# People Prefer Simpler Content When There Are More Choices: A Time Series Analysis of Lyrical Complexity in Six Decades of American Popular Music

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**Word Count:** 4692 Words (w/o references)

## Abstract

Song lyrics are rich in meaning. In recent years, the lyrical content of popular songs has been used as an index of shifting norms, affect, and values at the cultural level. One remarkable, recently-uncovered trend is that successful pop songs have increasingly simple lyrics. Why? We test the idea that increasing lyrical simplicity is linked to a widening array of novel song choices. To test this Cultural Compression Hypothesis (CCH), we examined six decades of popular music (N = 14,661 songs). The number of novel song choices predicted greater lyrical simplicity of successful songs. This relationship was robust, holding when controlling for critical ecological and demographic factors and also when using a variety of approaches to account for the potentially confounding influence of temporal autocorrelation. The present data provide the first time series evidence that real-world cultural transmission may depend on the amount of novel choices in the information landscape.

# People Prefer Simpler Content When There Are More Choices: A Time Series Analysis of Lyrical Complexity in Six Decades of American Popular Music

Music is a human universal (e.g. Dissanayacke, 2000; Mehr & Krasnow, 2017). Because song—and particularly popular song lyrics—can be so rich in meaning (e.g., Cooper 1985; Hayakawa, 1957), social scientists have long explored the ways that such lyrics intersect with some fundamental social processes, including identity formation and person perception (e.g., Hyden & McCandless, 1983; Marshall & Naumann, 2018; Reisman, 1957; Rentfrow & Gosling, 2003, 2006, 2007). More recently, social psychologists have begun to view music as a cultural product and to examine the ways that popular music lyrics reflect important aspects of psychology at the cultural level; the content in popular lyrics indexes changing norms, affect, and values (e.g., Brand, Acerbi, & Mesoudi, 2019; DeWall, Pond, Campbell, & Twenge, 2011; Diamond, Bermudez, & Schensul, 2006; Eastman, Pettijohn, & Terry, 2015; Lambert et al., 2019; Pettijohn & Sacco, 2009a, 2009b).

One seemingly remarkable trend in popular music is that the lyrics of successful pop songs have become increasingly simple (Morris, 2014). Why might this be the case, and what does this trend reveal about psychology at the cultural level? Here, we integrate theory and evidence from social and cognitive psychology, ecology, cultural evolution, and computer science—to develop and test the idea that increasing simplicity in successful song lyrics might be linked to a widening array of novel song choices; that is, we explore whether increasing information saturation (number of novel song choices) might actually lead our minds to prefer increasingly simply products (songs).

**The Cultural Compression Hypothesis (CCH)**

Why might people prefer simpler versions of products in environments with greater variety of such products to choose from? A number of lines of evidence from diverse literatures suggest that simpler information may have an advantage in environments where there is exposure to more information. First, our hypothesis is consistent with the notion that humans are cognitive misers. People have limited information-processing capacities (e.g., Cowan, 2001), and are known to conserve mental resources (Fiske & Taylor, 2013). Consequently, humans often use shortcuts in decision-making (Bargh, 1989; Tversky & Kahneman, 1974). For example, when confronted with the task of evaluating persuasive messages and/or complex decision environments, people are more likely to use heuristics, peripheral cues, and other automatic cognitive processes to evaluate these messages if cognitive resources are limited in some fashion (Eagly & Chaiken, 1993; Petty & Cacioppo, 1986). Thus, when there are many products to be evaluated, people may increasingly prefer products not requiring output of finite mental resources (i.e., simpler products).

Second, the idea that people show a preference for simpler information in increasingly information-saturated environments is consistent with some propositions from cultural evolutionary theory (e.g., Boyd & Richerson, 1988; Henrich, 2015) as well as ecologically-informed research on cultural change (Grossmann & Varnum, 2015; Varnum & Grossmann, 2016; 2017; 2019). One tenet of cumulative cultural evolutionary theory is that, over time, human innovation, transmission, and learning increase the amount and quality of cultural information—importantly, while also increasing he learnability of this information. One way to increase learnability is via simplicity (e.g., Kirby, Cornish, & Smith, 2008; Kirby Tamariz, Cornish, & Smith, 2015). Complex cultural products (e.g., hunting technologies, language) might also be expected to simplify over generations (i.e., in ways that make these products easier to learn; Henrich, 2015). For example, languages with more speakers are more likely to gain new words and maintain existing words (i.e., increase vocabulary), while also becoming more learnable (Bromham, Hua, Fitzpatrick, & Greenhill, 2015; Kirby et al., 2015; Muthukrishna & Henrich, 2016). More simple information has been shown to allow for easier information transmission by making information easier to learn and store in memory, and thus more likely to persist over time (Bartlett, 1932; Chater & Vitanyi, 2003; Tamariz & Kirby, 2015). Indeed, the particular sort of simplicity we examine here—compressibility—is considered a key cultural adaptation because of its ability to facilitate information transmission (Kirby et al., 2008; Tamariz & Kirby, 2015). Thus, if our collective cultural brains are continuously refining our cultural products (e.g., popular songs) to compete with other products—doing so in such a way that maximizes a product's transmissibility (e.g., Muthukrishna & Henrich, 2016)—then the simplest products might be the most transmitted.

Third, this idea is consistent with data revealing people's baseline preferences. Germane to music, experimental evidence implies that people have baseline preferences for simplicity in music; naïve listeners find more repetitive pieces of music (i.e., songs which are less information-dense and thus simpler) to be more enjoyable, engaging, and memorable (Margulis, 2013, 2014). The current theory also dovetails with the mere exposure effect, a phenomenon where repeated exposure to a non-aversive stimulus increases preference for it (Bornstein, 1989; Zajonc, 1968, 2001); more repetition in appealing songs may increase preference for those less information-dense songs. Finally, evidence from real-world and laboratory data suggest that these baseline preferences for simplicity might be exacerbated when there is more information in the environment. Across real-world studies and in-laboratory experiments, when people are confronted with a greater number of options to choose from, they prefer simpler options (Iyengar & Kamenica, 2010). Returning to our specific hypothesis, this insight implies that people will prefer simpler songs when there are more songs to choose from.

