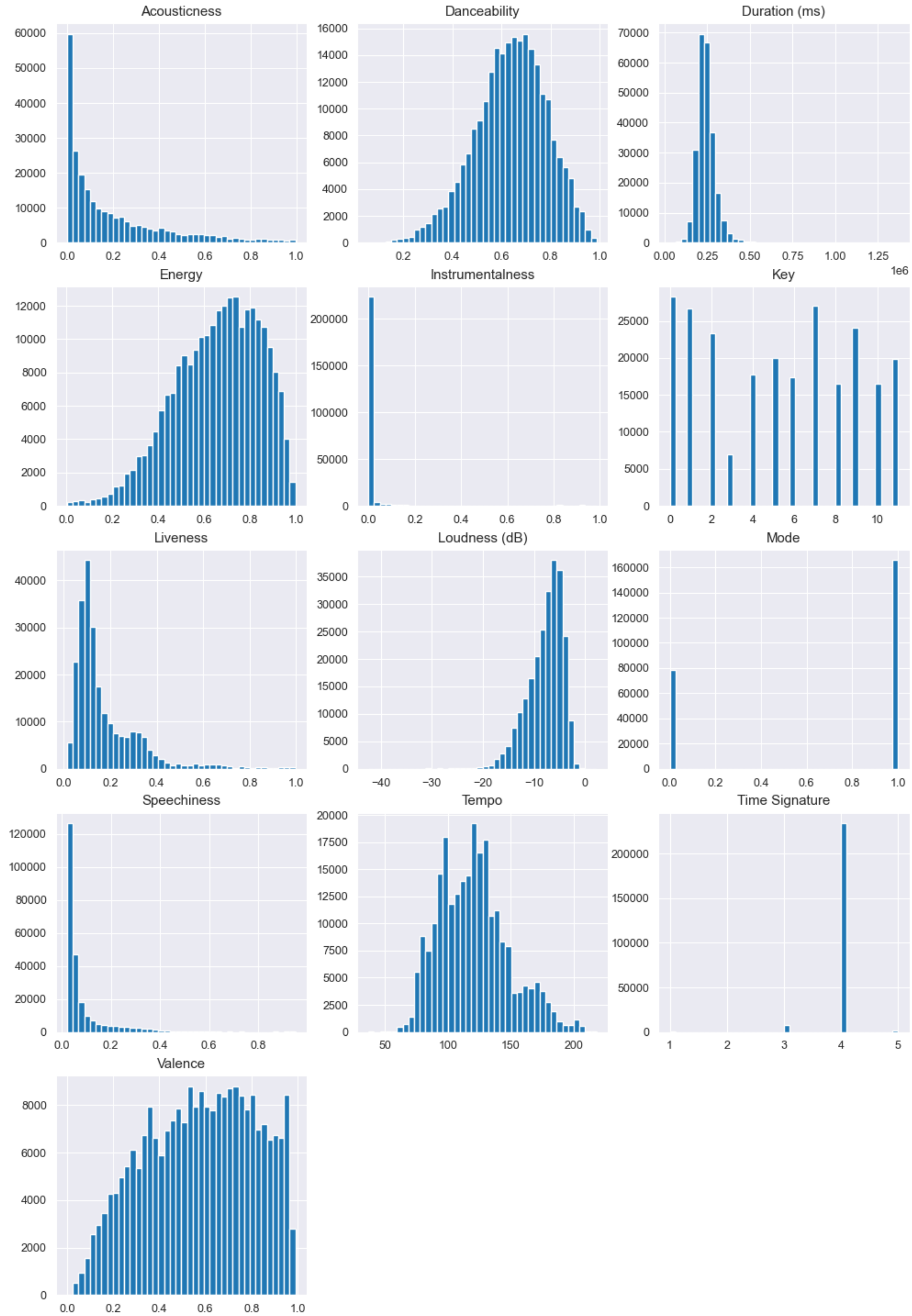


Figure 2

Monthly Average Billboard Hot 100 Audio Features and Unemployment Rate, 1975 to 2021

