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Unemployment Rate Predicts Anger in Popular Music Lyrics: Evidence From Top 10 Songs in the United States and Germany From 1980 to 2017

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Popular music has been shown to reflect cultural characteristics and psychological change in a society. However, little is known about how popular songs are related to the socioeconomic conditions. In this research, we analyzed the annual top 10 songs from United States and Germany between 1980 and 2017, and found that the unemployment rate predicted the amount of anger but not anxiety or sadness in lyrics in both countries. Our research contributes to the literature on popular media culture by revealing that top song lyrics may reflect public sentiment toward the socioeconomic environment. It highlights the possibility of using top song lyrics as an alternative measure of public sentiments.

Public Policy Relevance Statement
The unemployment rate in the United States and Germany predicted the amount of anger in the lyrics of each country's annual top 10 songs. The findings suggest that popular music can provide a glimpse of public sentiment in response to the socioeconomic environment.

Keywords: song, music, lyrics, emotion, unemployment

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Music is an important part of everyday life (Rentfrow, 2012; Rentfrow & Gosling, 2003). Popular songs in a country indicate what the majority likes and have been shown to reflect societal-level psychological and cultural changes in terms of individualism and self-promotion (DeWall, Pond, Campbell, & Twenge, 2011; McAuslan & Waung, 2018). Given that people like to listen to music that matches their mood and concerns (Chamorro-Premuzic & Furnham, 2007; Larson, 1995; Qiu, Chen, Ramsay, & Lu, 2019; Schwartz & Fouts, 2003), popular songs are likely to reflect the overall mood of a country. Because the socioeconomic environment can significantly influence people's affect and well-being (see Dolan, Peasgood, & White, 2008 for a review), it is possible that sentiments in popular songs can reflect the collective mood in a country in response to the socioeconomic environment. Therefore, in this study, we focused on unemployment—one of the most severe problems affecting socioeconomic environments—and aimed to examine how sentiments (i.e., anger, anxiety, and sadness) in top song lyrics are related to the unemployment rate. To the best of our knowledge, this is the first study that proposes top song lyrics as a measure of societal-level emotional reactions to socioeconomic conditions. It provides new insights into the popular media culture and suggests that popular music may be utilized as a proxy of public sentiment toward the socioeconomic environment.

Music Choices Reflect Individual Concerns and Cultural Characteristics

Although songs in noninstrumental genres contain both melodies and lyrics, lyrics have been found to have unique effects beyond those exerted by melodies (Ali & Peynircioğlu, 2006; Anderson, Carnagey, & Eubanks, 2003). For example, Ali and Peynircioğlu (2006) measured participants' affective reactions to melodies with or without lyrics and found that emotionally congruent lyrics reduced the positive emotion conveyed by happy and calm music but increased the negative emotion conveyed by sad and angry music. Anderson et al. (2003) asked participants to listen to tense music with either violent or nonviolent lyrics and found that the content of lyrics, rather than the tense rhythm or distorted sound, resulted in aggressive thoughts and hostile feelings. Furthermore, studies in psychophysics and neuroscience have shown that melodic and lyrical information are processed independently when people listen to music (Besson, Faita, Peretz, Bonnel, & Requin, 1998; Bonnel, Faita, Peretz, & Besson, 2001).

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Previous studies have suggested that individuals are often drawn to lyrics that match their mood and concerns. For example, adolescents with few friends prefer songs with themes of loneliness or independence (Burke & Grinder, 1966), whereas those who enjoy heavy music (e.g., hard rock) tend to face issues such as low self-esteem, poor social connectedness, and an unstable sense of identity (Schwartz & Fouts, 2003). Moreover, European Americans with a college degree favor rock songs, whereas those without a college degree prefer country songs (Snibbe & Markus, 2005). These distinct preferences may be due to the specific types of values portrayed in different genres of music. Values commonly depicted in rock songs such as individual uniqueness and environmental control are likely to be endorsed by individuals with high socioeconomic status, whereas values frequently depicted in country music such as personal integrity and self-control are likely advocated by individuals with low socioeconomic status. Qiu et al. (2019) showed that individuals high in neuroticism like songs with few positive emotion words, which matches their low desire for positive emotion.

Popular songs in a country reflect what the majority likes and have been found to reveal societal-level values and norms (DeWall et al., 2011; McAuslan & Waung, 2018). Researchers have considered popular songs, together with books and TV advertisements, as cultural products that are developed by people to reflect and reinforce psychological processes in a particular sociocultural environment (Lamoreaux & Morling, 2012; Morling & Lamoreaux, 2008). For instance, cultural products from Western cultures have been found to be more individualistic and less collectivistic than their counterparts from Eastern cultures (Morling & Lamoreaux, 2008). In fact, a number of studies have shown that cross-cultural differences in popular song lyrics reflect established cultural characteristics in a society. To illustrate, Rothbaum and Tsang (1998) demonstrated that popular love songs in China portrayed love as embedded within a larger context of a relationship as compared with American love songs. In addition, lyrics of popular songs in China contained more collectivist themes (e.g., expression of positive reciprocity toward one's parents) than those in the United States (Rothbaum & Xu, 1995). Studies have also shown that longitudinal changes in popular song lyrics parallel cultural changes. Analyzing the top 10 songs ranked in the United States between 1980 and 2007, DeWall et al. (2011) found an increased usage of first-person singular pronouns (e.g., I, me) and a decreased usage of social process words (e.g., mate, talk) over the years. McAuslan and Waung (2018) extended these findings by showing that the top 100 songs in 2010 had significantly more self-promotion lyrics than those in 1990 and 2000. These two studies suggest that lyrics of top songs can reflect the rise of self-focus and individualism in the United States.

Top Song Lyrics and Socioeconomic Environments

Pettijohn and colleagues have examined trends in top songs during times of socioeconomic difficulty (Eastman & Pettijohn, 2019; Pettijohn, Eastman, & Richard, 2012; Pettijohn & Sacco, 2009a, 2009b). They used an aggregated index combining unemployment rate, disposable personal income, consumer price index, death rate, birthrate, marriage rate, divorce rate, suicide rate, and homicide rate to indicate the socioeconomic condition in the United States. Pettijohn and Sacco (2009a) analyzed Billboard No. 1 songs from 1955 to 2003 and showed that longer sentences and words related to future and social processes appeared more frequently in lyrics during difficult socioeconomic times. Pettijohn and Sacco (2009b) further asked raters to listen to these songs and found that songs during threatening socioeconomic conditions were rated as longer in duration, more meaningful, more comforting, and more romantic. Pettijohn et al. (2012) examined the melodic attributes of Billboard No. 1 songs from 1955 to 2008 and showed that songs during social and economic bad times had less beats per minute and less common key signatures, suggesting that they were more reflective and serious. Finally, Eastman and Pettijohn (2019) analyzed Billboard rhythm and blues/hip-hop songs of the year between 1946 and 2010 and found that songs are more likely to be longer, slower, and about relationships with others rather than leisure or fun when socioeconomical conditions deteriorate.

