

## **A Comparative Analysis of Melodic Rhythm in Two Corpora of American Popular Music**

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This paper compares two corpora of melodies drawn from premillennial and postmillennial American popular music, and identifies several notable differences in their use of rhythm. The premillennial corpus contains melodies written between 1957–1997 (deClercq and Temperley 2011), while the postmillennial corpus (compiled for this study) consists of songs popular between 2015–2019. For both corpora, we analyzed 1) the distribution of note onsets within measures; 2) the distribution of four-note rhythmic cells, 3) the speed of melodic delivery, and 4) the tempo of the tactus. Our analyses indicated that the postmillennial melodies are delivered more quickly, are distributed more evenly throughout their measures, repeat rhythmic cells more frequently, and are annotated at slower tempos. Even when the tactus tempos were standardized into an allowable window of 70–140 BPM, this effect, though smaller, remained. We then use our techniques to observe the properties of three representative postmillennial tracks, finding that salient information can be located in both standardized and non-standardized tactus data, and that tempo-variant differences between corpora are closely connected to musical genre, with music designated as "pop" being more similar over both genres, and postmillennial rap and hip-hop introducing the most uniqueness.

**Keywords:** popular music; rhythm; meter; melody; corpus analysis; text

*2010 Mathematics Subject Classification:* 00A65; 62P15; 91E10; 94A17

*2012 Computing Classification Scheme:* Applied computing Sound and music computing

## 1. Introduction

In the last several decades, American popular music has undergone a number of stylistic shifts that distinguish it from previous popular genera. In particular, analysts of 20th-century popular music note a change in both the musical materials used in popular songs (Temperley 2018; Duinker 2021; White and Quinn 2015), as well as in the styles considered “mainstream” by influential compendia, in particular the Billboard charts (Burgoyne, Wild, and Fujinaga 2013; Sloan and Harding 2021). Recent scholarship has argued that such changes in contemporary popular music are at least in part due to the increasing influence of rap and hip hop, especially in the way that melodic materials are conceived and constructed (Barna 2019; Peres 2016; Duinker 2020a,b).

To investigate some aspects of this stylistic shift, this paper compares two popular-music corpora: 1) a corpus of 20th-century American popular-music melodies (deClercq and Temperley 2011), and 2) a new corpus of postmillennial melodies drawn from the five highest-ranked songs on the “Billboard Top 100” for each year, 2015–2019. We investigate aspects of the syllabic density, metric placement, and rhythmic motives in these repertoires; our analyses show that recent music involves a quicker melodic delivery, more repetition of its constituent rhythmic cells, a more even distribution of note attacks within its measures, and a slower tactus. Further analysis, however, shows that these differences are heavily dependent upon the chosen tactus, a choice influenced by multiple factors, including the competition between baseline tempo preferences and metrically-suggestive backbeat patterns, something which heavily interacts with notions of musical genre.

## 2. Computational investigations of melodic rhythm

Several previous computational and corpus-based projects have investigated melodic rhythm in the service of a variety of related research questions. For instance, much of this work has focused on how linguistic and national traditions influence the rhythms used in song melodies (VanHandel 2006; VanHandel and Song 2009; Temperley and David 2011), and as well as their expressions of meter (VanHandel 2009; VanHandel and Song 2010), finding in many cases that the pacing of syllables in a spoken language influences the rhythmic patterns used in the melodies of songs in that language. This line of inquiry has been extended into instrumental melodies (Daniele and Patel 2013), although Temperley (2017) has called into question the validity of such extensions. Relatedly, several corpus studies have also focused on how particular musical styles and genres use characteristic melodic rhythms to distinguish themselves from other repertoires. Volk and de Haas (2013) and Koops, Volk, and de Haas (2015), for instance, study a corpus of ragtime melodies and find that the frequency of certain patterns of syncopation change through the decades spanning that genre’s popularity, while Michelson, Xu, and Kirilin (2017) use a corpus-based generative model to transform common-practice musical sequences into ragtime rhythms, which – when subjected to human assessment – conform relatively well to listeners’ expectation of that style. Similarly, Huron and Ommen (2006) identify an increase in syncopation in American popular music between 1890 and 1939, but find that no particular type of syncopation is associated with this increase, while Temperley (2019) finds that “second position syncopation” (or, syncopation that emphasizes the weak pulse immediately after a strong pulse) is particularly prevalent in British 19th-century folk music and early 20th century American popular music, suggesting an influence between these two repertoires. On the other hand, Tan, Lustig, and Temperley (2018) study “anticipatory” syncopation (or, syncopation that occurs before a metrically-strong event) is particularly evident in rock music, notably taking an approach that foregrounds syllable stress in their quantification of syncopation. Applying many

of these techniques to transcribed instrumental solos within 20th-century jazz, [Abrams \(forthcoming\)](#) finds that the density and predictability of accents (rather than the usage of particular rhythmic patterns) seems to increase over time, with the notable exception of tunes marketed to mainstream audiences. And while the current study will focus on rhythmic features, parameters such as timbre and loudness ([Serrà et al. 2012](#)), sonic change ([Matthias et al. 2015](#)), and pitch and harmonic phenomena have also been used to distinguish popular music styles from one another ([Sears and Forrest 2021](#); [White 2022](#)).

Computational modeling of melodic rhythm has also been used to make some broader arguments about connections between genre, rhythm, and meter. [Esparza, Bello, and Humphrey \(2015\)](#) link musicological observation with computational modeling to argue that genre classification is often simply an approximation of rhythmic similarity, while [Volk and van Kranenburg \(2012\)](#) investigate this contention by testing which musical characteristics of melodies best align with expert ratings of similarity, finding that rhythm plays an important (but not exclusive) role in these similarity assessments. [Gómez, Thul, and Toussaint \(2007\)](#) investigate the representation and perception of rhythm – and particularly syncopation – to show which models of syncopation seem to align with human assessments of rhythmic dissonance; they find that formalizations based on participant ratings outperform those that are simply based on mathematics. Taking an even-more theoretical stance, [Temperley \(1999\)](#), [Sioros, Davies, and Guedes \(2018\)](#), and [Rohrmeier \(2020\)](#) each in their own way theorize the way that the complex and variegated rhythms of surface melodies can be both related to underlying metrically-regular templates and can be culturally and stylistically influenced.

Scholarship on spoken music has also focused on the rhythms of syllable delivery. [Ohriner \(2019\)](#) makes an in-depth investigation of how parameters like rhythmic density, motivic cells, micro timing, phrase length, and rhyme contribute to the musical expression of rap. [Adams \(2009\)](#), [Condit-Schultz \(2016\)](#) and [Gilbers et al. \(2020\)](#) focus on how these parameters might change over time and show regional differences in rap practice, while [Komaniecki \(2021\)](#) investigates the role of pitch height in rap delivery. In a similar vein, [Breen, Weidman, and Guarino \(2014\)](#) and [Breen \(2018\)](#) study the rhythm with which parents read the poetry of Dr. Seuss to children, and show how duration and emphasis can provide an impression of meter and phrasing. Popular music scholarship has also focused on how melodic parameters change between verses and chorus, with studies noting that the melodies of verses tend to be more rhythmically dense, less aligned with the underpinning harmonies, and less rhythmically regular than choruses ([Temperley 2007](#); [Nobile 2015](#); [Temperley 2018](#); [Arthur and Condit-Schultz 2021](#)). The role of clock time within popular music has also been used to show how absolute duration might influence the formal design of a track ([White 2021](#)) and in how the absolute duration of measures and beats changes over the span of the 20th century ([Tan, Lustig, and Temperley 2018](#); [deClercq 2016](#); [Temperley 2018](#)).