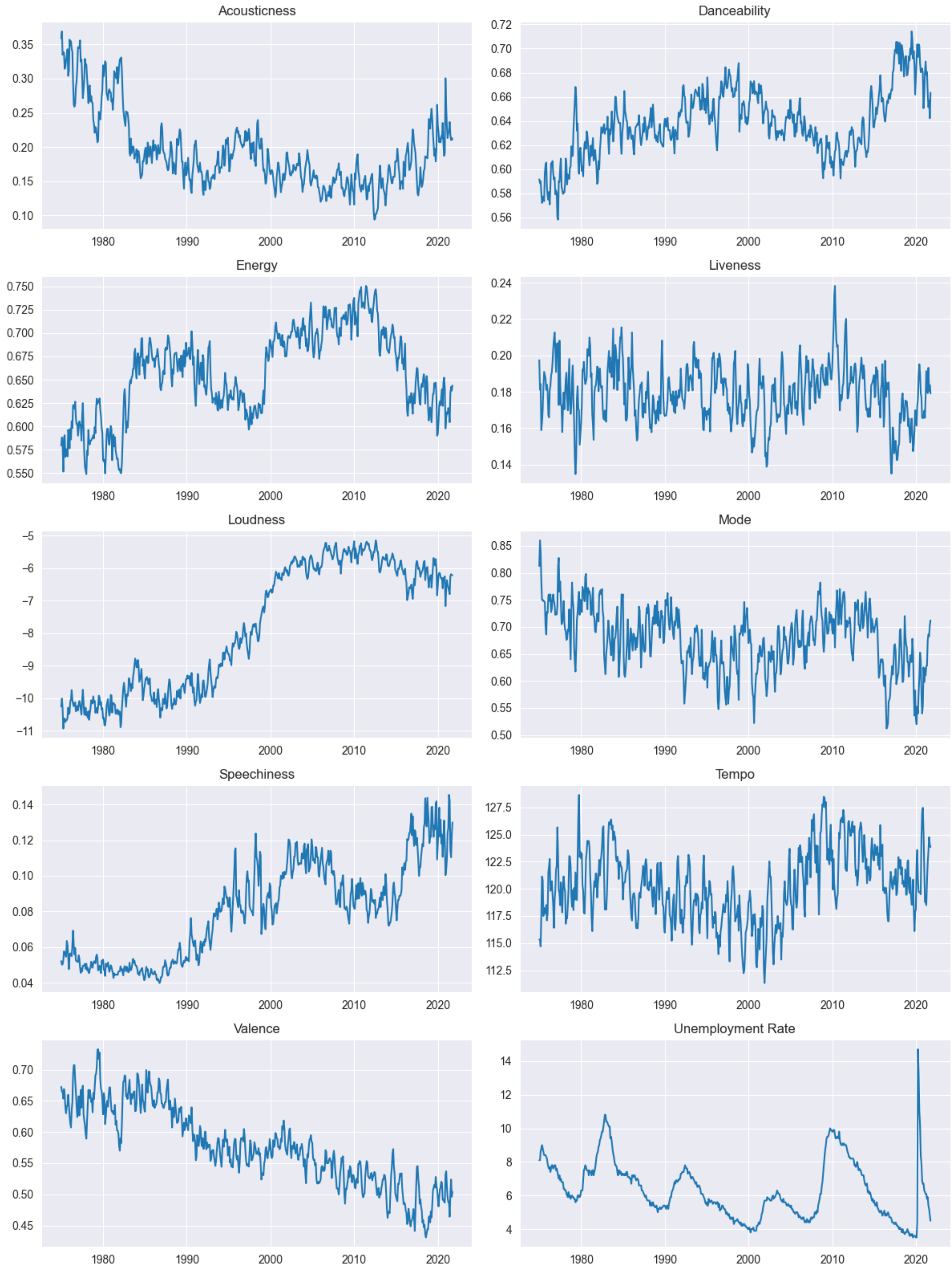