While the aforementioned studies have shown important evidence of how popular music changes according to the socioeconomic environment, the scope of their data was limited as only the top one song for each year was analyzed. In addition, it is unclear as to which socioeconomic condition was actually related to the change in lyrics because several distinct socioeconomic indicators were combined. The unemployment rate has been shown to affect societal perception of the state of the socioeconomic environment (Bianchi, 2016; Hill, Rodeheffer, Griskevicius, Durante, & White, 2012), and predicts self-reported unhappiness above and beyond personal unemployment as well as inflation rate (Di Tella, MacCulloch, & Oswald, 2001; Wolfers, 2003). Moreover, it has a robust and strong negative relationship with subjective well-being across different time periods and populations (Dolan et al., 2008). Therefore, in this study, we focused on unemployment rate and disentangled its relationship with lyrics by controlling for other possible socioeconomic indicators.

Present Study

This study aimed to examine how sentiments in top songs coincide with changes in national unemployment rate. In particular, we focused on three common negative emotions (i.e., anxiety, sadness, and anger) expressed in lyrics. Previous research has shown that anxiety, sadness, and anger are related to different decision-making processes (Raghunathan & Pham, 1999), social information judgment (Bodenhausen, Sheppard, & Kramer, 1994), and emotion-regulation strategies (Blanchard-Fields & Coats, 2008). Although we expected that the negative sentiments in top songs were related to a country's unemployment rate, we did not have specific hypotheses regarding how the three negative emotions would differ in their relationships to unemployment rate due to the lack of theoretical basis and empirical findings.

We used a widely used text analysis software program, the Linguistic Inquiry and Word Count (LIWC; Tausczik & Pennebaker, 2010), to compute the word frequencies in three predefined negative emotion categories: anger (e.g., hate, kill, annoyed), anxiety (e.g., worried, fearful, nervous), and sadness (e.g., crying, grief, sad). We considered top songs as a reflection of what the population likes to consume, regardless of where or when the song was produced. Therefore, we predicted that the relationship between sentiments in top songs and unemployment rate would hold in countries that are open to embracing foreign songs. Hence, we

wanted to choose a country whose chart is dominated largely by locally produced songs (Sample 1) and a country whose chart has a significant number of foreign songs (Sample 2). Our selection was made by first considering countries whose official language has a corresponding LIWC dictionary. LIWC currently has dictionaries in the following languages: English, Spanish, French, Russian, Italian, Dutch, German, Brazilian Portuguese, Chinese, and Norwegian. After which, we identified countries that have an official top 10 music chart and common socioeconomic variables for over 30 years. Consequently, the United States became Sample 1 and Germany became Sample 2.

Lyrics from the top 10 songs in the United States and Germany were gathered and analyzed using LIWC. We collected the national unemployment rate alongside other socioeconomic indicators (including gross domestic product [GDP] per capita, inflation rate, housing price, population density). Multiple regression models were conducted to examine the relationships between unemployment rate and three LIWC emotion categories (i.e., anger, sadness, and anxiety).

Method

The top 10 most popular songs between 1980 and 2017 in the United States and Germany were gathered, respectively.[1] Subsequently, song lyrics were downloaded from http://www.metrolyrics.com/ or https://genius.com/. For the U.S. sample (see the online supplemental materials), a total of 379 lyrics (out of 380 songs) were analyzed because one instrumental song has no lyrics. Apart from two multilanguage songs (i.e., English and Spanish), all remaining songs are in English. For the German sample (see the online supplemental materials), a total of 366 lyrics (out of 380 songs) were analyzed, after removing 14 songs that are instrumental ($n = 5$) or in languages (i.e., Latin, Hebrew, Duala, Hausa, Romanian, and Korean) that do not have a corresponding LIWC dictionary ($n = 9$). The German sample contains lyrics in German ($n = 63$), English ($n = 280$), Spanish ($n = 5$), Italian ($n = 5$), French ($n = 4$), and Portuguese ($n = 3$). There are six multilanguage songs, including German and English ($n = 2$), German and French ($n = 1$), English and French ($n = 1$), English and Italian ($n = 1$), and English and Spanish ($n = 1$). Their lyrics were first separated by language (e.g., English words and German words), and then each part was analyzed using its corresponding LIWC dictionary.

LIWC was used to compute word frequencies in three negative emotion categories (i.e., anger, sadness, and anxiety) in the lyrics. To illustrate, Kendrick Lamar's hit song in 2017 hit song *Humble* contains a line "Piss out your per diem, you just gotta hate 'em, funk." Because both *piss* and *hate* are in the anger category, the anger category will have a score of 2/11 = .18. Previous studies have shown that LIWC can reliably measure emotional processes expressed in language samples (Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010; Tov, Ng, Lin, & Qiu, 2013) and have used LIWC to analyze lyrics. For example, Qiu et al. (2019) used LIWC to analyze the lyrics of participants' favorite songs and revealed meaningful associations between personality traits and word use in these songs. DeWall et al. (2011) utilized LIWC to count the frequency of first-person singular pronouns (e.g., I, me), positive emotion words, and social process words in top song lyrics and suggested that frequency changes in these categories reflect changes in narcissism and individualism in the United States.

The U.S. employment rate was taken from the World Bank (2019c), and the German unemployment rate was taken from the Organisation for Economic Cooperation and Development (2019b). Previous work suggested a few other socioeconomic indicators that could influence emotional processes. For example, life satisfaction is related to the experience of positive emotions (Kuppens, Realo, & Diener, 2008), and GDP per capita has been found to be positively related to life satisfaction (Stevenson & Wolfers, 2008). Housing price has also been shown to be positively associated with life satisfaction because it indicates confidence in the economy (Ratcliffe, 2010). Both inflation (Di Tella et al., 2001) and population density (Li & Kanazawa, 2016) were found to be negatively related to life satisfaction. Therefore, these variables were included as control variables in the analyses. For both the United States and Germany, GDP per capita and population density were taken from the World Bank (2019a, 2009b), inflation was taken from Inflation.eu (2019), and housing price was taken from the Organisation for Economic Cooperation and Development (2019a).