Putting these insights together, we predict that in environments of greater information saturation, simpler products may be preferentially attended to and/or transmitted—as they are more likely to be preferred (Margulis, 2013), easier to remember (Margulis, 2014), and easier to transmit with fidelity (Bartlett, 1932; Henrich, 2015; Rubin, 1997). Here, specifically, we predict that the trend towards increasingly simple popular music lyrics might best be explained by the increasing number of songs released each year. Because a number of ecological variables other than information saturation have been examined as possible drivers of cultural change in related literature (e.g., Varnum & Grossmann, 2016), we also examine whether shifts in pathogen prevalence, climatic stress, unemployment, participation of the US in major armed conflicts, and/or immigration and residential mobility might better explain this remarkable trend toward increasingly simple lyrics in successful pop songs. By testing this proposition with time series data, we may shed light on a key cultural level variable affecting the dynamics of cultural transmission.

## Methods

We gathered cross-temporal data covering a period of six decades (1958-2016) on lyrical compressibility (information simplicity), amount of music (information saturation), and ecological threats/affordances linked to patterns of cultural change in previous research. All data are freely available at the Open Science Framework (https://osf.io/qnsmj).

**Lyrical compressibility of successful music.** We are able to gather data from 14,661 songs that entered the Billboard Hot 100 charts spanning the period from 1958 (the charts inception) to 2016. The Billboard Hot 100 tracks the 100 most popular songs each week based on music sales, radio airplay, and internet streaming. We used the degree to which a compression algorithm is able to shrink a song's lyrics as a measure of that song's repetitiveness and, in turn, its information saturation. . For example, more repetitive songs, chants, or visual patterns are less information dense and thus more compressible. By operationalizing complexity in this fashion, we avoid some of the conceptual ambiguity associated with operationalization of complexity in prior research (e.g., Jordan, Sterling, Pennebaker, & Boyd, 2018; Kempe et al., 2004; Rycroft, 2006): Whereas multi-purpose use of a single product may reflect product’s complexity from the operational standpoint, it may also represent greater simplicity from the standpoint of consumer psychology. Further, song lyrics are tractable to work with when using an automated compression algorithm.

Compressibility indexes the degree to which a data compression algorithm can compress a song's lyrics, such that more compressible songs have more repetitive and less information dense (i.e., simpler) content. Compressibility of popular song lyrics was according to a metric developed by the third author, based on the LZ77 compression algorithm. In brief, the LZ77 algorithm works by finding repeated substrings and replacing them with 'match' objects pointing back to the string's previous occurrence. A match is encoded as a tuple *(D, L)*, with *D* being the distance to the substring's previous occurrence, and *L* being its length. We treat these matches as costing 3 bytes. Therefore, a repeated string will only lead to space savings if it is of at least length 4, and longer repetitions lead to greater relative savings. Given a song *S*, and the set of matches *M* produced by the LZ77 algorithm when applied to that song, its compressed size is therefore:

$$compsize(S) \ = \ |S| - \sum_{(D,L) \in M} L - 3$$

Where $|S|$ is the original size of the song's lyrics, measured in characters/bytes. The compression ratios of songs in our dataset (i.e., |*S*|/*compsize(S)*) followed an approximately log-normal distribution, so we operationalized compressibility as the logarithm of this ratio:

$$compressibility(S) \ = \ log(\frac{|S|}{compsize(S)})$$

We computed mean compressibility for each year based on all songs that entered the Hot 100 charts in a given year for which we were able to scrape lyrics (1958-2016).

We used the LZ77 compression algorithm because of its intimate connection to textual repetition. Most of the byte savings when compressing song lyrics arise from large, multi-line sections (most importantly the chorus, and chorus-like hooks). Another significant contributor are multi-word phrases, which may be repeated in variations across different lines for poetic effect (e.g. the anaphoric verses in Lady Gaga's *Bad*

*Romance*: "I want your ugly / I want your disease / I want your everything..."). The compression may make use of repeated individual words, or even sub-word units that repeat (perhaps incidentally), but their contribution to the overall compressibility is low.

**Amount of music.** We used three separate indicators to assess the amount of new music to which people are likely exposed in a given year. For each year (1958-2016) we computed the total number of songs which made the Hot100 chart, the number of musical releases per year according to Discogs (Discogs.com), and the number of Wikipedia entries about songs first published or performed in a given year (Wikipedia.org).

**Ecological threats/affordances.** We used data from Varnum and Grossmann (2016) on four major ecological threats and affordances in the US: pathogen prevalence, climatic stress, unemployment, and participation of the US in major armed conflicts (Varnum and Grossmann, 2016). As the original indices ended in 2012-2013, we updated them from the same archival sources used to construct the original indices, so that data used in our analyses covered the years 1958-2016.

**Immigration and residential mobility.** We used data on the number of green cards issued from the Department of Homeland Security and data on the percentage of the US population that changed residence within the US from the US Census Bureau. Data on these and other control variables (ecological threats/affordances) originate from archival indicators that provide comprehensive population and environmental coverage.

**Analytical procedure.** Where possible we use non-parametric ordinal-level measures of correlation or partial correlation, as such indicators provide conservative estimates preferred when time series data are not normally distributed. Results were comparable when we used Pearson's $r$ or partial Pearson correlations. First, we examined zero-order and partial relationships and assessed the robustness of the hypothesized link between amount of new music produced and average lyrical compressibility of popular songs by controlling for a host of plausible ecological covariates. Next we created a composite index of novel song choices and we performed a series of corrective analyses, controlling for the possibly spurious nature of the relationship between our key time series due to temporal autocorrelation. First, we computed adjusted significance thresholds based on the Tiokhin-Hruschka procedure (Tiokhin & Hruschka, 2017). Second, using our composite index of novel song choices, we detrended our time series by residualizing for year and assessed the correlation between our detrended variables. Third using our composite index of novel song choices, we used auto.ARIMA (automated auto-regressive integrated moving average) to assess the relationship between novel song choices and lyrical compressibility. This technique involves a machine learning algorithm that tests a number of different possible models which vary in whether they include autoregressive components, differencing, and moving average components, as well as whether they include an exogenous predictor. Finally we used auto.ARIMA to generate a forecast for future patterns of lyrical compressibility (2017-2046).