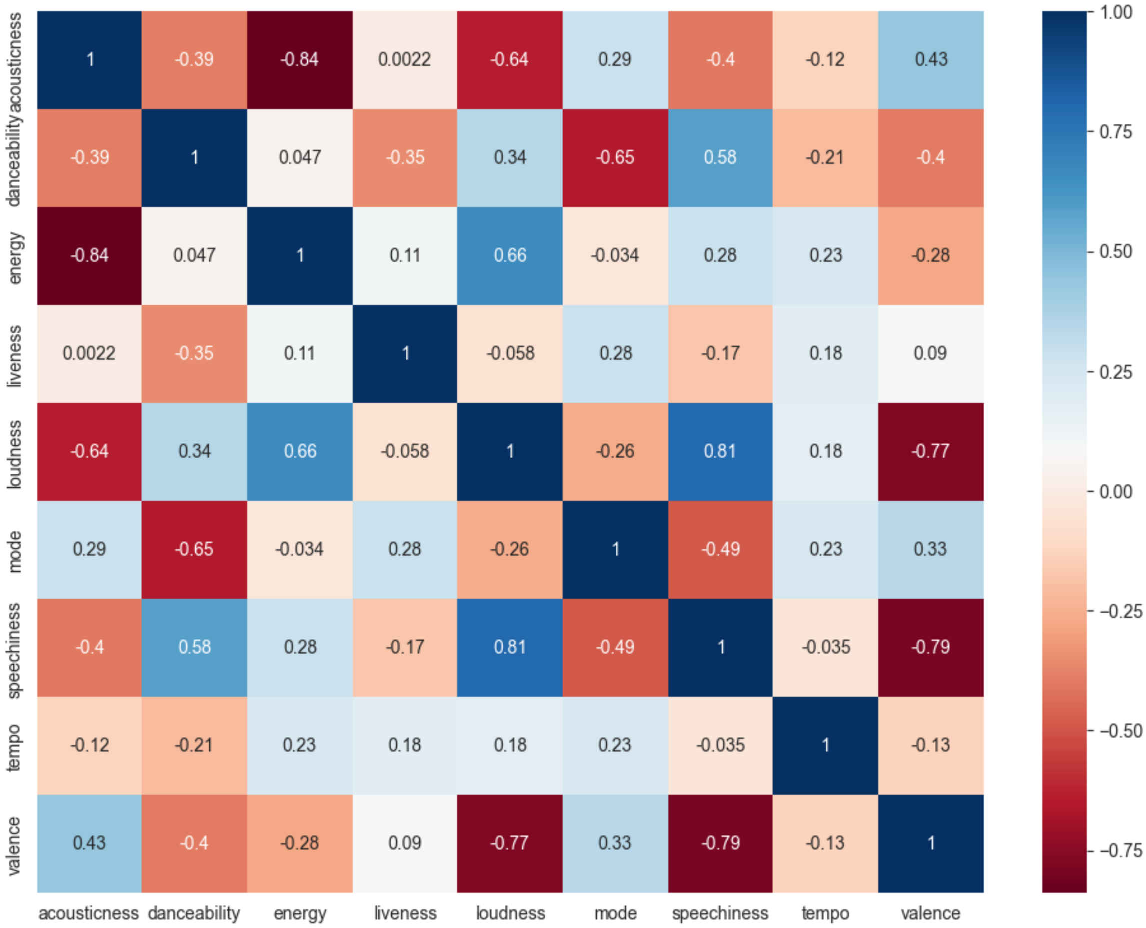