Results

There are a total of 149,660 words in the U.S. sample and 120,076 words in the German sample. Tables 1 and 2 present the descriptive statistics and intercorrelations among the variables for the U.S. and German samples, respectively. Anger was significantly correlated with inflation, $r = -.36$, $p = .03$, GDP per capita, $r = .54$, $p < .001$, population density, $r = .59$, $p < .001$, and housing price, $r = .51$, $p = .001$, in the U.S. sample. In contrast, anger was significantly correlated with unemployment rate in the German sample, $r = .34$, $p = .04$. Sadness and anxiety and were not correlated with any socioeconomic indicator in both samples (all $ps > .05$).

Because the socioeconomic variables were related to each other, separate multiple linear regressions for the U.S. and German samples were conducted to avoid the problem of multicollinearity. In the first model, we regressed the average percentage of anger words for each year's top 10 songs onto the unemployment rate. In the second model, we controlled for GDP per capita and inflation. In the third model, we controlled for population density and housing prices. This was repeated for both anxiety (Models 4–6) and sadness (Models 7–9). As shown in Table 3, results from the U.S. sample revealed that unemployment rate did not predict anger in Model 1 ($\beta = 0.14$, $f^2 = 0.02$, $p = .41$, 95% confidence interval [CI] [−0.04, 0.11]) but significantly predicted anger after controlling for GDP per capita and inflation (Model 2: $\beta = 0.38$, $f^2 = 0.21$, $p = .01$, 95% CI [0.02, 0.15]; see Figure 1 for corresponding partial correlation), and population density and housing prices (Model 3: $\beta = 0.36$, $f^2 = 0.19$, $p = .02$, 95% CI [0.02, 0.15]; see Figure 2 for corresponding partial correlation). This could be due to suppression effects where the addition of control variables in a regression increases the magnitude of the relationship between the predictor and outcome variable (MacKinnon, Krull, & Lockwood,

[1] Songs for the United States were retrieved from https://www.billboard.com/charts/year-end/2017/hot-100-songs. Songs for Germany were retrieved from https://www.offiziellecharts.de/charts/single-jahr/for-date-2016.

Table 1
Descriptive Statistics and Variable Intercorrelations for the U.S. Sample

Variable	*M*	*SD*	1	2	3	4	5	6	7
Linguistic Inquiry and Word Count categories									
1. Anger	0.49	0.37							
2. Anxiety	0.24	0.18	−0.26						
3. Sadness	0.79	0.49	−0.28	0.16					
National economic indicators									
4. Unemployment rate	6.33	1.61	0.14	−0.04	−0.02				
5. Inflation	3.29	2.47	−0.36*	0.05	0	0.15			
6. Gross domestic product per capita	41,745.68	7754.15	0.54***	−0.24	−0.12	−0.36*	−0.63***		
7. Population density	30.17	3.41	0.59***	−0.25	−0.14	−0.23	−0.63***	0.99***	
8. Housing price	84.91	15.96	0.51**	−0.22	−0.1	−0.41*	−0.43**	0.89***	0.84***

* $p < .05$. ** $p < .01$. *** $p < .001$, two-tailed.

2000). Because GDP per capita, inflation, population density, and housing price are all correlated with anger (Table 1), controlling for these confounding variables can extract the unique effects of unemployment rate. As shown in Table 3, unemployment rate did not predict anxiety (Models 4–6) or sadness (Models 7–9).

For the German sample (Table 4), we controlled for the percentage of songs in the German language (i.e., German %) in each model because we predicted that the relationship between sentiments in top songs and unemployment rate should hold regardless of how many songs are produced in the local language. Unemployment rate predicted anger in the following regression models when controlling for German % (Model 1: $\beta = 0.40$, $f^2 = 0.19$, $p = .01$, 95% CI [0.01, 0.11]), controlling for German %, GDP per capita, and inflation (Model 2: $\beta = 0.40$, $f^2 = 0.17$, $p = .03$, 95% CI [0.01, 0.12,]; see Figure 3 for corresponding partial correlation), and controlling for German %, population density and housing prices (Model 3: $\beta = 0.43$, $f^2 = 0.14$, $p = .04$, 95% CI [0.00, 0.13]; see Figure 4 for corresponding partial correlation). Like the U.S. sample, unemployment rate did not predict anxiety (Models 4–6) or sadness (Models 7–9).

As our data follow a time series and may violate the assumption of independent errors, we tested if there was any serial correlation in the error terms of each of the nine models by conducting the Breusch–Godfrey Lagrange Multiplier test of autocorrelation (Breusch, 1978; Godfrey, 1978) for a lag of 1 year. Results indicated that none of the models suffered from autocorrelated error terms in both the U.S. and German samples (all $p > .05$), except for Model 3 in the U.S. sample (Table 5). In response to the potential violation of the independence of errors, a time series regression analysis with Newey–West standard errors of 1-year autocorrelations was conducted for this model. Consequentially, unemployment rate still significantly predicted anger ($\beta = 0.36$, Newey–West $SE = 0.03$, $p = .01$, 95% CI [0.02, 0.14]).

Following Bianchi (2016; Study 4), we also conducted regression analyses at the individual song level. Specifically, we regressed the percentage of anger words of each song on the same series of variables mentioned earlier, with robust standard errors clustered by year to account for the nonindependence of multiple songs per year. Identical analyses were repeated for anxiety and sadness. For the U.S. data, unemployment rate again significantly predicted anger when controlling for GDP per capita and inflation ($\beta = 0.13$, robust SE clustered by year $= 0.03$, $f^2 = 0.02$, $p = .02$, 95% CI [0.02, 0.16]) and when controlling for population density and housing price ($\beta = 0.12$, robust SE clustered by year $= 0.04$, $f^2 = 0.01$, $p = .03$, 95% CI [0.01, 0.15]). Individual-level regressions also indicated little change in results for the German data. Unemployment rate significantly predicted anger in the following regression models when controlling for German % ($\beta = 0.11$, robust SE clustered by year $= 0.03$, $f^2 = 0.02$, $p = .04$, 95% CI [0.00, 0.11]), marginally predicted anger ($\beta = 0.11$, robust SE clustered by year $= 0.03$, $f^2 = 0.01$, $p = .06$, 95% CI [−0.00, 0.11]) when controlling for German %, GDP per capita and inflation, and significantly predicted anger when controlling for German %, population density and housing price ($\beta = 0.12$, robust SE clustered by year $= 0.03$, $f^2 = 0.01$, $p = .046$, 95% CI [0.00,

Table 2
Descriptive Statistics and Variable Intercorrelations for the German Sample

Variable	*M*	*SD*	1	2	3	4	5	6	7
Linguistic Inquiry and Word Count categories									
1. Anger	0.44	0.33							
2. Anxiety	0.27	0.26	0						
3. Sadness	0.81	0.64	0.32*	−0.15					
National economic indicators									
4. Unemployment rate	6.84	2.08	0.34*	0.07	0.2				
5. Inflation	2.12	1.55	−0.15	0.04	0.12	−0.33*			
6. Gross domestic product per capita	36294.71	6327.48	0.03	−0.12	−0.08	0.17	−0.50**		
7. Population density	231.33	5.10	0.21	−0.1	0.06	0.60***	−0.37*	0.78***	
8. Housing price	100.65	7.03	−0.01	−0.12	0.15	−0.34*	0.52***	−0.56***	−0.32

* $p < .05$. ** $p < .01$. *** $p < .001$, two-tailed.