**Data availability.** All data and code used in the analyses reported below have been posted to the Open Science Framework (OSF) and are freely available at (https://osf.io/qnsmj/).

## Results

Mean lyrical compressibility (i.e., simplicity) of songs increased over time, Kendall's $\tau = .726$, $p < .001$, as did number of songs making the Hot 100 charts per year, Kendall's $\tau = .425$, $p < .001$, number of music releases according to Discogs per year, Kendall's $\tau = .973$, $p < .001$, and number of Wikipedia entries for songs by year of publication, Kendall's $\tau = .871$, $p < .001$. Consistent with our predictions, mean lyrical compressibility per year was positively correlated with amount of music produced per year as operationalized by three distinct indicators, Kendall's $\tau$ (*n* songs in *Hot 100* charts/year) = .429, $p < .001$, Kendall's $\tau$ (*n Discogs* music releases / year) = .721, $p < .001$, Kendall's $\tau$ (*n* Wikipedia entries about songs/year) = .680, $p < .001$.

**Robustness analyses.** We first assessed the robustness of these associations by controlling for a suite of indicators of ecological threats/affordances that have been linked to other cultural changes in previous research (Bianchi, 2016; Grossmann & Varnum, 2015; Varnum & Grossmann, 2016, 2017; Oishi, Kesebir, & Diener, 2011; Santos, Varnum, & Grossmann, 2017; Twenge & Park, 2017): pathogen prevalence, climatic stress, armed conflict, and unemployment (see supplementary information for full zero-order correlations). Controlling for these variables, the partial correlations between all indicators of information saturation and mean lyrical compressibility remained statistically significant; $_{\text{partial}}$Spearman's $\rho$ (Hot 100 songs) = .588, $p = .001$, $_{\text{partial}}$Spearman's $\rho$ (Discogs releases) =.740, $p < .001$, $_{\text{partial}}$Spearman's $\rho$ (Wikipedia entries) = .709, $p < .001$.

Next, we tested whether links between information saturation and average lyrical compressibility held when controlling for other factors that might plausibly influence preference for simpler lyrics. For example, immigrants to the US tend to be less fluent in English compared to native-born residents, potentially resulting in preference for simpler, more repetitive English lyrics. Similarly, previous work has linked residential mobility to greater susceptibility to the mere exposure effect and greater preference for familiar cultural products (Oishi, Miao, Koo, Kisling, & Ratliff, 2012). Indices of novel song choices remained significant predictors of lyrical compressibility controlling for immigration, $_{partial}$Spearman's ρ (Hot 100 songs) = .453, $p < .001$; $_{partial}$Spearman's ρ (Discogs releases) =.731, $p < .001$; $_{partial}r$ (Wikipedia entries) = .666, $p < .001$. When controlling for residential mobility, indices of novel song choices remained significant predictors of lyrical compressibility, $_{partial}$Spearman's ρ (Hot100 song) =.347, $p = .014$; $_{partial}$Spearman's ρ (Discogs releases) =.515, $p < .001$; $_{partial}$Spearman's ρ (Wikipedia entries) = .453, $p = .001$.

Because auto-correlation can present a challenge for time-series analyses, potentially distorting the relationship between two variables, we conducted control analysis with a corrected significance threshold (Tiokhin & Hruschka, 2017). Specifically, we generated bootstrapped random time-series that have the same degree of autocorrelation and number of data points as our two time series to estimate the likelihood that a correlation of a given magnitude is due to chance. Here we use zero-order Pearson's correlations as this method generates adjusted significance threshold for such correlations. All three relationships remained significant when applying these corrected thresholds; $r$ (Hot 100 songs) = .686, $_{corrected}p < .01$, $r$ (Discogs releases) = .889, $_{corrected}p < .001$, $r$ (Wikipedia entries) = .872, $_{corrected}p < .001$ (see supplementary information for details).

**Analyses of the composite index of novel song choices.** Hot100 songs, Discog music releases, and Wikipedia song entries were highly correlated, .43 < *Kendall*'s τ's ≤ .87, and formed a single principle component with highest loadings by the Wikipedia song entries (.98), and weakest loading by the Hot 100 songs (.88). To avoid multicollinearity, we used component scores for further analyses. Overall, this index of amount of music produced was strongly positively related to compressibility, *Kendall*'s $\tau = .71$, $p < .001$. Further, this PCA-based composite index remained a significant covariate for lyrical compressibility when controlling simultaneously for pathogen prevalence, climatic stress, armed conflict, and unemployment, $_{partial}$Spearman's $\rho = .821$, $p < .001$. It also remained a significant predictor of average compressibility when performing separate analyses with immigration, $_{partial}$Spearman's $\rho = .729$, $p < .001$, and residential mobility, $_{partial}$Spearman's $\rho = .629$, $p = .019$, as control variables. Importantly, the correlation between this composite index of novel song choices and average lyrical compressibility remained significant when adjusting significance thresholds using the Tiokhin-Hruschka method to account for observed auto-correlation in two time series, $r = .88$, $_{corrected}p < .001$. As an alternative method for dealing with autocorrelation, we also detrended the time series by residualizing out the linear impact of year. The correlation for our detrended variables remained significant, Kendall's $\tau = .22$, $p < .02$.

