The Valuation of Songwriting Techniques:
An Analysis of How Song Elements Affect Song Value

by Frank Merlock

A thesis presented to the Honors College of Middle Tennessee State University in
partial fulfillment of the requirements for graduation from
the University Honors College

Spring 2020

The Valuation of Songwriting Techniques:
An Analysis of How Song Elements Affect Song Value

by
Frank Merlock

APPROVED:

____
Dr. Anne Anderson
Weatherford Chair of Finance

____
Dr. Trevor de Clercq
Recording Industry

____
Dr. Philip Phillips, Associate Dean
University Honors College

Acknowledgments

First, I would like to thank my family for their constant love and support. I would like to thank Dr. Anderson for all of her fantastic guidance throughout this project. Dr. Anderson was vital in helping me overcome several setbacks, as well as learning the process of putting together an academic paper. I would also like to thank Dr. de Clercq for pointing me in the right direction on a topic with which he is rather familiar. I would like to thank my roommate Oscar Fernandez for listening to hundreds of songs with me because he didn't have a choice. I would also like to thank Cedric Gilmer, Zack Medic, Maxwell Jamerson, and Stephen Borders for their friendship despite many hours working on this project. I would like to thank Kyle Mackulak for telling me to cut the skits from the introductions of my own songs. He was right all along. I would like to thank J.K. Simmons for teaching me about keeping rhythm. I would also like to thank Austin Rochez, Laura Les, Dylan Brady, David Duchovny and my cats for providing me endless inspiration.

Table of Contents

Abbreviations & Definitions

Buzz Angle Parameter Definitions

1. Audio Streams: Audio streams are through online interactive services (which allow for customers to choose specific songs) like Spotify and Apple Music, as well as video streams through services such as YouTube. According to BuzzAngle, "Streams will count on a 1:1 basis on all streams charts. There will not be any weighting for any of the various types of streams: on-demand audio, on-demand video, programmed, ad-supported or subscription streams" ("Methodology" 2020). Concerning video streams, BuzzAngle states that, "Music Video rankings reflect the sales of full-length music video projects, be they documentaries, clip compilations. Music-intensive films will be eligible in cases where digital and/or physical track such titles as music videos, but some that are released theatrically will not be reported" ("Methodology" 2020).
2. Song Sales: Song sales are actual sales through online services such as iTunes or Google Music. According to BuzzAngle, "Songs that are priced under $0.49 will not be counted within the first three months after the song's release" ("Methodology" 2020).
3. Spins: Spins are plays of songs on AM or FM radio.

Database Abbreviation Meanings

1. NOST - Number of Song Titles: How many times the name of the song appears within the lyrics of the song.

2. LTFCA - Length to First Chorus Average: The average of recorded lengths of time in seconds to the first chorus of the song.
3. LOIA – Length of Intro Average: The average of recorded lengths of time in seconds of the song's intro.
4. LOSA – Length of Song Average: The average of recorded length of time in seconds of the entire song.
5. MCWOC – Max Consecutive Weeks on Chart: Maximum consecutive number of weeks on the song's related chart.
6. P – Peak: The highest chart number the song received from release to 8/30/2019, the end of the sample period.
7. MCS – Multiple Charts: If the song appears on multiple charts simultaneously, it receives a 1. If the song doesn't appear on multiple charts, it receives a 0.
8. MSFSA – Multiple Songs from the Same Album: If the song has multiple songs from the same album on the charts simultaneously, it receives a 1. If the song doesn't have other songs from the same album charting, it receives a 0.
9. STO – Sales Total, On: Total sales while the song was on the chart.
10. SWAO – Sales Weekly Average, On: Weekly average of sales while the song was on the chart.
11. RTO - Radio Total, On: Total radio spins while song was on the chart.
12. STTO – Streams Total, On: Total streams while the song was on the chart.
13. STOB - Sales Total, Off Before: Total sales before the song charted.
14. RTOB – Radio Total, On Before: Total radio spins before the song was on the chart.

15. STTOB – Streams Total, Off Before: Total streams before the song appeared on the chart.
16. STOA – Sales Total, Off After: Total streams of a song while not on the chart after charting.
17. RTOA – Radio Total, Off After: Total radio spins of a song while not on the chart after charting.
18. STTOA – Stream Total, Off After: Total streams of a song while not on the chart after charting.