Table 3
Ordinary Least Squares Regressions Predicting the Amount of Anger, Anxiety, and Sadness in Top 10 Songs in the United States, 1980 to 2017

Variable	Anger			Anxiety			Sadness		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment rate	0.138 (0.04) [−0.04, 0.11] <.02>	0.378* (0.03) [0.02, 0.15] <.21>	0.358* (0.03) [0.02, 0.15] <.19>	−0.035 (0.02) [−0.04, 0.03] <.00>	−0.153 (0.02) [−0.06, 0.02] <.02>	−0.123 (0.02) [−0.06, 0.03] <.01>	−0.016 (0.05) [−0.11, 0.10] <.00>	−0.080 (0.05) [−0.14, 0.09] <.01>	−0.046 (0.06) [−0.13, 0.10] <.00>
Inflation		0.017 (0.03) [−0.05, 0.05] <.00>			−0.177 (0.02) [−0.05,0.02] <.02>			−0.141 (0.04) [−0.12, 0.06] <.01>	
Gross domestic product per capita		0.682*** (0.00) [0.00, 0.00] <.43>			−0.402 (0.00) [−0.00, 0.00] <.09>			−0.240 (0.00) [−0.00, 0.00] <.03>	
Population density			0.411 (0.03) [−0.01, 0.10] <.09>			−0.190 (0.02) [−0.04, 0.02] <.01>			−0.172 (0.05) [−0.12, 0.07] <.01>
Housing price			0.310 (0.01) [−0.00, 0.02] <.04>			−0.108 (0.00) [−0.01, 0.01] <.00>			0.022 (0.01) [−0.02, 0.02] <.00>
R^2	0.019	0.413	0.449	0.001	0.091	0.076	0.000	0.031	0.023
F	0.700	7.960***	9.232***	0.045	1.140	0.927	0.009	0.362	0.269

Note. Standardized beta coefficients reported. Standard errors are given in parentheses. 95% confidence intervals are given in square brackets. f^2 effect sizes are given in angle brackets.
* $p < .05$. ** $p < .01$. *** $p < .001$.

0.12]). Unemployment rate did not predict anxiety and sadness in other models (all $p > .05$).

One possible potential explanation for the convergence of results from the United States and German sample is that 41 songs were present in both the U.S. and German samples. To rule out this possibility, regressions were conducted with the German data after excluding the aforementioned 41 songs. Results remained largely the same as unemployment rate significantly predicted anger after controlling for German % ($\beta = 0.39$, $SE = 0.03$, $f^2 = 0.17$, $p = .02$, 95% CI [0.01, 0.12]), and German %, GDP per capita, and inflation ($\beta = 0.37$, $SE = 0.03$, $f^2 = 0.14$, $p = .04$, 95% CI [0.00, 0.12]), and marginally predicted anger when controlling for German %, population density and housing price ($\beta = 0.39$, $SE = 0.04$, $f^2 = 0.11$, $p = .06$, 95% CI [−0.00, 0.14]).

Discussion

Music plays an important role in human life. However, little is known about how popular music is related to the socioeconomic environment. In this study, we analyzed top 10 songs in the United States and Germany from 1980 to 2017 and found that unemployment rate predicted anger but not anxiety or sadness in lyrics. These relationships were robust after controlling for other socioeconomic variables in both countries. Although our study is exploratory, these findings suggest that popular song lyrics may reflect public sentiment toward the socioeconomic environment. This extends the theorizing of popular music as cultural products and highlights the influence of socioeconomic conditions on popular media.

There could be at least two reasons why the sentiment of popular songs is related to the socioeconomic environment. First, the socioeconomic environment may influence the public's mood, and the public prefers songs that match their mood, making the sentiment in top songs related to the socioeconomic environment (i.e., the consumer effect). Second, the socioeconomic environment may influence the mood of composers. As composers express their mood in their songs, songs produced in a given year will carry the mood resulted from the socioeconomic environment (i.e., the producer effect). Our study cannot provide direct evidence to disentangle the consumer and composer effect and tell which effect (or both) leads to our findings. With unprecedented opportunities provided by Big Data (Qiu, Chan, & Chan, 2018), future studies may examine the composer effect by collecting all lyrics produced in a year over several years and examine if the percentage of angry songs would change according to the socioeconomic condition.

Our study suggests that high unemployment rate resulted in anger but not anxiety and sadness in the public. This is consistent with preliminary research illustrating that unemployment can lead to various affective responses, but the central emotional response is anger when the adversity is attributed to external causes (Agnew, 1992; Baron, 2008). Existing studies that investigated reactions toward socioeconomic conditions (Easterlin, McVey, Switek, Sawangfa, & Zweig, 2010; Li & Kanazawa, 2016) or the consequences of job loss on individuals' well-being (Lucas, Clark, Georgellis, & Diener, 2004; McKee-Ryan, Song, Wanberg, & Kinicki, 2005; Wanberg, 2012) were largely focused on broad assessments, viewing it as either positive or negative. In contrast,

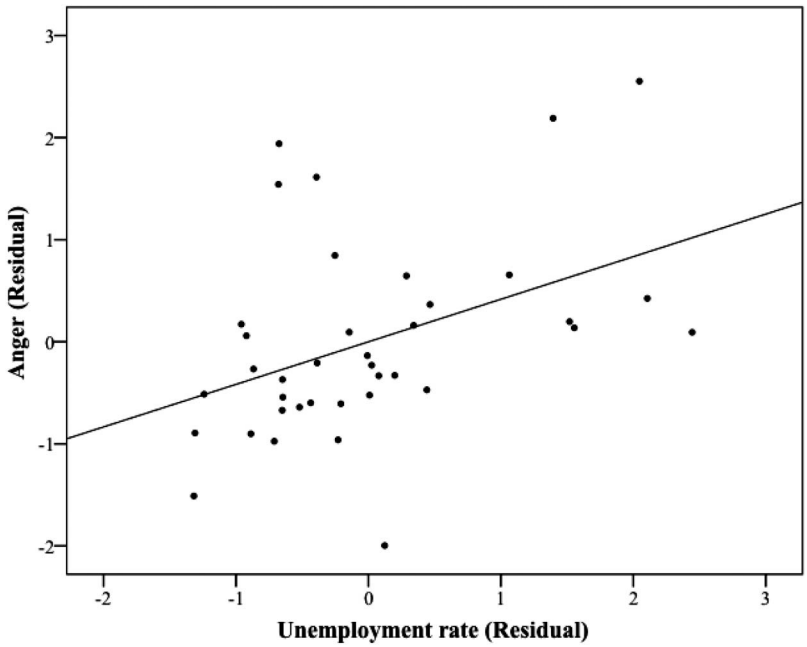

Figure 1. Scatterplot of the partial correlation between anger and unemployment rate in the United States (r = .42, p = .01), controlling for gross domestic product per capita and inflation.

our study sheds light on how unemployment leads to specific types of negative emotions on a societal level.