**ARIMA results.** Given the time series nature of our data, we conducted a primary test of the hypothesized link between amount of new songs available and average compressibility of these songs using an automated ARIMA algorithm (auto.ARIMA) within the forecast function in *R*. This machine-learning algorithm inspects the time-series data to fit the optimal forecasting function. The auto-regressive (*AR(p)*) component refers to the use of past values in the regression equation for the series Y. The auto-regressive parameter p specifies the number of lags used in the model. A moving average (*MA(q)*) component represents the error of the model as a combination of previous error terms $e_t$. The order $q$ determines the number of terms to include in the model. ARIMA models are well-suited for long-term time series, such as the historic patterns in the present data. The automated algorithm within the forecast package searches through combinations of order parameters and picks the set that optimizes model fit criteria, comparing Akaike information criteria (AIC) or Bayesian information criteria (BIC) of respective models. Notably, the automated forecasting approach allows us to specify an exogenous predictor such as novel song choices, such that the automated function can evaluate the extent to which this exogenous predictor improves the fit above and beyond the decomposition of the time-series of the dependent variable. In other words, the automated function provides a conservative way to see whether an exogenous predictor such as the novel song choices index improves accuracy in forecasts of the lyrical compressibility. If the final model selected by auto.ARIMA includes our putative exogenous variable (in this case amount of novel song choices) then this suggests that this variable helps the model to achieve optimal fit to the data.

The results of this automated forecasting procedure indicated that a model with a positive autoregressive component, $B = .527$, $SE = .024$, and a positive contribution of the music production index, $B = .059$, $SE = .008$, provides the best fit to the data:

$$y_t \text{ (compressibility function)} = .983 + .527y_{t-1} + .059x + e_t$$

This model estimation suggests that the index of novel song choices contributes to average lyrical compressibility above and beyond the temporal autocorrelation observed for average lyrical compressibility. Further, the coefficient for the index of novel song choices was statistically significant, $t = 6.98$, $p < .001$.

We also ran an alternative set of auto.ARIMA analyses where we set novel song choices as the dependent variable and average lyrical compressibility as an exogenous predictor. The results of this automated forecasting procedure indicated that a model with a two positive moving average components, *B* = 1.176, *SE* = .242, and *B* = .487, *SE* = .164, and a positive contribution of average lyrical compressibility, *B* = 5.067, *SE* = 2.207, provides the best fit to the data:

$$y_t \text{ (music production function)} = - 4.99 + 1.176\varepsilon_{t-1} + 0.487\varepsilon_{t-2}+5.067x + e_t$$

The coefficient for lyrical compressibility was statistically significant, t = 2.30, $p < .05$. Comparison of the Aikeke Information Criterion (AIC) and Bayesian Information Criterion (BIC) values for our primary and alternative models suggest that our primary model with novel song choices as an exogenous predictor and lyrical compressibility as the dependent variable, AIC=-235.84, BIC=-227.53, is superior to the alternate model with lyrical compressibility as an exogenous predictor and novel song choices as the dependent variable, AIC=58.36, BIC=68.75.

**Forecasting**

As a final step, we generated a forecast for average lyrical compressibility for four decades after the last data point in our time series. These forecasts enable a test of this theoretical model against concrete future cultural trends. Using the automated ARIMA algorithm, we also identified the best function for the novel song choices data, which we used to estimate the subsequent 40 data points. In turn, we used this estimated data in conjunction with the compressibility function to forecast the further development of lyrical compressibility. Results of this model suggest that lyrical compressibility will continue to increase over the next several decades (see Figure 1).

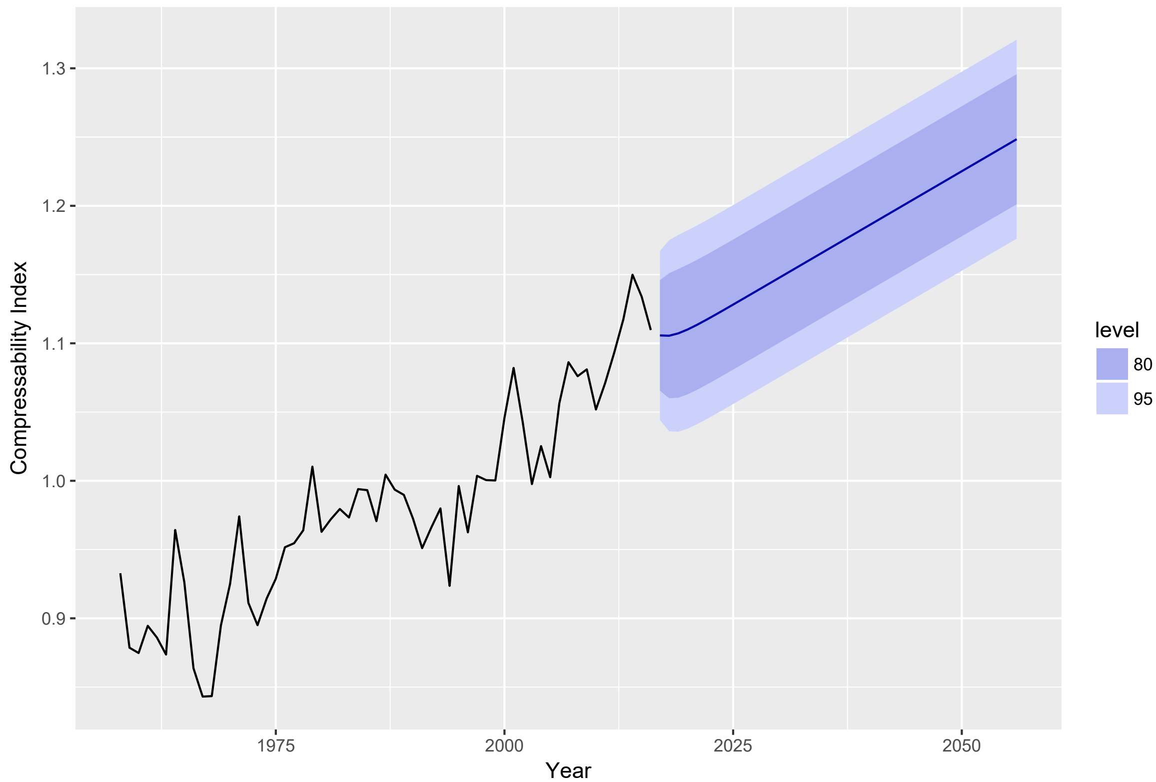


**Fig 1.** Music production-based forecast for future lyrical compressibility from regression with ARMIA (1,0,0) and index of novel song choices as an exogenous predictor.