Another crucial component of rhythmic and metric analysis in popular music studies concerns the song's *tactus*, or, a song's primary felt pulse. Given that popular music is generally not notated – at least not in a way that is a primary component of its performance and consumption ([Moore 2001](#); [Temperley 2018](#)) – decisions about which pulse level to associate with each metric level are left to the analyst. For instance, consider a song with three levels of pulses that group or divide one another by a factor of two. In this instance, one pulse might sound at 124 beats per minute, which is then grouped by a twice-as-long pulse at 66 BPM while being divided by a twice-as-short pulse at 248 BPM: should the measures be notated as four beats of a 66-BPM quarter notes? Or with quarter notes at 124 BPM? Several approaches to metric identification focus on the *backbeat* drum patterns that are nearly ubiquitous in this repertoire as a means to orient a *tactus*. Backbeat patterns feature high energy and high pitched percussive hits (often a snare drum) on beats 2 and 4 of quadruple pattern; this predictable pattern can be used to identify measure length by aligning the second and fourth quarter-measure pulse with those backbeats

(Moore 2001; Stephenson 2002), an approach that has historical (Tamlyn 1998) and well as embodied (Attas 2014; Toiviainen et al. 2009; Toiviainen, Luck, and Thompson 2010) evidentiary support. However, other work has argued that a song’s tactus should be identified within a set range of BPMs. Notably, perceptual experiments consistently identify a tempo window around 100 BPM as the most comfortable default at which humans tap their hands and feet to music (London 2004), while deClercq (2016) has argued that contemporary popular music centers around a pulse of 120 BPM. DeClercq furthermore argues that focusing purely on a backbeat-oriented tactus can obscure similarities and trends within rock/pop corpora that are more clearly observed when selecting the pulse layer closest to 120 BPM as the tactus. (Anecdotally, such an approach appears to be reflected in online BPM search engines: a survey of websites such as tunebat.com, getsongbpm.com, songbpm.com reveals a default preference to assess a track’s tempos roughly within deClercq’s preferred range.) Finally, the very notion of a single “correct” tactus in this repertoire is questioned by several sources, most recently Geary (2021), who argues that interpretive content can be derived from both definitions of the tactus, especially in songs whose pacing or drum patterns suggest multiple possible pulses as candidates for the tactus.

Our investigation explores the changes within text and melodic declamation in contemporary American popular music, and in so doing positions itself among each of these overlapping trends. In what follows, we describe an approach that compares premillennial and postmillennial melodic construction using various parameters, including the positions of note onsets within measures (i.e., similar to the syncopation work of Volk and de Haas (2013), Koops, Volk, and de Haas (2015), Tan, Lustig, and Temperley (2018), and Temperley (2019)), rhythmic cells and the intervals between melodic attacks (similar to VanHandel (2006), VanHandel and Song (2009) and Temperley (2017)), and the overall distribution of events within a metric grid (similar to the investigations of Temperley (2018), Arthur and Condit-Schultz (2021) and Ohriner (2019)). Finally, interacting with the issues of tempo and tactus (deClercq 2016; Geary 2021), we will examine the role that speed and pacing play in our datasets. It should also be noted that we aim to situate this research in such a way that it can be extended into various other lines of inquiry. We therefore construct our corpus such that it may be used to investigate various aspects of melodic construction, including the disposition of syllabic accents (i.e., similar to Abrams (forthcoming), Tan, Lustig, and Temperley (2018), Breen, Weidman, and Guarino (2014) and Breen (2018)), rhyme (Ohriner 2019; Condit-Schultz 2016), and melody/contour (Komaniecki 2021). In what follows, we describe the datasets under consideration, including our newly-constructed corpus of postmillennial melodies.

### 3. The Corpora

Two corpora of popular music were used in this study, one premillennial and one postmillennial. The corpus of 20th-century American popular-music melodies is drawn from the work of deClercq and Temperley (2011), and consists of 200 melodies drawn from the Rolling Stone’s “500 Greatest Songs of All Time.” The corpus includes songs from 1955 to 1997 and represents its constituent melodies using pitch and scale degree information, along with each melody note’s position within its measure, its corresponding measure number, and its clock-time position within the track. Clock-time positions for each measure’s onset was also provided. Eight songs were removed from the following analysis because they were annotated in compound or triple meter, or included some encoding error.

The postmillennial corpus consists of the 25 songs that appear at the five-highest ranked positions on the Billboard Top 100 for each year between 2015 and 2019. We annotated songs in Praat (Boersma and Weenink 2019) with multiple layers of pitch, meter, and accent information. To align with the the 20th-century corpus, only songs in quadruple meter were considered,

which excluded 1 song from the analyses and yielded a final dataset of 24 songs. We identified downbeats and measures by a) listening to the track to identify the metric levels associated with the tactus and measure, b) tagging the onsets of measures in the audio signal, and c) running an automated process that divided these measures into smaller pulses, continuing until the measure is divided into sixteenths. (This automated process was developed by Prof. Kristine Yu of the UMass Amherst Linguistics department.) An encoder’s judgment was supplemented by referencing the percussive backbeat pattern in the tracks (as described above). Encoders then added text to the Praat file in two layers. The first layer used the metric divisions, and either aligned text with the existing metric boundaries, or further divided those durations into smaller (quicker) rhythms, and aligned text with those divisions. (This step roughly corresponds to transcribing a melody into metrically-aligned notation.) For analysis, this layer was converted to text strings that followed the format of the premillennial corpus. A microtimed layer was also annotated, aligning syllables with their onset in the sound signal, a method similar to that of Adams (2008, 2009). We also added further accent annotations: while the syllables, accent patterns, and micro-timing information were not used in the current study, they were undertaken to support future work on prosody usage and melody construction in this repertoire. Research assistants annotated each file, and the annotations were checked by the authors, with disagreements resolved by group discussion. A full list of the songs used can be found in our online supplement at [chriswmwhite.com/popannotations](http://chriswmwhite.com/popannotations)).

For this analysis, genres were associated with each song in the postmillennial corpus using Spotify’s (Spotify.com) genre labels as rendered through its API via [chasic.com/music-genre-finder](http://chasic.com/music-genre-finder). Genre was initially encoded by choosing the most general designator, with “generality” being defined broadly as the designation with the fewest adjectives (i.e., “pop” would be more general than “adult pop”; “hip hop” is more general than “Minnesota hip hop.”) This method assigned over half of our corpus as “pop,” but introduced some ambiguity when choosing between the frequent co-occurrences of the rap, hip-hop, and trap genres. (This difficulty reflects the complications and slippage in contemporary genre designations outlined by Bradby (1993); McLeod (2001); Drott (2013); Butler (2006); and Komaniecki (2021).) To somewhat sidestep this issue, we added – and subsequently used – a broader genre registration for each song: the binary *pop* versus *not pop*. The latter category primarily contained songs from the rap/hip-hop/trap constellation, but also contained one song whose most general designation was “rock.”

Given that our analyses rely on metric and durational information, we assigned tempo and tactus in two ways. Our *non-standardized* data used the BPMs and measure lengths as reported in each corpus. This approach roughly corresponds to the backbeat-oriented definitions of tactus, outlined above. We also created *tempo standardized* data by shifting all songs’ tactuses to be between 70 and 140 beats per minute. Every song in either corpus with tempos faster than that window would be readjusted to half the initial BPM; conversely, every song whose tactus was paced slower than 70 BPM would be readjusted to consider events at twice that tempo as instantiating its tactus. This approach corresponds to a definition of tactus reliant on an invariant window of preferred tempos. The effects of this standardization on the ensuing analyses are considered below, as are the tempo distributions of the standardized songs in each corpus.

#### 4. Quantitative Analyses

The following analyses will rely on five features for the comparison of these two datasets: the tempo of the tactus, the speed of melodic delivery, the position of note onsets within measures, the repetition of rhythmic cells, and the variations between genres. In what follows, we analyze aspects of each feature in these corpora and compare and contrast the results. These analyses often rely on the comparison of means or use  $X^2$  distributions; because of the size of the post-

millennial corpus and to sidestep potential concerns about normalcy, bootstrapping was used in all means comparisons, and the bias corrected accelerated (BCa) confidence intervals from those tests are reported (Hall 1988).

#### 4.1. *Tempo and Density*

Table 1 shows several measurements of the pace of melodic delivery in these two corpora (along with several other parameters that will be subsequently discussed). The first column shows a measure of the melodies' speed of delivery: their events per second (EPS). For this calculation, we divided each corpus into its constituent measures. We removed measures containing no events, tallied the number of events within the remaining measures, and divided that number by the clock-time duration of the measures containing events. The arithmetic means of these values for each corpus are shown, along with the 95% confidence interval reported by the bootstrapping method. As this measurement of speed is not effected by tempo standardization (it is dependent on clock time, not which level is considered the tactus), the numbers are reported only in the chart. The later corpus delivers .84 more melodic events per second on average than the earlier corpus, a difference which is both significant according to a two-sided bootstrapped  $t$ -test ( $t(214) = -6.097$ ,  $p < .001$ ) and exhibits a large effect size (Cohen's  $d = .627$ ).

The next column reports beats per minute of the tactus, both with BPM standardized and non-standardized. The arithmetic means of these values in each corpus are shown, again with confidence intervals from the bootstrapping method. (Geometric means were also calculated, and were slightly lower in each instance.) In the standardized condition, the premillennial corpus is marginally faster than the postmillennial corpus: its songs are roughly 4–5 BPM faster.<sup>1</sup> However, this difference is not significant (an unsurprising result given that BPM is the explicitly standardized value in our analysis). The non-standardized average BPM values are significantly different ( $t(214) = 3.766$ ,  $p < .001$ ), with the earlier corpus's songs appearing at a pace roughly 25–29 BPM faster than the later corpus, and a remarkably large effect size (Cohen's  $d = 34.257$ ).