Figure 3

Correlation Matrix – Billboard Hot 100 Audio Features



4. Empirical Analysis

This section describes how to analyze the relationship between the attributes of popular music and the U.S. economy. As mentioned in the previous sections, some variables seem to have trended over time. When performing regression analysis on time series data, it is crucial to remove trends to prevent spurious regressions. Therefore, I first examine the stationarity of the datasets. Then, based on the results, I conduct regression analyses for each audio feature and the unemployment rate.

Following econometric literature, I examine the stationarity of the dataset using the Augmented Dickey-Fuller (ADF) test. If it rejects the null hypothesis that the series has a unit root, it is considered stationary. Table 2 shows the results of ADF tests. The results demonstrate that acousticness, liveness, liveness, mode, tempo, and unemployment rate are stationary, and the other variables are non-stationary.

Table 2

Results from Augmented Dickey-Fuller Tests

Variable	Dickey-Fuller	p-value
Acousticness	-3.061**	0.030
Danceability	-2.144	0.227
Energy	-2.381	0.147
Liveness	-8.542***	0.000
Loudness	-1.226	0.662
Mode	-4.425***	0.000
Speechiness	-0.694	0.848
Tempo	-2.951**	0.040
Valence	-1.171	0.686
Unemployment	-3.327**	0.014

Note: This table reports the results from the Augmented Dickey-Fuller test for the stationarity of time-series data. $^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Having the founding that the dataset is a mixture of stationary and non-stationary variables, I construct two different regression equations for stationary and non-stationary variables to estimate the relationship between the unemployment rate and each audio feature. Furthermore, since some variables have strong correlations, I conduct separate regression analyses for each audio feature. The equation for the stationary variables is specified as follows:

$$AudioFeature_t = \beta_0 + \beta_1 Unemployment_t + \varepsilon_t$$

where $AudioFeature_t$ represents the monthly averaged audio features at time t, and $Unemployment_t$ represents the unemployment rate at time t. $AudioFeature_t$ includes acousticness, liveness, mode, and tempo. For the non-stationary variables, a linear trend variable is added to remove the trend over time. Therefore, the equation for the non-stationary variables is specified as follows:

$$AudioFeature_t = \beta_0 + \beta_1 Unemployment_t + \beta_2 t + \varepsilon_t$$

where $t = 1, \dots, T$, and $AudioFeature_t$ are danceability, energy, loudness, speechiness, and valence.

5. Results

This section describes the results of the empirical analysis. As explained in the previous section, I estimated the simple linear regression models for stationary variables and the multiple linear regressions with a linear trend variable. Table 3 reports estimation results for both stationary and non-stationary variables. The first four variables, including acousticnesss, liveness, mode, and tempo, are stationary, and the rest are non-stationary.

Table 3

Regression Results

Variable	Unemployment Rate	R-squared
(1) Acousticness	0.0065***	0.041
	(0.001)	
(2) Liveness	0.0036***	0.163
	(0.000)	
(3) Mode	0.0110***	0.110
	(0.001)	
(4) Tempo	0.5834***	0.097
	(0.075)	
(5) Danceability	-0.0061***	0.410
	(0.001)	
(6) Energy	0.0039***	0.259
	(0.001)	
(7) Loudness	0.0218	0.812
	(0.022)	
(8) Speechiness	-0.0033***	0.759
	(0.000)	
(9) Valence	0.0011	0.810
	(0.001)	

Note: This table reports the results of the regression models for both stationary and non-stationary variables. The total number of observations is 562. Standard errors are reported in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Considering the majority of audio features have arbitrary scales between 0.0 and 1.0 (see Table A1), interpretation will largely be based on the sign of coefficients to determine how consumer preferences are changing as the economy shifts. I found statistically significant results for acousticness, liveness, mode, tempo, danceability, energy, and speechiness.

The positive coefficient in row 1, which is statistically significant at the 1% level, indicates that an increase in the employment rate is associated with an increase in acousticness. When evaluating this variable, it is important to understand that acousticness refers to a measure of confidence that the song is acoustic (see Table A1). Given that the acoustical content and emotion expressed by music contribute toward individuals' emotional engagement with music and enhance distraction from pain (Knox et al., 2011), during economic insecurity, people are more likely to listen to songs with more acousticness, which are often comforting. This finding is consistent with the research conducted by Pettijohn and Sacco (2009), as they state that the lyrics of popular songs were more positive during times of social and economic insecurity. Despite this, it is noteworthy that the sample's median acousticness rating is relatively low at 0.102. In other words, approximately half of the songs in the sample have an acousticness of below 0.1.

The positive coefficient in row 2, which is statistically significant at the 1% level, indicates that an increase in the employment rate is associated with an increase in liveness. Since liveness is defined as the confidence that a track was performed live (see Table A1), it is reasonable to think that songs with high liveness ratings are live recordings. It is important to note that it was common practice to record live songs and publish them as they were recorded before the 2000s. This process became less common with the advent of digital audio workstations, or DAWs, that allows music producers to edit post-recording sound and utilize electronic sound. In fact, most of the songs in the sample that have high liveness were released prior to the 2000s. However, for the songs released after the 2000s, liveness ratings seem to capture different components of songs. I discovered that some songs released in recent years have high liveness even though they are not live recordings. For instance, “The Box” by Roddy Ricch is not a live recording but still has a liveness of 0.785. This could be due to the vocal samples used in it being detected as an audience. Thus, in this study, liveness is considered improper to understand the relationship between the characteristics of popular songs and the U.S. economy.