## Discussion

Popular music lyrics have recently been used to inform the cultural transmission of emotional expression (Brand et al., 2019; Schellenberg & von Scheve, 2012), as an index of culture-level changes in self- versus other-focus (DeWall et al., 2011), and as a reflection of cultural mood in respond to economic and social threats (e.g., Sacco & Pettijohn, 2009a, 2009b). But one major trend in popular music lyrics remained unexplained: Why are these lyrics becoming increasingly simple over time? Our results were consistent with the Cultural Compression Hypothesis (CCH) that people to prefer simpler cultural products in information-saturated environments. Specifically, increases in the amount of novel song choices led to increasing preferences for songs with simpler lyrical content. Additionally, the results of the forecasting model suggest that the trend toward increasing lyrical simplicity will likely continue over the next several decades, assuming continuing growth in the volume of music produced annually.

The relationship between mean lyrical compressibility and the amount of music produced in a given year was robust. We observed significant positive associations across three operationalizations of amount of music produced, and these relationships remained significant when controlling for ecological affordances linked to other types of cultural change, and by and large these relationships also remained significant when controlling for other factors (immigration, residential mobility) which might plausibly affect preference for simpler lyrics. This was also the case for the composite index of novel song choices. Importantly, a linkage between amount of new music produced and average compressibility of popular songs also held when accounting for temporal autocorrelation using three distinct methods. Results thus suggest that the amount of music produced contributes to changes in average lyrical compressibility above and beyond their autoregressive components.

This work also adds to a growing body of empirical research using time-series data to test hypotheses about the process of cultural change (i.e., Bianchi, 2016; Grossmann & Varnum, 2015; Varnum & Grossmann, 2016; 2017; 2019; Oishi et al., 2011; Oishi et al., 2012; Santos et al., 2017; Twenge & Park, 2017). Whereas much of this prior empirical work has focused on how changes in dimensions of the *physical* ecology affect specific cultural patterns in terms of variables like individualism, subjective well-being, or gender equality, though often using the content of cultural products as markers, here we test a novel hypothesis regarding broad, basic features of cultural products (simplicity vs. complexity) that may increase their success as a function of features of the *information* landscape.

The present work also provides concrete forecasts for future patterns of cultural change in lyrical compressibility that can be tested against future observations. Of special interest might be years in which the number of musical releases plateaus or even drops. In such instances, one could explore whether this drop caused an increase in preference for more complex products.

**Limitations and Future Directions**

Even as the present data are consistent with our CCH, we cannot completely rule out all alternative explanations for increasing preferences for simplicity in music. Some research suggests that additional ecological factors might push toward increasing simplicity in expression over time; for example, emotional expressions become arguable simpler in multi-cultural environments (e.g., Rychlowska et al., 2015). So it might be that popular songs become simpler as they adapt to a larger (and ethnically diverse) audience. However, the effects of novel song choices on song preferences held controlling for immigration rates, which would seem to suggest that this alternative explanation could not fully account for the present pattern of findings. Although we did explore a number of ecological variables, we did not create models to test whether conformity or other biases, which may underlie trends in lyrical affect and music sampling (e.g., Brand, 2019; Youngblood, 2019), drove this trend toward increasingly similarity in successful pop lyrics, and future work may endeavor to do so.

The CCH was developed, in part, to explain a remarkable trend in popular music, but it should also be applicable to other products (e.g., novels, tweets), and future work may wish to test the CCH using other media. In addition to exploring the CCH in non-musical products, one might also explore it within other aspects of music. Lyrical compressibility is only one form of simplicity; others could include non-lyrical components of songs (e.g., melody; but see North, Krause, & Ritchie, 2020). Related research on language and communication suggests that a language becomes both more complex (e.g., has a greater number of words) and more learnable with a greater number of speakers (e.g., Bromham et al., 2015; Lupyan & Dale, 2010; see Muthukrishna & Henrich, 2016), and that communication may become optimally compressible—maximizing efficiency without sacrificing expressivity and meaning—over time (Ferrer-i-Cancho et al., 2013). One intriguing notion, then, is that popular music may facilitate relatively increased lyrical compressibility without sacrificing expressivity. In music, the form-function link may be universally recognizable, with Americans able to infer the function (e.g., dance, infant care, healing) of short snippets of music from even diverse small-scale and non-English speaking societies (Mehr, Singh, York, Glowacki, & Krasnow, 2017). Thus, relative to spoken language, song lyrics could perhaps be compressed more without sacrificing expressivity precisely because the melody communicates some of the meaning of the music; that is, greater lyrical compressibility could perhaps remain non-degenerate (i.e., able to maintain meaning conveyance) at a lower threshold than could spoken language.

Additional future research should also seek to assess the CCH using data drawn from societies other than the US. Although such an endeavor is beyond the scope of the present manuscript, it will be worthwhile to see if the relationships observed in the present work (drawn largely from American data) hold in regions of the world with different cultural values and practices and different ecological conditions. Although some cultural shifts in the past several decades appear to be fairly global in nature, such as rising individualism (Santos, Varnum & Grossmann, 2017), this need not be the case for all dimensions of culture. Future work may also use in-lab methods to explore and disentangle the possible causal mechanisms underlying the link between information saturation and simplicity preferences. For example, transmission chain methods (Mesoudi & Whiten, 2008) could be employed to explore whether participants might find simpler lyrics more pleasing and memorable when there is a greater number of other song-snippets competing for attention versus when there is not.