Our results support previous findings that popular songs are less likely to be about leisure or fun when socioeconomical conditions deteriorate (Eastman & Pettijohn, 2019). However, previous research suggests that popular songs during difficult socioeconomic times were sadder sounding because they were longer with slower tempos and minor keys (Eastman & Pettijohn, 2019), whereas our study suggests that popular song lyrics did not express more sadness. The difference regarding sadness could be due to two reasons. First, our sample contained top 10 songs from Billboard between 1980 and 2017, while Eastman and Pettijohn (2019) used

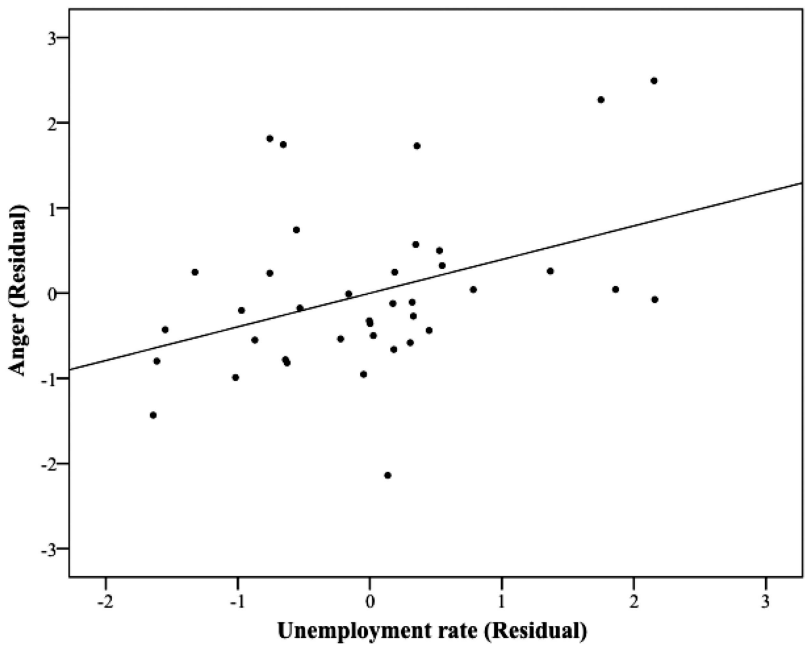

Figure 2. Scatterplot of the partial correlation between anger and unemployment rate in the United States (r = .40, p = .02), controlling for population density and housing prices.

Table 4
Ordinary Least Squares Regressions Predicting the Amount of Anger, Anxiety, and Sadness in Top 10 Songs in Germany, 1980 to 2017

	Anger			Anxiety			Sadness		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment rate	0.40* (0.02)	0.40* (0.03)	0.43* (0.03)	0.09 (0.02)	0.12 (0.02)	0.20 (0.03)	0.19 (0.05)	0.26 (0.06)	0.30 (0.07)
	[0.01, 0.11]	[0.01, 0.12]	[0.00, 0.13]	[−0.03, 0.06]	[−0.03, 0.06]	[−0.03, 0.08]	[−0.05, 0.16]	[−0.03, 0.19]	[−0.04, 0.23]
	<0.19>	<0.17>	<0.14>	<.01>	<0.01>	<0.03>	<0.04>	<0.07>	<0.06>
German percentage	−0.30	−0.30	−0.29	−0.07 (0.28)	−0.08 (0.29)	−0.10 (0.29)	0.05 (0.68)	0.03 (0.69)	0.06 (0.68)
	(0.32)	(0.33)	(0.33)						
	[−1.26, 0.03]	[−1.28, 0.05]	[−1.27, 0.07]	[−0.69, 0.46]	[−0.73, 0.45]	[−0.74, 0.42]	[−1.17, 1.59]	[−1.29, 1.52]	[−1.13, 1.65]
	<0.11>	<0.11>	<0.10>	<.00>	<0.01>	<0.01>	<0.00>	<0.00>	<0.00>
Inflation		−0.05			0.02 (0.04)			0.19 (0.08)	
		(0.04)							
		[−0.09, 0.07]			[−0.07, 0.07]			[−0.09, 0.25]	
		<0.00>			<0.00>			<0.03>	
Gross domestic product per capita		−0.07			−0.13 (0.00)			−0.03 (0.00)	
		(0.00)							
		[−0.00, 0.00]			[−0.00, 0.00]			[−0.00, 0.00]	
		<0.01>			<0.01>			<0.00>	
Population density			0.01 (0.01)			−0.27 (0.01)			−0.05 (0.03)
			[−0.03, 0.03]			[−0.04, 0.01]			[−0.06, 0.05]
			<0.00>			<0.05>			<0.00>
Housing price			0.10 (0.01)			−0.15 (0.01)			0.24 (0.02)
			[−0.01, 0.02]			[−0.02, 0.01]			[−0.01, 0.06]
			<0.01>			<0.02>			<0.06>
R^2	0.20	0.20	0.21	0.01	0.03	0.07	0.04	0.08	0.10
F	4.38*	2.12	2.18	0.19	0.25	0.58	0.80	0.73	0.92

Note. Standardized beta coefficients reported. Standard errors are given in parentheses. 95% confidence intervals are given in square brackets. f^2 effect sizes are given in angle brackets.
* $p < .05$. ** $p < .01$. *** $p < .001$.