The third column shows a representation of melodic density: the events per measure. The value is the result of the previous two, as slower or faster beats per minute will result in measures with longer or shorter clock-time durations, durations which are then filled according to the EPS pace of melodic delivery. Both standardized and non-standardized comparisons are significant using bootstrapped  $t$ -tests ( $t(214) = -8.877$ ,  $p < .001$ ;  $t(214) = -8.838$ ,  $p < .001$ ); however, given that BPM was not found to be significantly different between the standardized corpora, the difference in density is likely simply to be a fallout of the different EPS pacings. These values show that the combination of tempo and melodic delivery creates measures with roughly 2 more events per measure in the postmillennial data when BPM is standardized, and nearly 3 more events per measure in that corpus when tempo is not standardized. The fourth column then shows the pooled variance of these events per measure, capturing the variation in event density per measure within each corpus. In both standardized and non-standardized conditions, there exists markedly more variance between measures in the postmillennial corpus than in the premillennial corpus. (The final column of Table 1 is a measurement of how uniform the distribution of melodic onsets are within a measure, and shall be discussed in Subsection 4.3.)

These metrics show that songs in the more recent corpus use a quicker pace of melodic delivery, have slower tactuses, tend to have a greater overall density, and feature a wider array of densities within a single track.

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<sup>1</sup>There are arguments in favor of a number of reporting methods in the corpus analysis, machine learning, and popular-music analysis literature. Importantly, the goal of this study is to describe the differences between two corpora, not to claim experimental replicability (the general motivation behind confidence intervals). Throughout this paper, we therefore use a number of methods to describe variance, not with the motivation to claim replicable difference but to describe the difference between two datasets in their manifested versions and suggest provocative corpus properties which may inspire future studies.

Table 1.: Analysis of melodic events in both corpora (with bootstrapped conf. intervals' bounds)

	Events per second (EPM)	Beats per minute (BPM)	Events per measure (EPM)	Variance of EPM	Evenness of metric placement (Metric profile entropy)
1955–1997 (Standardized)	1.87(1.77/1.95)	103.91 (100.88/106.52)	4.294 (4.15/4.44)	1.84	0.81 (0.80/0.83)
2015–2019 (Standardized)	2.71 (2.46/2.93)	99.91 (91.59/108.21)	6.75 (5.99/7.49)	2.91	0.89 (0.86/0.93)
1955–1997 (Non-Stdrdzed)	–	119.53 (114.16/124.62)	4.43 (4.26/4.60)	1.90	0.83 (0.81/0.84)
2015–2019 (Non-Stdrdzed)	–	91.07 (84.33/ 98.35)	7.32 (6.52/ 8.13)	2.94	0.93 (0.89/ 0.95)

#### 4.2. Melodic-metric profiles

A *melodic-metric profile* represents the frequency with which melodic events fall within the measure. Figure 1 shows the melodic-metric profiles for both corpora, with all events averaged over all songs. Values are presented modulo 1: zero represents the downbeat, and subsequent points on the horizontal axis represent sixteenth notes (i.e., .0625 is the sixteenth-note pulse following the downbeat, .5 is the measure’s halfway point, .25 and .75 are the first and third quarter-note events, and so on). This approach tallies the relative proportion with which each melody’s constituent note attacks fall at all points within a measure of 4/4. Only note onsets are used (i.e., this representation does not capture how long notes are held after their attack). Here, solid lines represent standardized data, while dotted lines represent non-standardized data; red lines show premillennial profiles and blue lines show postmillennial profiles. Visually, the contours of these distributions track one another, with eighth-note pulses hosting more events than the intervening sixteenth-note events. However, when using the premillennial corpus’s events to produce the expected values in the postmillennial corpus’s melodic-metric profile using a  $X^2$  distribution, the observed postmillennial events mostly differ from the expected counts in several notable ways. The entire melodic-metric profiles differ significantly when comparing the pre- and postmillennial corpora both in the standardized ( $X^2(15) = 459.63, p < .001$ ) and non-standardized conditions ( $X^2(15) = 200875.54, p < .001$ ). Isolating each metric position within the  $X^2$  test, all observed counts in all individual positions differed significantly from their expected counts using the non-standardized corpus comparisons, but only those marked with an asterisk in Figure 1 differed in the standardized condition. These points includes the downbeat (0), the 5th (.3125), 11th (.6875), 13th (.8125), and 14th (.875) sixteenth pulse; the ninth sixteenth (.5625) was marginally significant at  $p < .1$ ). Note that each of these events are offbeat 16th pulses, with the exception of .875, which is the final eighth-note pulse of the measure. In other words, these differences manifest in ways that correspond to the metric weight of the pulses: proportions of events on the weaker pulses are higher in the postmillennial corpus (i.e., on the offbeat 16th pulses), while this dynamic is swapped on the more accented pulses (i.e., the downbeat and final eighth-note pulse). (Interestingly, while the strongest effects in the  $X^2$  test in the standardized data result from the postmillennial corpus having more onsets than expected on weak pulses, the non-standardized data’s strongest effects arose from stronger pulses hosting fewer melodic attacks than expected!) These findings suggest that the change from the premillennial to the postmillennial profile involves shifting some portion of the profiles’ probability mass from stronger pulses to the weaker pulses, especially away from the downbeat. In sum, the quicker deliveries and slower beats of postmillennial music makes more use of the quicker pulse



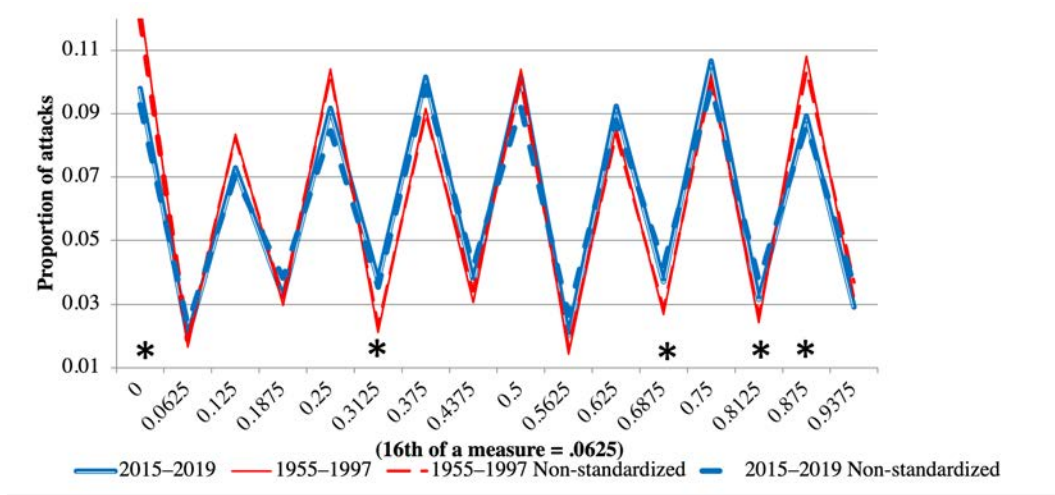


Figure 1.: The melodic-metric profile for both standardized and non-standardized corpora; asterisks indicate significantly different values between the corpora’s standardized profiles.

than does 20th-century popular music.<sup>2</sup>

### 4.3. Entropy, order, and disorder in the metric profiles

Entropy is a measurement of the how equally-distributed some set of probabilities is: the value increases as probability is spread more equally over outcomes. Distributions dominated by a few very-frequent outcomes will feature lower entropies than those with many equally-possible outcomes. As shown in the numerator of Equation 1, the formula for entropy sums the logarithms of each event within a probability distribution ( $\log(p(x_i))$ ) weighted by the overall amount that each event occurs ( $p(x_i)$ ). Standardized entropy (the value of the full equation) then represents the measurement as a proportion of the maximum entropy, which – given that maximum entropy occurs when all events are uniformly distributed and equally probable – is the logarithm of the number of events ( $\log(n)$ ). The resulting value is between 0 and 1, with 1 indicating a maximally complex (evenly distributed) distribution. Standardized entropy will be used for the remainder of this essay.

$$\eta_p(x) = \frac{Entropy}{Entropy_{max}} = \frac{\sum_{i=1}^n \log p(x_i)p(x_i)}{\log(n)} \quad (1)$$

standardized entropy was calculated for the distributions of onsets in each song’s melodic-metric profile. Table 1 shows the average entropy of each corpus’s songs, in both standardization conditions. Here, lower entropy would mean a more skewed distribution, with higher peaks