References

Bargh, J. A. (1989). Conditional automaticity: Varieties of automatic influence in social perception and cognition. *Unintended thought*, *3*, 51-69.

Bartlett, F. C. (1932). Remembering: An experimental and social study. *Cambridge: Cambridge University Press*.

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*(4), 567.

Bornstein, R. F. (1989). Exposure and affect: overview and meta-analysis of research, 1968–1987. *Psychological bulletin*, *106*(2), 265.

Boyd, R., & Richerson, P. J. (1988). *Culture and the evolutionary process*. Chicago: University of Chicago press.

Brand, C. O., Acerbi, A., & Mesoudi, A. (2019). Cultural evolution of emotional expression in 50 years of song lyrics. *Evolutionary Human Sciences*,

Bromham, L., Hua, X., Fitzpatrick, T. G., & Greenhill, S. J. (2015). Rate of language evolution is affected by population size. *Proceedings of the National Academy of Sciences, 112*, 2097–2102.

Chater, N., & Vitányi, P. (2003). Simplicity: A unifying principle in cognitive science?. *Trends in cognitive sciences*, *7*(1), 19-22.

Cooper, V. W. (1985). Women in popular music: A quantitative analysis of feminine images over time. *Sex roles*, *13*(9-10), 499-506.

Cowan, N. (2001). Metatheory of storage capacity limits. *Behavioral and brain sciences*, *24*(1), 154-176.

DeWall, C. N., Pond Jr, R. S., Campbell, W. K., & Twenge, J. M. (2011). Tuning in to psychological change: Linguistic markers of psychological traits and emotions over time in popular US song lyrics. *Psychology of Aesthetics, Creativity, and the Arts*, *5*(3), 200.

Diamond, S., Bermudez, R., & Schensul, J. (2006). What's the rap about ecstasy? Popular music lyrics and drug trends among American youth. *Journal of Adolescent Research*, *21*(3), 269-298.

Dissanayake, E. (2000). Antecedents of the temporal arts in early mother-infant interaction. *The origins of music*, 389-410.

Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes*. Harcourt Brace Jovanovich College Publishers.

Eastman, J. T., Pettijohn, I. I., & Terry, F. (2015). Gone country: An investigation of Billboard country songs of the year across social and economic conditions in the United States. *Psychology of Popular Media Culture*, *4*(2), 155.

Ferrer-i-Cancho, R., Hernández-Fernández, A., Lusseau, D., Agoramoorthy, G., Hsu, M. J., & Semple, S. (2013). Compression as a universal principle of animal behavior. *Cognitive Science*, *37*(8), 1565-1578.

Fiske, S. T., & Taylor, S. E. (2013). *Social cognition: From brains to culture*. Sage.

Grossmann, I., & Varnum, M. E. (2015). Social structure, infectious diseases, disasters, secularism, and cultural change in America. *Psychological Science*, *26*(3), 311-324.

Hayakawa, S. I. Popular songs vs. the facts of life. In B. Rosenberg & D. M. White (Eds.), *Mass culture: The popular arts in America*. Glencoe, I11.: Free Press, 1957.

Henrich, J. (2015). *The secret of our success: how culture is driving human evolution, domesticating our species, and making us smarter*. Princeton University Press.

Hobday, M. (1998). Product complexity, innovation and industrial organisation. *Research policy*, *26*(6), 689-710.

Hyden, C., & McCandless, N. J. (1983). Men and women as portrayed in the lyrics of contemporary music. *Popular Music & Society*, *9*(2), 19-26.

Iyengar, S. S., & Kamenica, E. (2010). Choice proliferation, simplicity seeking, and asset allocation. *Journal of Public Economics*, *94*(7-8), 530-539.

Johnson, S. (2005). Everything Bad is Good for You: How Popular Culture is Making Us Smarter. Penguin: London.

Jordan, K. N., Sterling, J., Pennebaker, J. W., & Boyd, R. L. (2019). Examining long-term trends in politics and culture through language of political leaders and cultural institutions. *Proceedings of the National Academy of Sciences*, *116*(9), 3476-3481.

Kirby, S., Cornish, H., & Smith, K. (2008). Cumulative cultural evolution in the laboratory: An experimental approach to the origins of structure in human language. *Proceedings of the National Academy of Sciences*, *105*(31), 10681-10686.

Kirby, S., Tamariz, M., Cornish, H., & Smith, K. (2015). Compression and communication in the cultural evolution of linguistic structure. *Cognition*, *141*, 87-102.

Lambert, B., Kontonatsios, G., Mauch, M., Kokkoris, T., Jockers, M., Ananiadou, S., & Leroi, A. M. (2020). The pace of modern culture. *Nature Human Behaviour*, 1-9.

Lupyan, G., & Dale, R. (2010). Language structure is partly determined by social structure. *PloS one*, *5*(1).

Margulis, E. H. (2014). Verbatim repetition and musical engagement. *Psychomusicology: Music, Mind, and Brain*, *24*(2), 157.

Margulis, E. H. (2013). Aesthetic responses to repetition in unfamiliar music. *Empirical Studies of the Arts*, *31*(1), 45-57.

Marshall, S. R., & Naumann, L. P. (2018). What's your favorite music? Music preferences cue racial identity. *Journal of Research in Personality*, *76*, 74-91.

Mehr, S. A., & Krasnow, M. M. (2017). Parent-offspring conflict and the evolution of infant-directed song. *Evolution and Human Behavior*, *38*(5), 674-684.

Mehr, S., Singh, M., York, H., Glowacki, L., & Krasnow, M. (2017). Song Excerpts. https://osf. io/5x3qv/

Mesoudi, A., & Whiten, A. (2008). The multiple roles of cultural transmission experiments in understanding human cultural evolution. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1509), 3489-3501.

Morris, C. (2014). Pop music is stuck on repeat (TedXPenn) [Video file]Retrieved from https://www.youtube.com/watch?v=_tjFwcmHy5M.