Row 3 shows a significant positive coefficient at the 1% level, indicating that an increase in the employment rate is associated with an increase in mode. An indication of the modality (major or minor) is given by 1 for major and 0 for minor. The result suggests that songs with major chords tend to be more popular during times of economic decline. Considering that major chords are perceived as positive (Bakker & Martin, 2014), it can be said that people are more likely to listen to tracks with a positive attribute. This finding is also consistent with the research conducted by Pettijohn and Sacco (2009).

Row 4 shows a significant positive coefficient at the 1% level, suggesting that an increase in the employment rate is associated with an increase in tempo. Tempo is defined as the overall estimated tempo of a track in beats per minute (see Table A1). Typically, songs with a slower tempo sound calm, comforting, and romantic, whereas those with faster tempos are energetic and positive. Although this finding is not consistent with the research conducted by Pettijohn and Sacco (2009), it may imply consumers' preference for the music genre. Tempo is one of the essential song attributes that define what genre a track is categorized into. For instance, typical electronic dance music songs have beats per minute around 128, while reggaeton songs are usually about 90 to 100 beats per minute. Given that the average tempo is approximately 120 (see Table 1) and the monthly average of it is closer to 128 during the economic declines (see Figure A2), this result suggests that people tend to listen to songs that have relatively similar to electronic dance music.

The negative coefficient in row 5, which is statistically significant at the 1% level, indicates that an increase in the employment rate is associated with a decrease in danceability. Danceability is a measure of how suitable a track is for dancing (see Table A1). This finding contradicts my assumption that people are more likely to listen to tracks with higher danceability to enhance their moods in difficult economic circumstances. This result rather supports the previous study by Pettijohn and Sacco (2009), which states that people tend to listen to comforting songs.

The positive coefficient in row 6, which is statistically significant at the 1% level, indicates that an increase in the employment rate is associated with an increase in energy. Although songs with higher energy are not necessarily comforting, they are likely to sound positive compared with songs with lower energy. Thus, this finding implies that people tend to listen to songs with higher energy to uplift their moods during economic insecurity.

Row 8 shows a significant positive coefficient at the 1% level, indicating that an increase in the employment rate is associated with a decrease in speechiness. Speechiness detects the presence of spoken words in a track, and a song with speechiness of lower than 0.33 is most likely to be music or a non-speech-like track. This is an intriguing result, although it should be noted that more than half of the sample songs have speechiness ratings that are less than 0.1 (see Table 1). Nevertheless, when circumstances are difficult economically, individuals tend to listen to melodic music more and less spoken-word songs.

Notably, rows 7 and 9 show statistically insignificant results. This is mainly because loudness and valence/positiveness have a strong trend over time. As previously discussed, the upward trend in loudness is due to the “loudness war” in the music industry. Although this is not deeply investigated in this study, the overall decline in valence seems to be due to the recent dominance of hip-hop because many hip-hop songs are considered sad. For example, “The Plan” by Travis Scott has one of the lowest valence ratings in the data set, which is 0.0363.

6. Conclusion

This paper empirically examined the relationship between the audio features of popular songs on the Billboard Hot 100 and the U.S. unemployment rate from 1975 to 2021. There were two research objectives. First, I investigated the characteristics of audio features to grasp the relationship between them and the chronological variation. Second, I conducted a series of two different regression analyses based on the unit root tests.

The results of the empirical analysis demonstrated an association between the unemployment rate and the audio characteristics of popular music in the United States. As the unemployment rate increases, acousticness, mode, tempo, and energy increase, while danceability and speechiness decrease. In other words, in times of economic decline, people tend to listen to songs with faster tempos, major modalities, higher levels of acoustics and energy, as well as lower levels of danceability and speechiness. Overall, the results indicate that people are likely to seek comfort and positivity through music during periods of economic insecurity.