<sup>2</sup>This is an interesting reversal of the trend noted in [Tan, Lustig, and Temperley \(2018\)](#), in which songs seem to use fewer offbeat sixteenth notes in the later decades in their corpus; they speculate this is because of an increase in average tempo in the later 20th century. However, this quickening of pulse in popular song is also noted in recent hip-hop music in [Duinker \(2020a\)](#). Additionally, the increase in quicker note values tracks with the centuries-long trend associated with quickening metric values in Medieval and Renaissance vocal music identified in [DeFord \(2015\)](#). Additionally, it should be noted that [Tan, Lustig, and Temperley \(2018\)](#) mark the last eighth-note in the measure as a frequent position for syncopation in their analysis of premillennial popular melodies, something evidenced by the relatively high probability mass at that point in our premillennial metric profiles; given that our analysis shows a significant decrease in attacks at that point in the postmillennial profiles, it would seem that this tendency may disappear in postmillennial popular melodies.

and lower valleys in the metric profile; higher entropy would mean a more even distribution, with lower peaks and more shallow valleys in the profile. In both the standardized and non-standardized pairings of the two corpora, the entropies are lower in the premillennial profiles compared to their postmillennial counterparts. This finding quantifies what is visually apparent in Figure 1: because the earlier profiles concentrate more of their onsets on stronger pulses, their level of organization is higher and their probability mass is more centralized in a few outcomes; their evenness and entropy is therefore lower. Conversely, because the postmillennial profiles make greater use of the weakest pulses, their evenness and entropy will be higher. While the entropy of the earlier and later datasets is significantly different under both standardized and non-standardized conditions using bootstrapped  $t$ -tests ( $t(215) = -3.885, p < .001, \text{Cohen's } d = .095$ ;  $t(215) = -4.762, p < .001, \text{Cohen's } d = .094$ , respectively), the absolute difference between the means is greater in the non-standardized versions (.1) compared with the standardized version (.08).

#### 4.4. *Repetition of Rhythmic 4-grams*

To describe some differences between the rhythmic figures used in each dataset, we tracked 4-member rhythmic cells used in each song in both corpora, or what we will call *rhythmic 4-grams*. These 4-grams consist of sequences of metrically situated onsets modulo 1 (that is, following *beat class* nomenclature (Cohn 1992), events are indexed by their position within a measure), following the same designations as used in Figure 1. To investigate the amount of repetition that was used in both corpora, we tracked how often each 4-gram occurred in each piece, and ordered that distribution by frequency rank (most frequent to least frequent). We then measured the relationship between these frequencies by fitting an equation that describes the rate of decrease by rank for these distributions. As suggested in Figure 2, this rate will describe how “front-loaded” a distribution of 4-grams is: if a song is saturated with the same few rhythmic cells, its most-repeated 4-grams will be much more frequent than its less-repeated 4-grams while a song whose internal repetition is more evenly distributed amongst many rhythmic cells would then have a less-steep slope relating its ranked 4-grams. As is often the case in natural linguistic and musical production (Fechner 1951; Zanette 2006), the initial ranks for the 4-gram frequencies follow a sort of exponential curve, with more frequent events occurring exponentially more often than less frequent events. Table 2 fits the frequency distributions of each song’s 50 most-frequent 4-grams to a logarithmic curve, with the penultimate column showing the slope that describes the decrease in 4-grams by rank, averaged over each piece within a corpus. The table’s final column shows the average  $R^2$  for these fitted curves, a value that captures the amount of variance in the data described by the curve. The 95% confidence intervals provided by the bootstrapping method are shown; we also measured the pooled variance of the standard deviations of each individual fitted curve using the square roots of the diagonal of their covariance: this method produced margins of error very similar to the bootstrapping intervals. The relatively high  $R^2$  values indicate that these logarithmic curves are reasonable representations of these data’s frequency distributions. Figure 2 visually depicts the differences that arise in these two distributions. On the one hand, these curves show that the most frequent 4-grams of the later corpus repeat more often than those in the earlier corpus: more probability mass is concentrated under the initial ranks of the later corpus’s curve. On the other hand, while both corpora’s distributions plummet decisively in the less-frequent ranks, the earlier corpus features a less-steep drop, meaning that its 4-grams with middling frequencies occupy relatively more of the overall probability distributions than they do in the later corpus.

Importantly, these differences are roughly the opposite of what one would expect given the greater entropy (i.e., more uniform distribution) of the postmillennial corpus’s melodic rhythmic

Table 2.: Various representations of repetition within both corpus’s rhythmic 4-grams

	Slope of logarithmic curve with 95% conf. intervals from bootstrapping	$R^2$ of logarithmic slopes as geometric mean and median
1955-1997	-4.22 (-4.06/-4.39)	0.92/0.89
2015-2019	-6.93 (-6.81/-7.07)	0.92/0.94

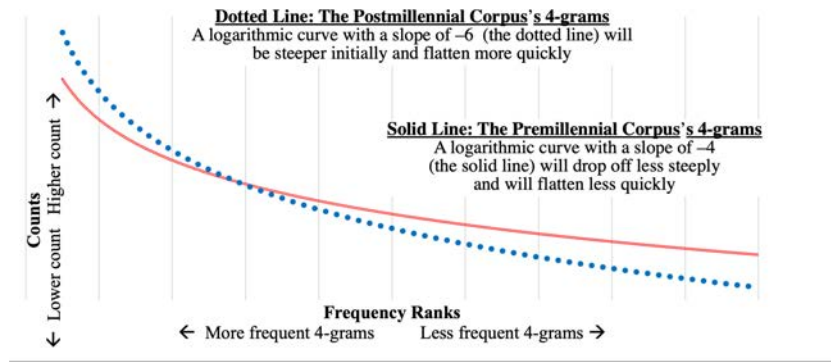


Figure 2.: Generic representation of the different logarithmic curves that describe the rhythmic 4-grams of both corpora.

profile: greater probability mass distributed throughout the measure could indicate that a greater number of rhythmic options are available when constructing rhythmic 4-grams, producing more rhythmic options and more uniform/less repetitive 4-gram practice. However, the opposite appears to be true. While the overall corpus might use more positions within the measure with greater frequency, individual pieces in the postmillennial corpus reuse rhythmic cells relatively more often than the premillennial corpus. We return to the expressive potentials surrounding these observations in Section 6; however, it is worth noting these differences may indicate a greater emphasis on motivic repetition within postmillennial popular music.

#### 4.5. Effects of standardization on the difference between corpora

As suggested by several of the above analyses, the differences between these corpora is affected by whether the tempos of a corpus’s constituent pieces are standardized or not. This section investigates the differences in the outcomes of the standardization procedure when applied to both corpora, and examines the extent to which the procedure reduces or increases the differences between the corpora. We first tested the number of changes made to each dataset by tempo standardization. 12.5% and 27% of songs were standardized (i.e., their BPM was either lower than 70 or higher than 140) in the premillennial and postmillennial corpus, respectively. The number of songs that were standardized did not differ significantly between corpora,  $X^2(1) = 1.178$ ,  $p = .313$ . In the postmillennial corpus, 5.2% of songs were standardized upward (i.e., their BPMs were annotated at less than 70, and their standardized tactus was considered as the pulse twice that BPM) and 22% of songs were standardized downward (i.e., their BPMs were greater than 140 and the standardized tactus was half that tempo). 12.5% of songs were standardized upward in the premillennial corpus and none were standardized downward. Categorizing songs in this manner was significant,  $X^2(2) = 7.649$ ,  $p = .022$ . In sum, while the number of songs standard-

ized in each corpus was not significantly different, more songs were standardized upward in the premillennial corpus than in the postmillennial corpus.

To investigate differences in standardized versus non-standardized data, Table 3 shows two measurements of the difference between the aggregated melodic-metric profiles in each corpus with tempo both standardized and non-standardized. First, we treated the profiles as 16-member coordinates, and calculated the Euclidean distance between them. These values will be symmetrical (the distance between profile A and profile B is the same as between profile B and profile A), and this symmetry is evident around the central diagonal of the table. Due to the fact that all profiles share an overall contour, with more onsets occurring on the eighth pulses than on the intervening sixteenth pulses, none of these distances are especially high. However, standardized and non-standardized profiles of the same corpus are consistently the closest in this representation, followed by the other corpus in the same standardization condition, and finally the alternate corpus with its tempos treated differently. The proximity observed between standardized and non-standardized profiles is not surprising. In both corpora, the majority of pieces are not annotated with tempos below 70 or above 140 BPM, meaning that most of each corpus's underlying tempo-dependent data points remain constant between both standardized and non-standardized representations. However, such comparisons show that the standardization process increases the differences between the two corpus's profiles.