Tables & Figures

Tables

Appendix Tables

Figures

Abstract

Although the music industry continues to capitalize on the power of big data and analytics, the job of predicting a song's future value is left to Artists and Repertoire (A&R) representatives who must trust their experiences and use their gut instinct. There remains an opportunity for analytics to unearth the science behind what gives popular music value. This paper analyzes four quantitative structural elements of a song to determine how they impact a song's value. Using a systematic method of listening and data mining, each element was measured and tested for a relationship with the song's sales, radio spins, and streams. These are songs that made appearances on various Billboard charts between 2015 and 2018. The difficulty of data cleansing, data accessibility, and data collecting artistic products is emphasized. Certain elements, including the repeated lyrics and length of the intro, did show some relationship with song value, and the extent to which this is true is also emphasized. While the model does not explain all elements that impact value, this paper could serve to start the discussion on using big data and analytics to guide music labels on predicting a song's value.

Background

Many aspiring musical artists want to write or perform a song that will catapult their careers to financial stability. However, a clear path to financial sustainability and success is unclear since many aspects of music's value are intangible, such as creating societal connectivity and a community of belief (Reimer et al. 2002, 3). Perhaps resulting from this understanding of intangible value, the music industry uses an above-average amount of intuition on the corporate side of the business (Schrieber and Rieple 2018). That said, some companies eschew the use of intuition in the decision-making process and instead leverage big data and analytic research. The industry for business analytics has grown by $20 billion between 2013 and 2016 (Grover 2018, 390). A report in 2015 showed that companies across all industries that implemented big data and analytics were showing a 15%-20% increase in annual ROI ("Marketing & Sales Big Data…" 2015, 25). This is evidence of big data's effectiveness in decision making, as well as its growing usage in the corporate world.

As the music industry continues to expand, pulling in an additional two billion dollars of revenue in music sales alone between 2015 and 2017, one can expect the same usage of big data and analytics within the music industry (Friedlander 2018, 1). Several companies have emphasized the advancement of technology and analytics to increase business performance. For example, in 2016, Warner Music Group organized a new business structure and data analytics department with the hiring of an official Chief Information Officer and Chief Data Officer (Schneider 2016). Their press release emphasized the firm's mission of implementing big data to improve performance in artist payouts and finances (Schneider 2016). Alternatively, in November 2019, Sony Music introduced a new listening system called 360 Reality Audio, which is a reinvention of stereo imaging (*Introducing Sony's 360…* 2019). The company plans to rerelease older songs remixed in this new listening format.

However, major music companies and distributors have not publicized any attempts to use big data to analyze musical structure and how it is connected to a song's value. The purpose of this study is to analyze trends in a specific set of structural elements in American popular music to determine how they contribute to the song's commercial value (i.e., its "popularity"), how these relationships evolve through time, and how they have changed during the rising popularity of music streaming. Focusing on the years between 2015 and 2018, this study will use sales data from BuzzAngle to assess the value of elements for the industry's most popular genres (11-12). Furthermore, by focusing on elements of songs that are quantitative, one can determine whether the use of big data and trend analysis can be used effectively in the music industry to determine the possible value of specific song structures and therefore lead to making impactful business decisions. While subjectivity plagues the usefulness of many musical studies in the business sense, this study aims to determine whether quantitative elements can be of use to artists and recording companies.

Music has existed for centuries; however, it was not until the invention of the phonograph and reproducible musical recordings that companies could profit from music beyond the revenue gained from live performances. While there will always be niche markets for styles and genres of music, it is evident that some types of music, through sales and other mediums, are more profitable than others. The terms used to describe different types of music can be easily confused, though. “Popular music,” as described by Philip Tagg, is recorded music that is funded by the free enterprise for mass consumption (1982, 42). This is not to be confused with “pop music,” which is a specific genre derived from the rock-n-roll revolution beginning in the late 1950s (Middleton et al. 2019). While other genres of music may be produced and released for many reasons, popular music’s worth is found through maximizing value for those who release it.

As popular music entered into the recording era, music in the mainstream grew to fit an incredibly specific mold of structural elements. The first elements are “sectional elements,” which are elements or themes that are repeated in the song. This is in contrast to music which is “through-composed,” a term which James Webster defines as “based on run-on movements without internal repetitions,” a technique associated mostly with classical music (2004, 7). Sectional elements in popular music include verses, choruses, and bridges. “Verses” are the details and story of the song, and the lyrics typically vary with each iteration. The “chorus” or “refrain” is normally a repeated, catchy segment of the song. The “bridge” is a transitional element within the song and can tie the storytelling of the verse with the theme of the chorus (Davidson 1997).