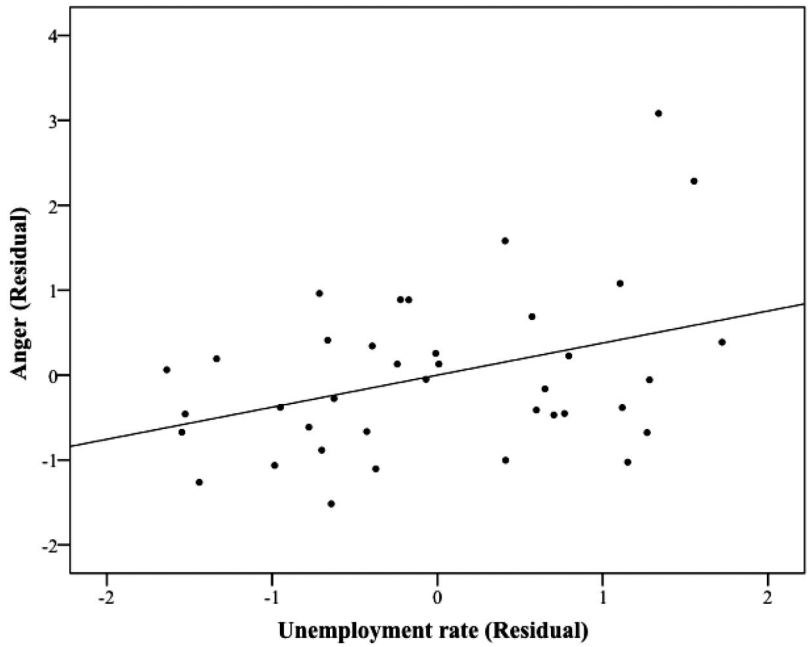

Figure 3. Scatterplot of the partial correlation between anger and unemployment rate in Germany ($r = .38$, $p = .03$), controlling for German percentage, gross domestic product per capita, and inflation.

Billboard rhythm and blues/hip-hop No. 1 songs of the year between 1946 and 2010. Second, our finding is based on the frequency of sad words in lyrics, whereas Eastman and Pettijohn (2019) derived sadness from the length and tempo of the melody. It is possible that sadness was only expressed in the melody of the songs, or it was not accurately detected by LIWC. Future studies may use other linguistic tools or human ratings to evaluate sadness in lyrics and validate our findings.

Though it was not a main objective of this study, we found that GDP per capita was positively associated with angry lyrics in the United States but not in Germany. At the first glance, this may appear surprising. However, a possible explanation comes from

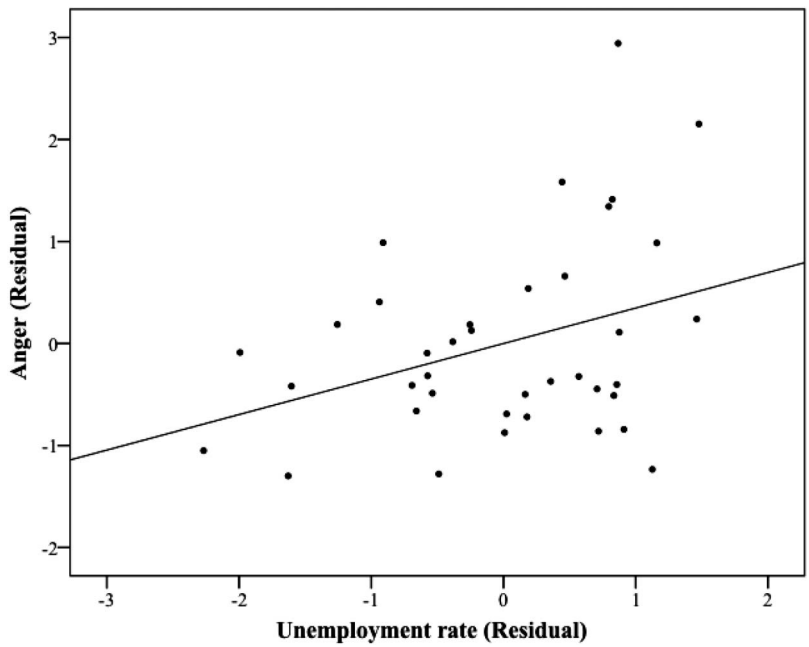

Figure 4. Scatterplot of the partial correlation between anger and unemployment rate in Germany ($r = .35$, $p = .04$), controlling for German percentage, population density, and housing prices.

Table 5
Results of Breusch–Godfrey LM Test of Autocorrelation in the U.S. and German Data

	United States		Germany	
Model	χ^2	p	χ^2	p
Model 1	1.33	.25	0.19	.67
Model 2	3.77	.05	0.17	.68
Model 3	4.37	.04	0.11	.74
Model 4	0.00	.98	0.16	.69
Model 5	0.53	.47	0.30	.58
Model 6	0.16	.69	0.47	.49
Model 7	2.19	.14	1.27	.26
Model 8	3.06	.08	1.50	.22
Model 9	2.61	.11	2.40	.12

the highly influential Easterlin paradox (Easterlin, 1974, 1995), which refers to the fact that despite substantial economic growth in the United States and other developed countries, this increase in wealth was not accompanied by an increase in happiness. This phenomenon has been shown to hold in the long-run where data over 10 years or more are considered (Easterlin et al., 2010). Oishi and Kesebir (2015) further showed that income inequality can explain why happiness does not always follow economic growth. Income inequality in the United States substantially increased in the 1980s and 1990s (Frank, 2009), and as of 2014, it is starkly higher than those in other developed countries, including Germany, despite comparable levels of GDP per capita (Holodny, 2016). Hence, income inequality may be a possible explanation for the positive relationship found between GDP per capita and angry lyrics in the United States but not Germany. In a related vein, income inequality may also explain why a considerably higher amount of variance is accounted for in the regression models for anger in the United States (see Models 2 and 3 in Table 3) compared to Germany (see Models 2 and 3 in Table 4). Income inequality in the United States has been shown to be positively associated with GDP per capita (Frank, 2009) and population density (Glaeser, Resseger, & Tobio, 2008) and thus could be a possible reason why greater variance is accounted for in the United States than Germany. However, the interaction effect of income inequality and other socioeconomic indicators on sentiments in top songs is beyond the scope of this research and warrants further research.

Besides theoretical contributions, our work also has significant practical implications. Specifically, it shows how popular music can be used to discern public sentiment in response to socioeconomic change and points out the potential for using popular music to track distinct emotions toward economic changes. Because millions are listening to music online, their listening records can be easily aggregated to identify popular music and generate a real-time measure of public sentiment. This may provide an alternative measure of public sentiment besides the traditional survey methods, which can be particularly useful when large-scale surveys are expensive and difficult to conduct.

There are several limitations in the present research. First, our study is exploratory, in that we did not have specific hypotheses regarding how the three types of negative emotions are related to unemployment rate. Further work is needed to confirm our findings. For example, lab studies can be conducted by manipulating participants' perception of the socioeconomic environment and measuring their choices of songs expressing different types of emotion. Second, our attention was solely directed to lyrics of popular music. Previous research suggests that melodic attributes such as beats and key signatures may also provide cues on emotional responses to socioeconomic fluctuations (Pettijohn et al., 2012). Therefore, researchers may control for melodic attributes in future studies to tease out the unique effects of lyrics. Finally, U.S. and German data sets were used to improve the reliability of our findings. Nevertheless, our choice of countries were limited to the languages that LIWC can analyze. Future studies may increase the sample size by using different sentiment analysis tools or human coding in data analysis.