Spearman's rank correlation coefficient  $\rho$  was used to compare the 4-gram distributions of each corpus under both standardization conditions. We first ordered the 4-grams of each version of each corpus by their frequency rank, and selected those 4-grams that maximized their rank over the four datasets, a process done by averaging the ranks across the datasets and isolating those ten trigrams of highest average rank. A correlation matrix was then produced comparing the ranks of each of those trigrams within each dataset. If datasets use the same 4-grams with similar relative frequencies, this consistency will result in similar frequency-ranks orderings of their 4-grams, and their correlation will be high; dissimilar usage of 4-grams will result in a low correlation. All correlations are significant at  $p < .05$ . Once again, the greatest similarities (highest correlations) result from intra-corpus comparisons, while the greatest differences arise from comparing between corpuses. Interestingly, while the 4-grams of standardized corpora are more highly correlated to the standardized versions of the other corpus, non-standardized 4-grams are *less* correlated to non-standardized 4-grams of the other corpus than to that corpus's standardized 4-grams, something which indicates the standardization procedure seems to alter the kinds of 4-grams being used in both corpora in different ways.

These analyses show that, while the standardization process was applied to a similar proportion of both corpora, more tempos were higher than the standardization window in the premillennial corpus and more tempos were lower in the postmillennial. Our comparisons of standardized and non-standardized profiles and 4-grams indicated that – while there exist differences between the standardized versions of the corpora – these differences are increased when the annotated tempos are used. Furthermore, our findings suggest that the standardization procedure alters the constituent 4-grams of each corpus in different ways, likely because of the different prevailing directions of tempo standardization in both corpora. Our analyses of individual pieces that end this essay will return to some of these topics to investigate the extent to which tempos outside of the standardization window may or may not be justified as legitimate tactuses; but first, we turn our attention to the role of genre in our musical comparisons.

#### 4.6. *Genre*

The earlier analyses indicate that notes per second, BPM, 4-gram repetition, and the melodic-metric profiles' entropies seem to differ between the premillennial and postmillennial corpora. In

Table 3.: Two ways of measuring similarity between the melodic/rhythmic events of each corpus: 1) Euclidean distance, and 2) Spearman’s  $\rho$  comparing the ranks of the 10 most-frequent 4-grams in each corpus

	1955–1997 standardized	1955–1997 non-standardized	2015–2019 standardized	2015–2019 non-standardized
1955–1997 standardized	—	0.01 / 0.99	0.05 / 0.12	0.06 / 0.00
1955–1997 non-standardized	0.01 / 0.99	—	0.04 / 0.09	0.05 / -0.05
2015–2019 standardized	0.05 / 0.12	0.04 / 0.09	—	0.02 / 0.96
2015–2019 non-standardized	0.06 / 0.00	0.05 / -0.05	0.02 / 0.96	—

this section, we ask whether these differences appear to be concentrated in either of our generic categories. We therefore isolated the data of the postmillennial corpus and considered whether several parameters differed significantly between the binary (pop/not-pop) generic designators within this corpus.

We compared notes per second, beats per minute, and the entropy of the metric profiles between songs with the pop and not-pop generic designations in the postmillennial corpus. Notes per second differed significantly with genre ( $t(23) = 12.246, p = .002$ ), differences in beats per minute (BPM) approached significance when not standardized ( $t(23) = 3.516, p = .075$ ), and were marginally significant when standardized ( $t(23) = 4.305, p = .05$ ). However, note that these variables show overlap in the bootstrapped confidence intervals. Similarly, the differences between entropies of the standardized and non-standardized profiles approached significance in the former instance ( $t(23) = 4.081, p = .06$ ) and is significant in the latter instance ( $t(23) = 5.310, p = .032$ ). Again, the bootstrapped confidence intervals somewhat overlap in these comparisons. The slopes of 4-gram repetitions in each genre were also considered, but these values did not vary significantly by genre.

These findings, while being somewhat statistically fragile, indicate that not-pop music within the postmillennial corpus may have more notes per song, slower beats per minute, and a more evenly distributed melodic-metric profile. Additionally, these differences seem to increase in the non-standardized versions of the corpus. While these differences are consistent across a number of parameters, the confidence intervals produced by our bootstrapping method often overlapped. The consistency of these findings, however, suggests that the ways in which the postmillennial corpus differs from the premillennial corpus appears to be exacerbated in music not in the pop genre, and somewhat lessened in music in the pop genre.

To visualize these relationships, we treat each melodic profile as a point in 16-dimensional space: profiles that distribute their events with proportional similarity at each 16th pulse in a measure (i.e., within in each of the 16 dimensions) will be proximate within this space (Albrecht and Shanahan 2013). Figure 3 plots the Euclidean distances between the melodic-metric profiles of the standardized and non-standardized pop and not-pop genres, as well as between these

Table 4.: Some differences between genres in the postmillennial corpus

	Not pop (42%)	Pop (58%)
Notes per second	3.58 (3.00/4.16)	2.48 (2.21/2.79)
Non-standardized BPM	83.50 (76.27/92.33)	96.89 (84.54/109.29)
Standardized BPM	90.32 (80.59/102.16)	107.28 (96.23/119.08)
Entropy of non-standardized Melodic-metric profiles	0.96 (0.93/0.97)	0.89 (0.86/0.93)
Entropy of standardized Melodic-metric profiles	0.93 (0.88/0.97)	0.86 (0.81/0.90)
Entropy of standardized Melodic-metric profiles	0.93 (0.88/0.97)	0.86 (0.81/0.90)

profiles and both versions of the premillennial corpus. Each sub-corpus’s profile is color-coded for ease of comparison. On the left-hand side the pop and not-pop profiles act as points in this 16-dimensional space, and we show the distances between these profiles and each other profile on the left-to-right axes. The most-similar profiles will be plotted more towards the left on each axis (closer to the respective pop or not-pop profiles), and more-different profiles will be plotted increasingly rightward (further from the pop and not-pop profiles). Reading the figure from top to bottom, we see that both the standardized and non-standardized versions of the pop genre’s profile (the solid line and dotted line) are closest to the pop profile in the opposite standardization condition (the blue standardized pop profile is closest to the magenta non-standardized profile). After this relationship, however, the distances diverge for the standardized and non-standardized versions. The standardized version is most similar to the premillennial profiles and relatively unlike the not-pop profiles, while the non-standardized pop profile is more similar to the not-pop profiles. Like the pop profiles, the not-pop profiles are closest to their standardized/non-standardized sibling. Unlike the pop profiles, the not-pop profiles are relatively distant from the premillennial profiles. They are relatively close/similar to pop profile, but, notably, only to the non-standardized version.

These relationships would seem to suggest that rhythm is distributed in the measures of tracks within the pop genre more similarly to that of premillennial music than is the rhythmic distribution of music not in the pop genre. We also see that standardizing tempo to focus on a pulse between 70 and 140 BPM increases these similarities, while using the annotated tempos in the postmillennial corpus draws closer affinities to the rhythmic/metric distributions of the not-pop music in the postmillennial corpus. In other words, the rhythmic practices present within a stable window of tappable/danceable BPMs are more similar to premillennial music, while the rhythmic events within slower BPMs show greater affinity with other postmillennial practices. It seems plausible that this illustrates two complementary characteristics of postmillennial pop’s melodic rhythm: one in dialogue with 20th century practice, and one expressing newer postmillennial conventions. This phenomenon is echoed in the similarities between the profiles of not-pop post-postmillennial music and those of the *non-standardized* pop genre: again, the

notated tempos show more rhythmic affinities between postmillennial music than do standardized tempos. Additionally, the not-pop profiles were distinctly less like those of premillennial profiles.

The amount that we can learn these analyses should not be overstated. Recall that when songs are standardized in this corpus, it is more often because their annotated tactuses/tempos are below 70 BPM. These analyses are simply observing that the distributions of events will be less saturated within a measure if that measure's tactus – its quarter-note pulse – is associated with a moderate tempo between 70 and 140 BPM, and will be more saturated when that quarter-note pulse is half that tempo. Not only will a twice-slower tactus create measures of twice the length, but all eighth-notes will be demoted to sixteenths, thereby articulating the measure's weakest pulses more often. From this perspective, much of the similarities and differences we are observing will be a fallout of this aspect of the standardization procedure. However, there are three broader points to be gleaned from these observations. As we observed above, tracks that are not in the pop genre tend to have slower BPMs and quicker melodic delivery than those in the pop genre. This combination of slower BPMs and quicker delivery will produce longer and more saturated measures, which in turn leads to the differences between the premillennial and postmillennial melodic-metric profiles. Second, these findings suggest that postmillennial pop may use a multivalent tactus to operate both in dialogue with earlier music while retaining a distinctly postmillennial metric profile. Comparing with Table 1, we see that postmillennial pop's non-standardized BPMs are markedly slower in premillennial music, while its standardized BPMs are more in line with premillennial BPMs. With its delivery being also notably quicker than premillennial delivery (but not as quick music in the not-pop genre!), its metric profiles will look much more similar to the earlier corpus when standardized, but more like their not-pop postmillennial counterparts when not standardized. This provocatively suggests that music with two tactus candidates can potentially indicate different relationships and affinities at both BPMs, a topic to which we will return in our close readings, below. Finally, as much scholarship has noted, postmillennial popular music has both increasingly incorporated the spoken-word techniques of rap and hip-hop into its musical materials, while more music explicitly in those genres appear in the curated and popularity-based collections of popular music (Barna 2019; Duinker 2020a,b; Peres 2016; Tatar 2019). These results suggest that the quicker and denser melodic deliveries observed in postmillennial music is reflecting these trends. Indeed, the fact that our not pop genre is primarily composed of a constellation of rap, hip-hop, and trap tracks would add evidence to such a conjecture.