This study gives considerable room for future expansion. As discussed in the previous section, valence, a measure of a track's positiveness, seems to be primarily influenced by the recent rise of hip-hop. To further investigate the relationship between the valence/positiveness of popular music and the U.S. economy, music genre dummy variables can be added to the regression equation. In addition, Spotify Daily Top 50 charts or Viral 50 charts can be utilized to gain an in-depth understanding of consumers' preferences in music in association with the state of the U.S. economy. While the physical format, such as CDs and vinyl, was the primary means of listening to music before the 2010s, streaming has been the most popular music consumption in recent years. In the past, music sales were not only affected by consumer preference but rather influenced by the marketing efforts of recording labels and physical music stores. On the other hand, charts in Spotify are sorely based on the numbers of streaming, and thus, they reflect consumers' tastes more accurately. However, since these charts are only available after 2007, they do not have enough data to estimate the long-term relationship with a country's economy.

Furthermore, as the relationship between the unemployment rate and some of the audio features of popular music was established, audio features could be used in forecasting models for stocks. Most economic indicators are only available monthly or quarterly, whereas music data is available weekly or even daily. Although the most accurate way to gauge market sentiment in the U.S. economy in real time may not be through music data, it provides some insight into consumer sentiment by analyzing and utilizing data on listening patterns and popular music preferences across the country.

References

Apple Newsroom. (2001, Oct 23). *"Apple Presents iPod."* News release. https://www.apple.com/newsroom/2001/10/23Apple-Presents-iPod/

Apple Newsroom. (2003, Apr 28). *"Apple Launches the iTunes Music Store."* News release. https://www.apple.com/newsroom/2003/04/28Apple-Launches-the-iTunes-Music-Store/

Bakker, D. R., & Martin, F. H. (2014). Musical chords and emotion: Major and minor triads are processed for emotion. *Cognitive, Affective, & Behavioral Neuroscience*, *15*(1), 15–31. https://doi.org/10.3758/s13415-014-0309-4

Billboard. (n.d.). *Billboard Charts Legend*. https://www.billboard.com/billboard-charts-legend/

Billboard. (2022, December 28). *Billboard Hot 100*. https://www.billboard.com/charts/hot-100/

Hobara, N. (2010). Do Japanese hit songs hit Japanese Economy? II. *Journal of Behavioral Economics and Finance, 3*, 160-161. https://doi.org/10.11167/jbef.3.160

IFPI: International Federation of the Phonographic Industry. (2022). "Engaging with Music 2021." IFPI: Representing the Music Industry Worldwide. https://www.ifpi.org/wp-content/uploads/2021/10/IFPI-Engaging-with-Music- report.pdf

Knox, D., Beveridge, S., Mitchell, L. A., & MacDonald, R. A. R. (2011). Acoustic analysis and mood classification of pain-relieving music. *The Journal of the Acoustical Society of America*, *130*(3), 1673–1682. https://doi.org/10.1121/1.3621029

Pettijohn, T. F., & Sacco, D. F. (2009). The Language of Lyrics: An Analysis of Popular Billboard Songs Across Conditions of Social and Economic Threat. Journal of Language and Social Psychology, 28(3), 297–311. https://doi.org/10.1177/0261927X09335259

Pettijohn, T. F., Eastman, J. T., & Richard, K. G. (2012). And the Beat Goes On: Popular Billboard Song Beats Per Minute and Key Signatures Vary with Social and Economic Conditions. *Current Psychology, 31*(3), 313–317. https://doi.org/10.1007/s12144-0129149-y

Qiu, L., Chen, J., Ramsay, J., & Lu, J. (2019). Personality predicts words in favorite songs. *Journal of Research in Personality, 78,* 25–35. https://doi.org/10.1016/j.jrp.2018.11.004

Qiu, L., Chan, S. H. M., Ito, K., & Sam, J. Y. T. (2021). Unemployment rate predicts anger in popular music lyrics: Evidence from top 10 songs in the United States and Germany from 1980 to 2017. *Psychology of Popular Media, 10*(2), 256-266. https://doi.org/10.1037/ppm0000282

Rentfrow, P. J., & Gosling, S. D. (2003). The do re mi's of everyday life: The structure and personality correlates of music preferences. *Journal of Personality and Social Psychology, 84*(6), 1236–1256. https://doi.org/10.1037/0022-3514.84.6.1236