References

Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology, 30,* 47–88. http://dx.doi.org/10.1111/j.1745-9125.1992.tb01093.x

Ali, S. O., & Peynircioğlu, Z. F. (2006). Songs and emotions: Are lyrics and melodies equal partners? *Psychology of Music, 34,* 511–534. http://dx.doi.org/10.1177/0305735606067168

Anderson, C. A., Carnagey, N. L., & Eubanks, J. (2003). Exposure to violent media: The effects of songs with violent lyrics on aggressive thoughts and feelings. *Journal of Personality and Social Psychology, 84,* 960–971. http://dx.doi.org/10.1037/0022-3514.84.5.960

Baron, S. W. (2008). Street youth, unemployment, and crime: Is it that simple? Using general strain theory to untangle the relationship. *Canadian Journal of Criminology and Criminal Justice, 50,* 399–434. http://dx.doi.org/10.3138/cjccj.50.4.399

Besson, M., Faita, F., Peretz, I., Bonnel, A. M., & Requin, J. (1998). Singing in the brain: Independence of lyrics and tunes. *Psychological Science, 9,* 494–498. http://dx.doi.org/10.1111/1467-9280.00091

Bianchi, E. C. (2016). American individualism rises and falls with the economy: Cross-temporal evidence that individualism declines when the economy falters. *Journal of Personality and Social Psychology, 111,* 567–584. http://dx.doi.org/10.1037/pspp0000114

Blanchard-Fields, F., & Coats, A. H. (2008). The experience of anger and sadness in everyday problems impacts age differences in emotion regulation. *Developmental Psychology, 44,* 1547–1556. http://dx.doi.org/10.1037/a0013915

Bodenhausen, G. V., Sheppard, L. A., & Kramer, G. P. (1994). Negative affect and social judgment: The differential impact of anger and sadness. *European Journal of Social Psychology, 24,* 45–62. http://dx.doi.org/10.1002/ejsp.2420240104

Bonnel, A. M., Faita, F., Peretz, I., & Besson, M. (2001). Divided attention between lyrics and tunes of operatic songs: Evidence for independent processing. *Perception and Psychophysics, 63,* 1201–1213. http://dx.doi.org/10.3758/BF03194534

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian Economic Papers, 17,* 334–355. http://dx.doi.org/10.1111/j.1467-8454.1978.tb00635.x

Burke, R. S., & Grinder, R. E. (1966). Personality-oriented themes and listening patterns in teen-age music and their relation to certain academic and peer variables. *The School Review, 74,* 196–211. http://dx.doi.org/10.1086/442771

Chamorro-Premuzic, T., & Furnham, A. (2007). Personality and music: Can traits explain how people use music in everyday life? *British Journal of Psychology, 98,* 175–185. http://dx.doi.org/10.1348/000712606X111177

DeWall, C. N., Pond, R. S. J., Campbell, W. K., & Twenge, J. M. (2011). Tuning in to psychological change: Linguistic markers of psychological

traits and emotions over time in popular U.S. song lyrics. *Psychology of Aesthetics, Creativity, and the Arts, 5,* 200–207. http://dx.doi.org/10.1037/a0023195

Di Tella, R., MacCulloch, R. J., & Oswald, A. J. (2001). Preferences over inflation and unemployment: Evidence from surveys of happiness. *The American Economic Review, 91,* 335–341. http://dx.doi.org/10.1257/aer.91.1.335

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology, 29,* 94–122. http://dx.doi.org/10.1016/j.joep.2007.09.001

Easterlin, R. A. (1974). Does economic growth improve the human lot? Some empirical evidence. In P. A. David & M. W. Reder (Eds.), *Nations and households in economic growth* (pp. 89–125). New York, NY: Academic Press. http://dx.doi.org/10.1016/B978-0-12-205050-3.50008-7

Easterlin, R. A. (1995). Will raising the incomes of all increase the happiness of all? *Journal of Economic Behavior and Organization, 27,* 35–47. http://dx.doi.org/10.1016/0167-2681(95)00003-B

Easterlin, R. A., McVey, L. A., Switek, M., Sawangfa, O., & Zweig, J. S. (2010). The happiness–income paradox revisited. *Proceedings of the National Academy of Sciences of the United States of America, 107,* 22463–22468. http://dx.doi.org/10.1073/pnas.1015962107

Eastman, J. T., & Pettijohn, T. F. (2019). Good times and endless love: Billboard R&B/hip hop songs of the year across social and economic conditions. *Psychology of Popular Media Culture, 8,* 243–250. http://dx.doi.org/10.1037/ppm0000176

Frank, M. W. (2009). Inequality and growth in the United States: Evidence from a new state-level panel of income inequality measures. *Economic Inquiry, 47,* 55–68. http://dx.doi.org/10.1111/j.1465-7295.2008.00122.x

Glaeser, E. L., Resseger, M. G., & Tobio, K. (2008). *Urban inequality* (NBER Working Paper No. 14419). Cambridge, MA: National Bureau of Economic Research. http://dx.doi.org/10.3386/w14419

Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica, 46,* 1293–1301. http://dx.doi.org/10.2307/1913829

Inflation.eu. (2019). *Historic inflation – consumer price index (CPI) by country*. Retrieved from https://www.inflation.eu/inflation-rates/cpi-inflation.aspx

Hill, S. E., Rodeheffer, C. D., Griskevicius, V., Durante, K., & White, A. E. (2012). Boosting beauty in an economic decline: Mating, spending, and the lipstick effect. *Journal of Personality and Social Psychology, 103,* 275–291. http://dx.doi.org/10.1037/a0028657

Holodny, E. (2016). The U.S. is a big outlier when it comes to income inequality. *Business Insider U.S.* Retrieved from https://www.businessinsider.in/The-US-is-a-big-outlier-when-it-comes-to-income-inequality/articleshow/53606049.cms?src=as_nsw

Kuppens, P., Realo, A., & Diener, E. (2008). The role of positive and negative emotions in life satisfaction judgment across nations. *Journal of Personality and Social Psychology, 95,* 66–75. http://dx.doi.org/10.1037/0022-3514.95.1.66

Lamoreaux, M., & Morling, B. (2012). Outside the head and outside individualism-collectivism: Further meta-analyses of cultural products. *Journal of Cross-Cultural Psychology, 43,* 299–327. http://dx.doi.org/10.1177/0022022110385234

Larson, R. (1995). Secrets in the bedroom: Adolescents' private use of media. *Journal of Youth and Adolescence, 24,* 535–550. http://dx.doi.org/10.1007/BF01537055