## 5. Discussion: an intermediate summary and a reconsideration of tempo

Figure 4 recalls the information presented in Table 1, but now illustrating the distribution of non-standardized BPMs in each corpus, along with indications for which annotations would be halved or doubled by the standardization procedure. Recall from above the amount of standardization did not significantly differ between corpora, but that the corpora did differ in whether they contained more pieces slower than 70 BPM or higher than 140 BPM, a difference clearly shown in the figure. We also found that the standardization procedure affected the statistical properties of the corpora in question, leading to postmillennial melodic-metric profiles having more probability mass on the relatively strong eighth-note pulses when tempo was standardized, and more mass on alternate sixteenth notes when not standardized. This difference – when combined with the overall faster melodic delivery in postmillennial music – increases the statistical differences between the premillennial and postmillennial datasets when tempo is non-standardized versus when it is standardized. Furthermore, splitting postmillennial tracks into a sub-corpus of songs in the pop genre and a sub-corpus of those not in that genre showed that the former differed

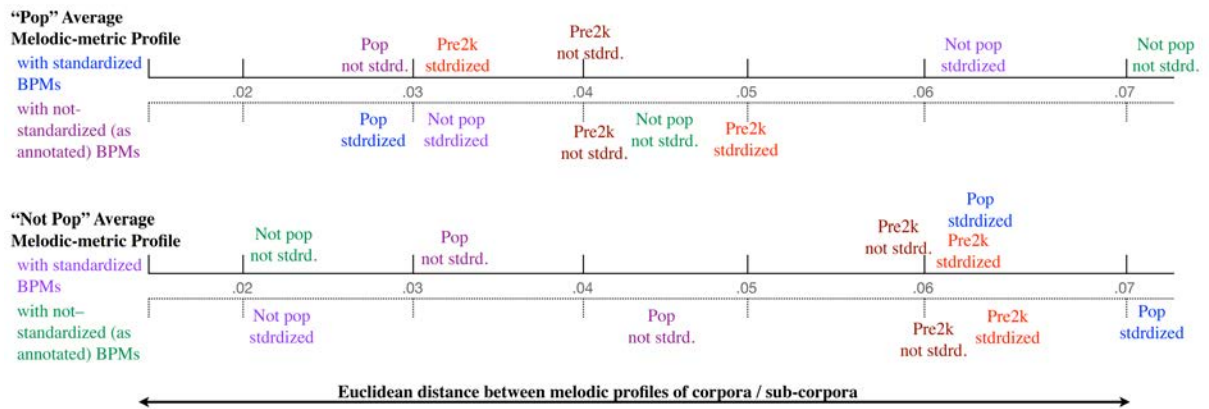


Figure 3.: Euclidean distances between the average melodic-metric profiles of the pop and not-pop genres (in standardized and non-standardized form) and the profiles of other genres and corpora

less extremely from premillennial music than did music of the latter category. The similarities between the premillennial corpus and the postmillennial pop sub-corpus increased when using tempo standardization, but this sub-corpus was conversely more similar to the remainder of the postmillennial corpus (i.e., music in genres like rap and hip-hop) when using their annotated non-standardized tempos, although these statistics appeared fragile. We speculated that different BPM levels – that is, different tactus candidates – in postmillennial music could express different relationships with their premillennial predecessors.

At the beginning of this investigation, we noted that different definitions of the concept of tactus can guide an analyst toward different pulse levels in the same piece, with approaches being generally either based on a preferred range of BPMs or on the underlying backbeat pattern. Markedly, there are also approaches to the study of meter in this repertoire that resolve such either/or arguments with both/and approaches, especially within research into the embodied experience and performance of rhythm and meter (Attas 2014; Toiviainen et al. 2009; Toiviainen, Luck, and Thompson 2010). Additionally, Geary (2021) argues that pairs of tactus candidates often feature a stable characteristic: one tactus candidate will generally manifest within a comfortable tapping tempo (i.e., roughly corresponding to our standardization window) with the other either twice as fast or twice as slow and specifically aligns with drums’ backbeat pattern. With these issues of tempo, genre, backbeats, melodic speed, and tactus candidates in mind, we end this article by observing how these parameters manifest in three tracks within our postmillennial corpus.

## 6. Quantitative analytical vignette: Three Postmillennial Tracks

While our statistical and computational observations are primarily framed in terms of the larger style, they can also be usefully applied to individual pieces. On the one hand, such approaches can situate the events of individual pieces relative to a larger corpus. On the other, broader and emergent characteristics of a corpus (such as average BPMs, measure density, and text delivery) are beholden to the individual choices made over the individual tracks of that corpus. This section undertakes a brief analysis of three individual songs within our postmillennial corpus. To begin, we outline the statistical properties of the three pieces, after which we investigate aspects of



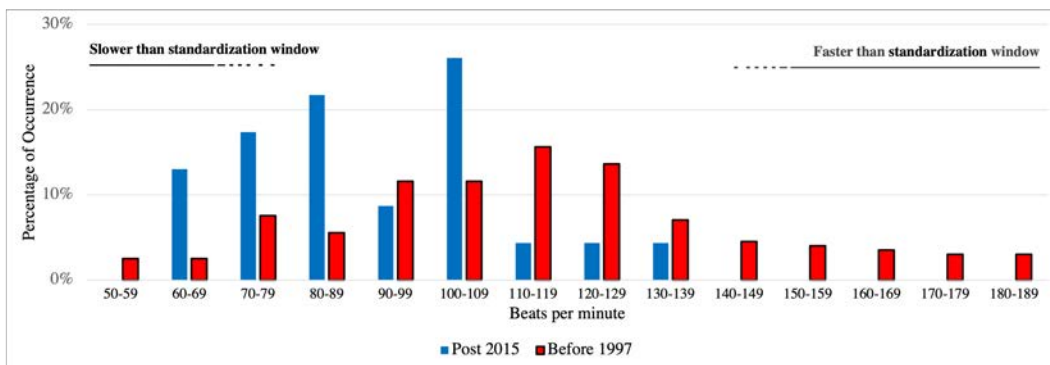


Figure 4.: Non-standardized tempo distributions in both corpora

their tactuses and tempos, and end by revisiting some of the speculative ideas broached above, namely the of the role played by multivalent tactuses in postmillennial popular music.

### 6.1. Overview of three postmillennial tracks

Table 5 shows several characteristics of three tunes from the postmillennial dataset. The first song is Ed Sheeran’s “Thinking Out Loud,” #2 on Billboard’s year-end chart for 2015. The song has the slowest declamation of the three (slower than the average postmillennial tune), and the only of the three with a single possible BPM: our annotators assigned this track a tactus of 79 BPM, a tempo both within our standardization window and an assessment reinforced by on-line references devoted to the topic (we referenced the websites [tunebat.com](http://tunebat.com), [getsongbpm.com](http://getsongbpm.com), [songbpm.com](http://songbpm.com) for such assessments). This tempo places this track solidly slower than either of the corpus’s averages; however, this slower-than-average tempo and declamation can be attributed to the track being a “lovesong” (a genre listed on [choisic.com](http://choisic.com)). These values combine to create an onset density situated somewhat between both corpora, and a melodic-metric profile entropy also situated within the range of both corpora’s entropies. Finally, the slope of the 4-grams’ distributions is quite low, indicating relatively less repetition in the 4-grams more in line with expectations from the premillennial corpus than the postmillennial corpus to which the track belongs.

“That’s What I Like” by Bruno Mars, #3 in the 2017 year-end charts, is the second song displayed in Table 5. The track has one of the quickest declamations in our corpus, and was also annotated with a BPM of 67. This combination produces one of the highest events-per-measures and entropies in the corpus (9.2 events per measure). Our standardization procedure doubles the tactus pulse to 134 BPM, a preferred tempo echoed by all online resources referenced, and which produces a much more average density. The slope of the 4-gram distribution is  $-9.2$ , putting it solidly within the boundaries of the postmillennial corpus and suggesting the piece has markedly more internal repetitions than the average premillennial and postmillennial piece of music.