Muthukrishna, M., & Henrich, J. (2016). Innovation in the collective brain. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *371*(1690), 20150192.

Norenzayan, A. (2006). Evolution and transmitted culture. *Psychological Inquiry*, *17*(2), 123-128.

North, A. C., Krause, A. E., & Ritchie, D. (2020). The relationship between pop music and lyrics: A computerized content analysis of the United Kingdom's weekly top five singles, 1999–2013. *Psychology of Music*, 0305735619896409.

Oishi, S., Kesebir, S., & Diener, E. (2011). Income inequality and happiness. *Psychological Science*, *22*(9), 1095-1100.

Oishi, S., Miao, F. F., Koo, M., Kisling, J., & Ratliff, K. A. (2012). Residential mobility breeds familiarity-seeking. *Journal of Personality and Social Psychology*, *102*(1), 149.

Pettijohn, T. F., & Sacco Jr, D. F. (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*(3), 297-311.

Pettijohn, T. F., & Sacco Jr, D. F. (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*(2), 155-179.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and persuasion* (pp. 1-24). Springer New York.

Rubin, D. C. (1997). *Memory in oral traditions: The cognitive psychology of epic, ballads, and counting-out rhymes*. Oxford: Oxford University Press.

Rasmussen, E. E., & Densley, R. L. (2017). Girl in a Country Song: Gender Roles and Objectification of Women in Popular Country Music across 1990 to 2014. *Sex Roles*, *76*(3-4), 188-201.

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.

Rentfrow, P. J., & Gosling, S. D. (2006). Message in a ballad: The role of music preferences in interpersonal perception. *Psychological Science*, *17*(3), 236-242.

Rentfrow, P. J., & Gosling, S. D. (2007). The content and validity of music-genre stereotypes among college students. *Psychology of music*, *35*(2), 306-326.

Riesman, D. Listening to popular music. In B. Rosenberg & D. M. White (Eds.), *Mass culture: The popular arts in America*. Glencoe, Ill.: Free Press, 1957.

Rychlowska, M., Miyamoto, Y., Matsumoto, D., Hess, U., Gilboa-Schechtman, E., Kamble, S., ... & Niedenthal, P. M. (2015). Heterogeneity of long-history migration explains cultural differences in reports of emotional expressivity and the functions of smiles. *Proceedings of the National Academy of Sciences*, *112*(19), E2429-E2436.

Schellenberg, E. G., & von Scheve, C. (2012). Emotional cues in American popular music: Five decades of the Top 40. *Psychology of Aesthetics, Creativity, and the Arts*, *6*(3), 196.

Santos, H. C., Varnum, M. E., & Grossmann, I. (2017). Global increases in individualism. *Psychological Science*, *28*(9), 1228-1239.

Tamariz, M., & Kirby, S. (2015). Culture: copying, compression, and conventionality. *Cognitive science*, *39*(1), 171-183.

Tiokhin, L., & Hruschka, D. (2017). No evidence that an Ebola outbreak influenced voting preferences in the 2014 elections after controlling for time-series autocorrelation: A Commentary on Beall, Hofer, and Schaller (2016). *Psychological Science*, *28*(9), 1358-1360.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124-1131.

Twenge, J. M., & Park, H. (2017). The Decline in Adult Activities Among US Adolescents, 1976–2016. *Child Development*.

Varnum, M. E. W., & Grossmann, I. (2016). Pathogen prevalence is associated with cultural changes in gender equality. *Nature Human Behaviour*, *1*(1), 003.

Varnum, M. E. W., & Grossmann, I. (2017). Cultural change: The how and the why. *Perspectives on Psychological Science*, *12*(6), 956-972.

Varnum, M. E. W., & Grossmann, I. (2019). The wealth -> life history -> innovation account of the industrial revolution is largely inconsistent with empirical time series data. *Behavioral and Brain Sciences, 42,* e212.

Youngblood, M. (2019). Cultural transmission modes of music sampling traditions remain stable despite delocalization in the digital age. *PloS one*, *14*(2).

Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology*, *9*(2), 1-27.

Zajonc, R. B. (2001). Mere exposure: A gateway to the subliminal. *Current Directions in Psychological Science*, *10*(6), 224-228.

## Supplementary Materials

### Lyrical Compressibility

We sought out the lyrics for all songs that entered the Billboard Hot 100 from its inception (in 1958) until the end of 2016. Data collection took place in mid 2017 and some song were retrieved from 2017, however we included only data through 2016 in order to ensure comparability of the data across years, partial 2017 data is available at (https://osf.io/qnsmj/) but was not used in any analyses reported in this paper. We used billboard.py to access metadata for charting songs, and sought out the corresponding lyrics by visiting lyrics websites. Of the 27,404 songs that charted in this interval, we were able to glean quality lyrics for slightly more than half ($N$ = 14,661).

We stored the lyrics of each song in an ASCII text file. A song's uncompressed size was simply the size of its text file in bytes. (Or, equivalently, its length in characters.)

We compressed each file using the software gzip (www.gzip.com) with the -9 option (maximum compression, at the cost of speed). Importantly, we do not consider the results of the full DEFLATE compression implemented by gzip, which consists of an LZ77 step followed by a Huffman coding step. The former exploits repeated substrings in the input text to produce a more compact representation. The latter exploits varying character frequencies, which is unlikely to bear on a listener's perception of repetitiveness or redundancy. Instead, we used the software infgen (https://github.com/madler/infgen) to parse the LZ77 structure from the compressed encoding produced by gzip, bypassing the Huffman coding step.

We counted text that was untouched by LZ77 in the normal way (1 byte per character). We counted each match (i.e. each reference to an earlier substring) as costing 3 bytes. This accords closely with the reality of typical implementations of LZ77 (in terms of number of bits used to encode match length and distance), but more importantly, it's appropriate to our data.