Schwartz, K. D., & Fouts, G. T. (2003). Music Preferences, Personality Style, and Developmental Issues of Adolescents. *Journal of Youth and Adolescence, 32*(3), 205–213. https://doi.org/10.1023/a:1022547520656

U.S. Bureau of Labor Statistics. (2022, December 22). *Unemployment Rate*. Retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/UNRATE

Web API | Spotify for Developers. (2022). Spotify. https://developer.spotify.com/documentation/web-api/

Wykes, AJ. (2021, June 17). “What’s the loudness war?” SoundGuys. https://www.soundguys.com/the-loudness-war-51513/

Appendix

Figure A1

Music Sales by Format Market Share, 1973 to 2021.

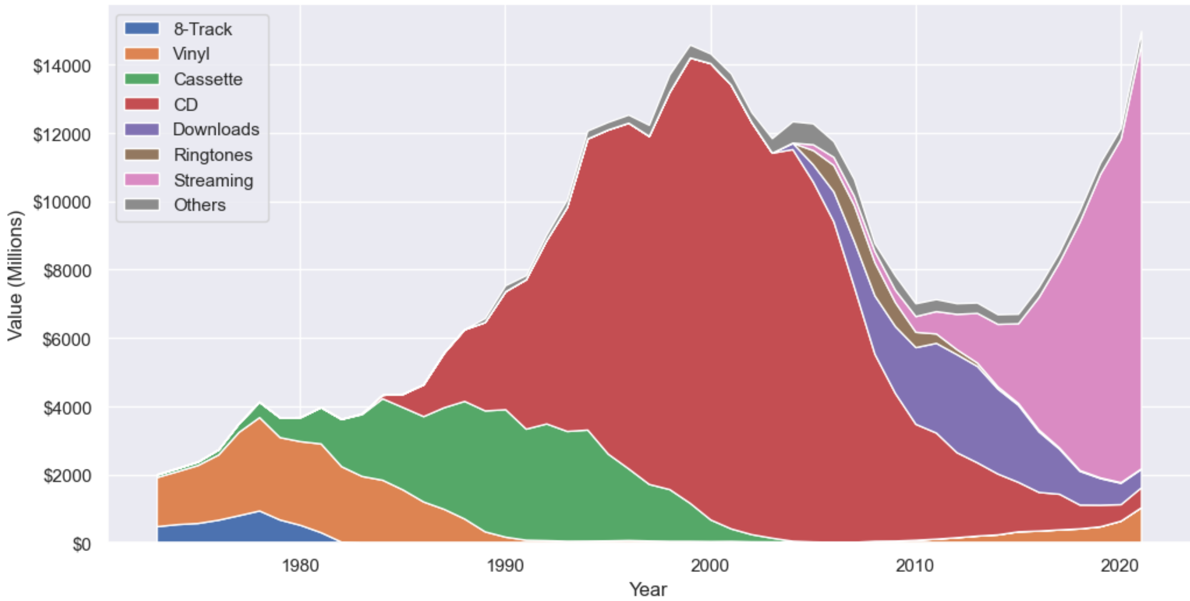


Table A1

Spotify API Audio Features

Name	Scale	Definition
Acousticness	0 to 1	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
Danceability	0 to 1	How suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.
Duration	-	The duration of the track in milliseconds.
Energy	0 to 1	A measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.

Instrumentalness	0 to 1	Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.
Key	-1 to 11	Integers map to pitches using standard Pitch Class notation. E.g. 0 = C, 1 = C♯/D♭, 2 = D, and so on. If no key was detected, the value is -1.
Liveness	0 to 1	Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.
Loudness	-60 to 0	The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks.
Mode	0 or 1	Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.
Speechiness	0 to 1	Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.
Tempo	-	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.
Time signature	3 to 7	The time signature is a notational convention to specify how many beats are in each bar. The time signature ranges from 3 to 7 indicating time signatures of "3/4", to "7/4".
Valence	0 to 1	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

Note: Descriptions were obtained from Spotify for Developers WEB API website. (https://developer.spotify.com/documentation/web-api/reference/#/operations/get-audio-features)

Figure A2

Spotify API Audio Features