Li, N. P., & Kanazawa, S. (2016). Country roads, take me home . . . to my friends: How intelligence, population density, and friendship affect modern happiness. *British Journal of Psychology, 107,* 675–697. http://dx.doi.org/10.1111/bjop.12181

Lucas, R. E., Clark, A. E., Georgellis, Y., & Diener, E. (2004). Unemployment alters the set point for life satisfaction. *Psychological Science, 15,* 8–13. http://dx.doi.org/10.1111/j.0963-7214.2004.01501002.x

MacKinnon, D. P., Krull, J. L., & Lockwood, C. M. (2000). Equivalence of the mediation, confounding and suppression effect. *Prevention science: The official journal of the Society for Prevention Research, 1,* 173–181. http://dx.doi.org/10.1023/a:1026595011371

McAuslan, P., & Waung, M. (2018). Billboard hot 100 songs: Self-promoting over the past 20 years. *Psychology of Popular Media Culture, 7,* 171–184. http://dx.doi.org/10.1037/ppm0000118

McKee-Ryan, F., Song, Z., Wanberg, C. R., & Kinicki, A. J. (2005). Psychological and physical well-being during unemployment: A meta-analytic study. *Journal of Applied Psychology, 90,* 53–76. http://dx.doi.org/10.1037/0021-9010.90.1.53

Morling, B., & Lamoreaux, M. (2008). Measuring culture outside the head: A meta-analysis of individualism-collectivism in cultural products. *Personality and Social Psychology Review, 12,* 199–221. http://dx.doi.org/10.1177/1088868308318260

Oishi, S., & Kesebir, S. (2015). Income inequality explains why economic Growth does not always translate to an increase in happiness. *Psychological Science, 26,* 1630–1638. http://dx.doi.org/10.1177/0956797615596713

Organisation for Economic Cooperation and Development. (2019a). *Housing prices*. http://dx.doi.org/10.1787/63008438-en

Organisation for Economic Cooperation and Development. (2019b). *Unemployment rate*. http://dx.doi.org/10.1787/997c8750-en

Pennebaker, J. W., Mehl, M. R., & Niederhoffer, K. G. (2003). Psychological aspects of natural language use: Our words, our selves. *Annual Review of Psychology, 54,* 547–577. http://dx.doi.org/10.1146/annurev.psych.54.101601.145041

Pettijohn, T. F., II, 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,* 313–317. http://dx.doi.org/10.1007/s12144-012-9149-y

Pettijohn, T. F., II & Sacco, D. F., Jr. (2009a). The language of lyrics: An analysis of popular billboard songs across conditions of social and economic threat. *Journal of Language and Social Psychology, 28,* 297–311. http://dx.doi.org/10.1177/0261927X09335259

Pettijohn, T. F., II, & Sacco, D. F., Jr. (2009b). Tough times, meaningful music, mature performers: Popular Billboard songs and performer preferences across social and economic conditions in the USA. *Psychology of Music, 37,* 155–179. http://dx.doi.org/10.1177/0305735608094512

Qiu, L., Chan, S. H. M., & Chan, D. (2018). Big data in social and psychological science: Theoretical and methodological issues. *Journal of Computational Social Science, 1,* 59–66. http://dx.doi.org/10.1007/s42001-017-0013-6

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

Raghunathan, R., & Pham, M. T. (1999). All negative moods are not equal: Motivational influences of anxiety and sadness on decision making. *Organizational Behavior and Human Decision Processes, 79,* 56–77. http://dx.doi.org/10.1006/obhd.1999.2838

Ratcliffe, A. (2010). *Housing wealth or economic climate: Why do house prices matter for well-being?* (Working Paper Series No. 10/234). Bristol, United Kingdom: Centre for Market and Public Organisation, University of Bristol. Retrieved from https://www.bristol.ac.uk/media-library/sites/cmpo/migrated/documents/wp234.pdf

Rentfrow, P. J. (2012). The role of music in everyday life: Current directions in the social psychology of music. *Social and Personality Psychology Compass, 6,* 402–416. http://dx.doi.org/10.1111/j.1751-9004.2012.00434.x

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, 1236–1256. http://dx.doi.org/10.1037/0022-3514.84.6.1236

Rothbaum, F., & Tsang, B. Y.-P. (1998). Lovesongs in the United States and China: On the nature of romantic love. *Journal of Cross-Cultural Psychology, 29,* 306–319. http://dx.doi.org/10.1177/0022022198292003

Rothbaum, F., & Xu, X. (1995). The theme of giving back to parents in Chinese and American songs. *Journal of Cross-Cultural Psychology, 26,* 698–713. http://dx.doi.org/10.1177/0022022195026006011

Schwartz, K. D., & Fouts, G. T. (2003). Music preferences, personality style, and developmental issues of adolescents. *Journal of Youth and Adolescence, 32,* 205–213. http://dx.doi.org/10.1023/A:1022547520656

Snibbe, A. C., & Markus, H. R. (2005). You can't always get what you want: Educational attainment, agency, and choice. *Journal of Personality and Social Psychology, 88,* 703–720. http://dx.doi.org/10.1037/0022-3514.88.4.703

Stevenson, B., & Wolfers, J. (2008). Economic growth and subjective well-being: Reassessing the Easterlin paradox. In *Brookings papers on economic activity, economic studies program, the Brookings institution* (Vol. 39, pp. 1–102). Cambridge, MA: National Bureau of Economic Research. http://dx.doi.org/10.3386/w14282

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29,* 24–54. http://dx.doi.org/10.1177/0261927X09351676

Tov, W., Ng, K. L., Lin, H., & Qiu, L. (2013). Detecting well-being via computerized content analysis of brief diary entries. *Psychological Assessment, 25,* 1069–1078. http://dx.doi.org/10.1037/a0033007

Wanberg, C. R. (2012). The individual experience of unemployment. *Annual Review of Psychology, 63,* 369–396. http://dx.doi.org/10.1146/annurev-psych-120710-100500

Wolfers, J. (2003). Is business cycle volatility costly? Evidence from surveys of subjective well-being. *International Finance, 6,* 1–26. http://dx.doi.org/10.1111/1468-2362.00112

World Bank. (2019a). World Development Indicators. *GDP per capita (constant 2010 U. S.$)* [Data file]. Retrieved from https://data.worldbank.org/indicator/NY

World Bank. (2019b). World Development Indicators. *Population density (people per sq. km of land area)* [Data file]. Retrieved from https://data.worldbank.org/indicator/EN

World Bank. (2019c). World Development Indicators. *Unemployment, total (% of total labor force) (modeled ILO estimate)* [Data file]. Retrieved from https://data.worldbank.org/indicator/SL

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