If we classify repeated strings as "true" repetitions (i.e., deliberate repetitions used to some poetic effect which listeners will perceive as such), and artefactual or incidental repetitions (e.g., repetitions of minor function words like "the" or "and" in unrelated contexts, or simply character ngrams that are common in English morphology, like "ing", or "er"), then we're faced with a trade-off between precision and recall, for which the cost of a match acts as a fulcrum. Smaller costs increase recall at the cost of precision and vice versa. 3 bytes is small enough to allow matches on some short content words, but these are relatively inefficient. A match of the shortest length (e.g., "then") turns a 4 byte string into 3 bytes, for a reduction of 1 byte or 25%. A match of length 6 (e.g., "lovers") gives a 50% reduction. These savings pale compare to the long repeated sections that abound in pop lyrics; for example, the chorus of "Call Me Maybe" which repeats 4 times and is compressed 98%.

**Compressibility of Successful Song Lyrics vs. All Song Lyrics**

It is worth noting that the measure of average lyrical compressibility was restricted to songs that were highly successful, those among that were among the Top 100 for sales and streaming during a given year. Patterns of average compressibility for this subset of songs may differ from those for *all* songs produced in a given year. To our knowledge, no such comprehensive database of all song lyrics organized by year of release exists, but it may become available in the future. Further, the primary focus of the present study was how the characteristics of successful cultural products may vary as a function of number of choices in the environment, rather than how *all* cultural products might vary in such conditions. Future research may explore whether the cross-temporal dynamics in the features of cultural products are systematically different among products that succeed vs. all such products.

**Tiohkin-Hruschka Corrected p-values.**

We computed corrected p-values for the key correlations between measures of amount of music per year and average lyrical compressibility to account for the fact that our time series were non-stationary using the Tiokhin-Hurschka method (*20*). Hot 100 songs had first order autocorrelation of .806, Discogs releases had first order autocorrelation of .953, Wikipedia entries had first order autocorrelation of .935, and lyrical compressibility had first order autocorrelation of .869. The Tiokhin-Hruschka method creates significance thresholds for correlations that are adjusted for the autocorrelation observed in the time series by generating a bootstrapped null-distrubtion for 10000 datasets containing the same amount of data points and the same degree of autocorrelation as observed in the actual time series. Thus, this method can be used to create *p*-values adjusted for the degree to which autocorrelation is present in time series. R code and resulting adjusted significance thresholds are provided below:

```
###Compressibility & Hot 100 songs###
> simnum<-10000
> simul <- matrix(nrow=simnum, ncol=1, 0)   >   > for (i in 1:simnum){
+ ar.sim<-arima.sim(model=list(ar=c(.869)),n=59)
+ ar.sim2<-arima.sim(model=list(ar=c(.806)),n=59)
+ simul[i] <- cor(ar.sim,ar.sim2)
+}
> hist(simul)
> quantile(simul,c(0.005,0.995))
      0.5%      99.5%
-0.6318524  0.6364586
###Compressibility & Discogs releases###
> simnum<-10000
> simul <- matrix(nrow=simnum, ncol=1, 0)   >   > for (i in 1:simnum){
+ ar.sim<-arima.sim(model=list(ar=c(.869)),n=59)
+ ar.sim2<-arima.sim(model=list(ar=c(.953)),n=59)
+ simul[i] <- cor(ar.sim,ar.sim2)
+}
> hist(simul)
> quantile(simul,c(0.0005,0.9995))
0.05%     99.95%
-0.8220027  0.8136738
###Compressiblity & Wikipedia entries###
> simnum<-10000
> simul <- matrix(nrow=simnum, ncol=1, 0)   >   > for (i in 1:simnum){
+ ar.sim<-arima.sim(model=list(ar=c(.869)),n=59)
+ ar.sim2<-arima.sim(model=list(ar=c(.935)),n=59)
+ simul[i] <- cor(ar.sim,ar.sim2)
+}
> hist(simul)
> quantile(simul,c(0.0005,0.9995))
     0.05%     99.95%
-0.8148316  0.8129081
###Compressibility & PCA-based Music Production Composite###
> simnum<-10000
> simul <- matrix(nrow=simnum, ncol=1, 0)
>
> for (i in 1:simnum){
+ ar.sim<-arima.sim(model=list(ar=c(.869)),n=59)
+ ar.sim2<-arima.sim(model=list(ar=c(.919)),n=59)
+ simul[i] <- cor(ar.sim,ar.sim2)
+ }
> hist(simul)
> quantile(simul,c(0.0005,0.9995))
     0.05%     99.95%
-0.8116713  0.7866148
```

**Table S1. Zero-order correlations.** Zero-order Pearson correlations for time-series variables

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1.Year** | - | | | | | | | | | | |
| **2.Lyrical Compressibility** | .894*** | - | | | | | | | | | |
| **3.Total Songs Hot 100** | .678*** | .686*** | - | | | | | | | | |
| **4.Total Songs Discogs** | .994*** | .889*** | .683*** | - | | | | | | | |
| **5.Total Songs Wikipedia** | .932*** | .872*** | .792*** | .936*** | - | | | | | | |
| **6.Pathogen Prevalence** | -.864*** | -.663*** | -.539*** | -.875*** | -.823*** | - | | | | | |
| **7.Climatic Stress** | -.197 | -.132 | .022 | -.186 | -.162 | .243 | - | | | | |
| **8.Major Armed Conflict** | .326* | .308* | .519*** | .359** | .480*** | -.476*** | -.052 | - | | | |
| **9. Unemploy-ment** | .162 | .211 | .314* | .152 | .205 | .084 | .155 | -.037 | - | | |
| **10. Immi-gration** | .816*** | .672*** | .442*** | .803*** | .745*** | -.701*** | -.274* | -.309* | .128 | - | |
| **11. Residential Mobility** | -.937*** | -.882*** | -.745*** | -.948*** | -.955*** | .822*** | .115 | -.512*** | -.183 | .713*** | - |

*Notes. N*'s for correlations range from 45-59. ***p < .001, **p < .01, *p < .05