The third piece under consideration is “Trap Queen” by Fetty Wap, #4 on the Billboard top 100 for 2015. With its annotated tactus of 74 BPM, it was not standardized by the approaches used above; however, the online BPM resources we referenced uniformly placed the tempo at 148 BPM. Using the broader tactus, the track represents some extremes in the corpus, with 11.4 events per measure and a melodic-metric profile entropy of .97, but the quicker tempo modulates these values into more average ranges. The slope of its 4-gram distribution was also the highest within the corpus at  $-12.5$ , indicating that a small handful of rhythmic cells are repeated very often.

Table 5.: Some properties of three postmillennial tracks

	Notes per second	Tactus(es) in BPM	Density at tactus(es)	Entropy at tactus(es)	Slope of 4-gram distribution
“Thinking Out Loud” Ed Sheeran, 2015	2.2	79	5.35	.85	-3.51
“That’s What I Like” Bruno Mars, 2017	3.8	67 / 134	9.2 / 4.6	.96 / .81	-9.2
“Trap Queen” Fetty Wap, 2015	3.1	74 / 148	11.40 / 5.68	.97 / .79	-12.5

## 6.2. *Tempo-invariant observations*

Table 5 features two characteristics that do not depend on the BPM of the track: the speed of delivery and the slope of the 4-gram distribution. Along each of these parameters, “Thinking Out Loud” has the lowest values, placing its statistics nearer to the premillennial corpus’s averages than to postmillennial averages. On the other hand, “Trap Queen” features a remarkably steep slope to its 4-gram distribution, indicating that it repeats a very few rhythmic cells very frequently, and suggesting that rhythmic repetition may be an important characteristic of this song. Finally, in “That’s What I Like,” Bruno Mars delivers a scintillant 3.8 onsets per second, potentially suggesting this domain as an important feature of this track.

Each of these features can be connected to qualitative analyses and critical reception of these pieces, as well as to their styles and genres. For instance, the slow and meandering/non-repetitive rhythms of the Ed Sheeran tune likely contribute to the sentiments underpinning such assessments that Sheeran’s music “fits right in with everyone” and that the track is a “lugubrious, wedding-ready ballad” (Molanphy 2016), but can also simply be characteristic of a mainstream pop tune (with these two option not mutually exclusive!). Indeed: comparing Sheeran’s values to those of Figure 4, the song aligns more with other pop songs than other songs in the postmillennial corpus. Similarly, the quickness of Mars’s delivery might be evidence of the “preening” virtuosic bravado characteristic of this song (Molanphy 2017) and Fetty Wap’s dense motivic repetition might contribute to its “soaring” quality that makes it an exciting “amalgam of the relatable and the niche” (Abad-Santos 2015). Additionally, it’s also not hard to imagine that “Trap Queen”’s dense motivic repetitions might be indicative of the rap genre, and that Mars’s pace of delivery could be related to the broader postmillennial style. The positioning of “That’s What I Like” regarding both postmillennial genre categories will be discussed below, as will the connections between genre and these quantifiable properties.

## 6.3. *Tempo-variant observations*

As we have observed throughout this study, many of the quantitative properties of postmillennial tracks – and the extent to which those properties align with averages from the premillennial corpus – are beholden to which pulse level is used for the analysis. Following this trend, the resulting profiles for each song show different affinities to different corpora at different BPMs. To illustrate this phenomenon, Figure 5 follows the format of Figure 3 and shows the Euclidean distance between each profile for each corpus and the profile of each tactus candidate in each track. At the top of the figure with its one possible tactus level, the rhythmic disposition of “Thinking Out Loud” shows an affinity for both the standardized and non-standardized postmillennial melodic-metric profiles, followed by both versions of the premillennial corpus: this

## non-standardized

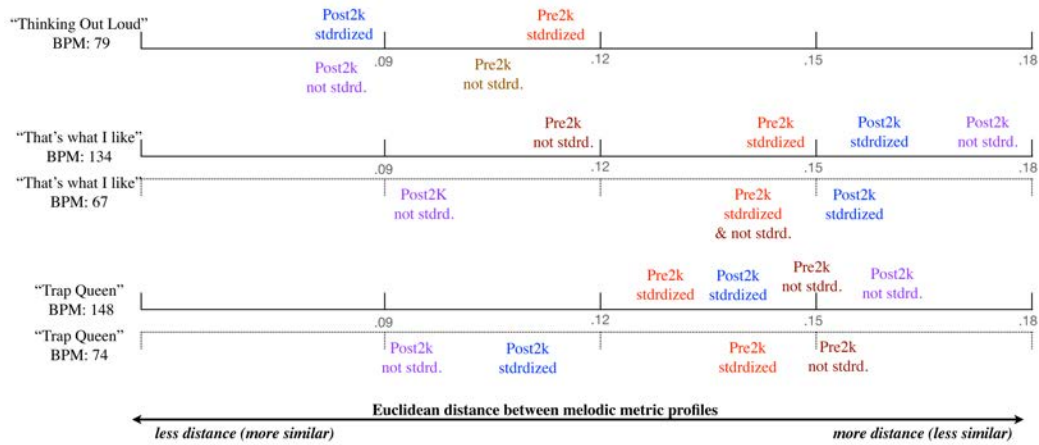


Figure 5.: Euclidean distances between the melodic-metric profiles of each song and of each corpus at both possible BPMs.

track’s rhythmic/metric disposition fits well within postmillennial practice, and relatively well with premillennial practices. “That’s what I Like,” on the other hand, shows different affinities at different tactus levels. In its standardized form, its profile aligns best with premillennial profiles. Using its annotated slower tactus, however, the song’s profile becomes quite close to the average non-standardized postmillennial profiles. Finally, “Trap Queen” is quite unlike any average profile at its faster BPM, although that profile is closest to the premillennial averages. At its annotated tempo, it shows a close affinity for the premillennial profiles, especially that derived from the non-standardized tempos.

To further investigate the relative salience of both tactus candidates, Figure 6 represents excerpts from the sound signals for each of these tunes as spectrograms. The top spectrogram shows a selection from Sheeran track, in the middle of which the voice drops out, isolating only the accompaniment. The signal shows peaks in the high partials/high timbral range within the second and fourth beats (shown by the figure’s boxes), spectral profiles indicative of the high-pitched, high-energy articulations of the backbeat (Temperley 2018; Lavengood 2017). In other words, these sonic events indicate beats 2 and 4 in a quadruple pattern, thereby indicating a tactus and bar length aligned with their periodicities (Moore 2001; Stephenson 2002; Tamlyn 1998). The tactus at 79 BPM is therefore supported by the track’s clear backbeat pattern.

Because both “That’s What I Like” and “Trap Queen” feature two plausible tactuses, two backbeats patterns are boxed at both quicker and slower periodicities with solid and dotted boxes, respectively. In both instances, the most clear high timbre and high energy peaks appear at the slower tempo: visually, the dotted boxes contain some of the brightest and more pervasive vertical walls of sound in the excerpts, indicating a high-energy saturation across the spectrum at those points. Such moments aurally translate into the tinny percussive moments indicative of backbeats. The faster tactuses, however, are not completely devoid of plausible backbeats. “That’s What I Like” and “Trap Queen” contain some high-timbre-d percussive hits on these faster backbeat candidates, particularly observable in the brief saturation in high-pitch spectra in the first “2” at the quicker pulse in “That’s What I Like”, and in the brief midrange high-energy events in the first “2” in “Trap Queen’s” quicker pulse. These events are, however, undoubtedly more sparse and lower energy than the backbeat candidates at the slower pulse. In both examples, the slower pulses are supported by the clearer backbeat patterns.

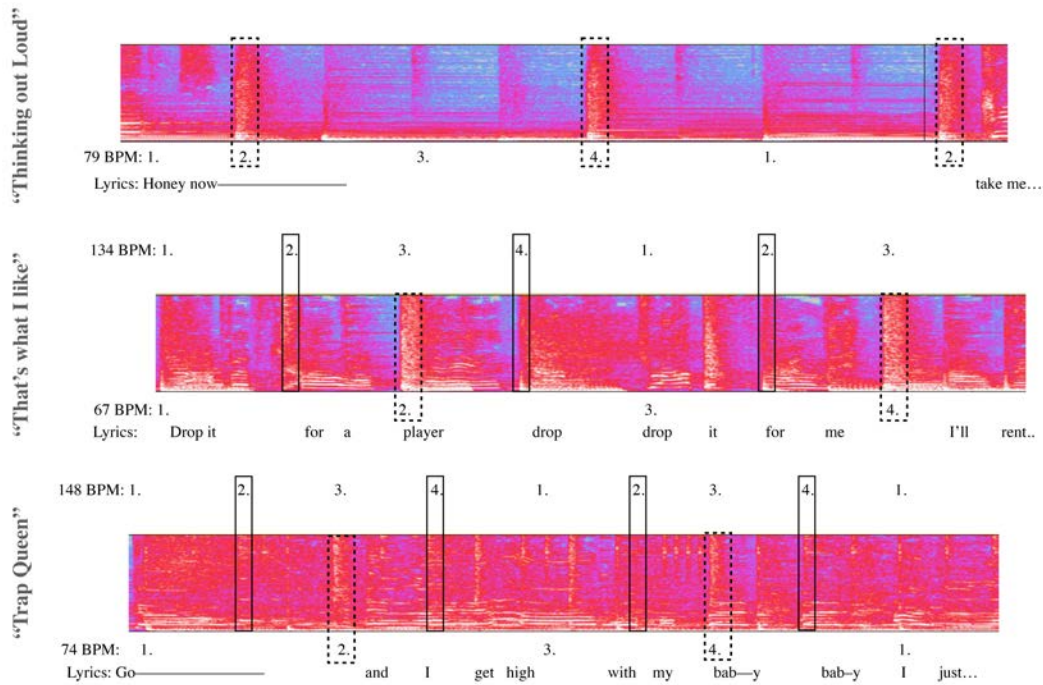


Figure 6.: Spectrograms of selections from three postmillennial tracks.

#### 6.4. A Hypothesis for the Tempo Change in Postmillennial Music

These observations recall the research outlined above that argues that two tactus candidates can co-exist within a track, one based on a salient backbeat and one based on a comfortable, midrange BPM. Our examination showed two instances in which there was a clear backbeat at a somewhat slow tempo, and also found less plausible backbeat support at the quicker pulse. In both examples, the two tactus candidates involved one pulse within the midrange (“standardized”) window at  $x$  BPM and a second backbeat-supported pulse twice as slow at  $x/2$  BPM.

This phenomenon could invert as well, with the backbeat at a tempo that doubles that of the more comfortable standardized tempo. Consider, for instance The Who’s well-known song “My Generation” (1965), labeled in the premillennial corpus as a frantic 194 BPMs, a tempo at which the track’s most salient backbeat manifests. (A spectrogram of an excerpt from this track can be found in our online supplement, and outlines the potential backbeats in the manner of Figure 6.) A backbeat-based logic would focus on this quicker tempo, while a logic favoring an invariant window of more comfortable tempos would halve this tempo (indeed, most online resources place this track at the midrange tempo of 97 BPM). In this case, the two tactus candidates now include one within the standardization window ( $x$  BPM) and a second backbeat-supported tactus at twice that speed ( $2x$  BPM).

We hypothesize that many of the tempo-dependent differences between premillennial and postmillennial music described in this paper can be located in this phenomenon. Recall that the average standardized tempos do not significantly differ between the two corpora (as shown in Table 1), but average postmillennial tempos are markedly slower in non-standardized data (as shown in Table 1 and in Figure 4). Also, the earlier corpus contains significantly more note attacks on offbeat sixteenth pulses (as seen in Figure 1), but again only reliably when tempo was non-standardized. If much of the music in our corpora activates two possible tactus candidates – one within a set tempo window of comfortable/dance-able pulses and another either double

or half that pace – it seems entirely possible that the observed differences between these corpora are a result of premillennial music activating the doubling relationship more often than the halving relationship, and postmillennial tracks inverting that tendency. That is, while the standardized tempo  $x$  remains relatively stable between corpora, mainstream popular music in the 20th century may be more likely to present a salient backbeat pulse at  $2x$  than at  $x/2$ , while 21st century popular music may be more likely to feature salient backbeats at  $x/2$  than  $2x$ . This phenomenon could then account for why the rhythmic events of "Trap Queen" and "That's What I Like" are more similar to their fellow postmillennial songs when the annotated tempos are used. Conversely, tempo standardized data shows the affinities between these songs and older popular music. In other words, the standardized tempo captures what is shared between these corpora, while the annotated (backbeat-dependent) tactus candidates show this corpus's uniqueness.

Genre also would seem to play a central role in this hypothesized phenomenon. As many commentators and practitioners of hip-hop have noted, this style's prototypical underlying rhythmic pattern can be described as a "halftime feel," sometimes analyzed as having roots in the halftime shuffle (Duinker 2020a). As a rap song, it's not surprising that "Trap Queen" would feature such a "halftime" tactus candidate; as a mainstream pop song it's not surprising that "Thinking Out Loud" does not. While "That's What I Like" is characterized as "pop" according to our annotation methods, Bruno Mars's music is strongly influenced by hip-hop, a fact that he both freely admits and for which he has received criticism, (Jenkins and Guan 2018). It is therefore plausible that within these three tracks we see three distinct strains of postmillennial music, as expressed in their various usage of musical parameters and deployment of possible tactus levels: 1) a mainstream pop song that shows the highest level of similarity to 20th century popular music, 2) a pop track that shows the influence of hip-hop on postmillennial mainstream music, and 3) a rap song whose musical material substantially differs from 20th-century mainstream popular music by virtue of rap's hip-hop provenance (and – it should be noted – is an example of the new "Trap" sub-genre).

## 7. Conclusions and Future Directions

This brief study suggests some quantifiable ways that postmillennial American popular music may differ from its 20th-century counterparts, and ways those differences are exacerbated or reduced depending on issues of tempo or genre. In particular, more recent music seems to deliver its melodic onsets at a quicker pace than earlier music and distributes these onsets more evenly both throughout the measure and throughout metric levels than in earlier music. Melodies in our postmillennial corpus also had a markedly higher slope to their ranked distribution of rhythmic 4-grams than did melodies in the premillennial corpus, indicating that the most-used 4-grams in a postmillennial song are repeated more often than those in premillennial songs. We also tracked these variables using both the BPMs annotated within the corpora and using "standardized" BPMs, in which tempos below 70 were doubled and tempos above 140 were halved for the purpose of analysis. We found that the tempo-dependent differences increased when using annotated BPMs versus standardized BPMs, and also found that many of these differences were also less pronounced in postmillennial music in the pop genre versus not in the pop genre. A closer analysis of three postmillennial tracks found each melody to contain characteristics similar to the broader postmillennial corpus. However, we also saw that aspects of these melodies' tempos, rhythmic densities, and 4-gram repetitions seemed to express the genre of each piece. In particular, mainstream pop featured characteristics that were more aligned with premillennial music while rap and hip-hop-influenced music exhibited more divergent characteristics. Finally, by observing the backbeat patterns in these tracks and connecting them to broader trends within the two larger corpora, we speculated that the structure of plausible tactus candidates might be

different in premillennial and postmillennial music, and that this difference might account for a large portion of the variation we observe between these two corpora. Specifically, many songs in both corpora feature two plausible tactus candidates – one associated with a comfortable tap-pable/danceable midrange pace, and another supported by the track’s backbeat pattern at either twice or half the midrange pace. We speculate that postmillennial music is more likely to activate slower/halved backbeat patterns, while premillennial music is more likely to use faster/doubled backbeat patterns. Aligning with recent popular-music scholarship, we noted that these quantitative differences might evidence the increasing inclusion and influence of hip-hip and rap-based genres in 21st-century popular music.

Importantly, this work has limitations. For one, our postmillennial corpus is somewhat limited in scope. Additionally, comparing two musical corpora created by different research teams under different circumstances can be difficult, as subtly different priorities and methods may affect the quantitative comparisons between them. However, our goals are to suggest connections between musicological research and the quantitative properties of these repertoires, to offer future directions for study, and to encourage avenues for computational- and empirically-guided analyses of postmillennial popular music. Additionally, it should be noted that the trends identified here are by no means ubiquitous, and that melodic rhythm is certainly not the only musical characteristics important to musical expression in this repertoire: parameters such as timbre, melodic pitch, and accompanimental harmony are important aspects of this music’s construction. Finally, our speculations outline a potential avenue for future studies concerning tempo’s role in these repertoires, specifically how multiple tactus candidates might be experienced differently in pre- and postmillennial popular music.

## Acknowledgements

We would like to thank Trevor de Clercq, the anonymous reviewer, and Jason Yust for their guidance on the preparation of these materials.

## Supplemental online material

Supplemental online material for this article can be accessed at [chriswmwhite.com/popannotations](http://chriswmwhite.com/popannotations)

## ORCID

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