Songwriter and Canadian Country Music Hall of Fame member Ralph Murphy noted that there are only a handful of combinations that make up the larger portion of popular music. While some song structures can be defined through the lyrical content alone, several songs and genres use a linked combination of the above-stated elements. For example, Intro–Verse–Chorus–Verse– Chorus–Instrumental–Chorus–Outro is a popular combination of structural elements in country and rock music. Ralph Murphy goes on to say that the combination Intro–Verse–Pre-chorus–Chorus–Bridge–Pre-chorus–

Chorus is seen statistically as the most profitable structure ("Ralph Murphy Lecture," 2011). These elements of song structure are difficult to determine, as the subjectivity inherent to music means these elements can have equal standing even if people perceive them differently. For example, in a study done by Soundfly on the chord progressions of the most popular songs of 2017, the author admits that many songs can be interpreted differently. In the song "That's What I Like" by Bruno Mars, researcher Dean Olivet states that depending on which chords were focused on, the song's tonal center could be interpreted as either minor or Lydian (Olivet et al. 2018).

From a business perspective, the technology involved with how music reaches the consumer has evolved systemically in the last 120 years. As would be expected, these differences have created changes in the financial landscape of the music industry. At one point, music could only be accessed by attending live performances. This changed with the invention of the phonograph by Thomas Edison in 1877 and the improvement of flat disc technology with the gramophone by Emile Berliner. By 1902, these flat discs could be mass-produced, and by 1910, they were the best-selling medium of commercial music (Starr and Waterman 2018, 65). This trend continued with the introduction of 8-track tapes, cassettes, CDs, and streaming services.

Every new technological development brought a change in the landscape to the music industry. For example, when cassettes surged in popularity during the 1980s, people could record "mixtapes," or a compilation of specific songs (Starr and Waterman 2018, 466). This meant that some people could not only bootleg versions of albums, they could also create cassettes with only the songs they wanted. Another example of this market disruption comes with the introduction of the CD. When record companies would produce vinyl singles, they would include only one popular song by an artist. However, the majority of CDs would include an entire album. Music consumers were being prompted to purchase entire albums instead of having the freedom to purchase single songs. This would change again when streaming services such as Spotify or Apple Music gave the power of choice back to consumers (Starr and Waterman 2018, 562–563). Regardless of the period, every technological innovation within the music world has directly impacted the financial elements of the industry.

Beginning in 2016, on-demand streaming services created the majority of revenue in recorded music sales. CDs, which at their peak generated $13.2 billion in revenue in 2000, have been waning in popularity (RIAA 2016). Recently, vinyl has seen a resurgence in popularity due to collectability. According to Giantsteps Media Technology Strategies, vinyl will easily outpace CD sales if both new and used markets are considered (Rosenblatt 2019). Download purchases from iTunes and other paid download music providers are also trending downwards. Streaming services currently make up 75-80% of music sales, which is an estimated $8.9 billion according to The International Federation of the Phonographic Industry (IFPI). Similar to the popularity of cassette mixtapes and single-song vinyl records, people have more control over the songs they choose to listen to. This is in contrast to CDs, which require one to buy a collection of songs without the ability to customize one's selection. Streaming services also have an element of convenience, as they can be played from mobile devices. These are all contributing factors to the growth of streaming services.

The business model for streaming services is not complex. For example, Spotify offers two accounts for its service: a free account and a premium account. Free Spotify accounts do not require a subscription fee but offer limited features on the platform. For example, users are not able to pick individual songs and are subject to advertisements every thirty minutes. Premium Spotify accounts charge users a monthly fee, but they allow for unlimited online and offline streaming options. In 2019, Spotify charged $9.99 a month and included a subscription to the video streaming service Hulu. Spotify's main expense is paying music labels and artists for using their music. Generally, payouts are made based on how much the artist is listened to compared to all other artist. For example, if a major artist was 10% of the world's streams, and Spotify generated $1 million from streams, the artist would receive $100,000. While most artists are paid on an individual basis through aggregators (services that help put music on streaming services), Spotify has reportedly secured blanket licenses from some major labels in an attempt to reduce their payout amounts. However, Spotify has faced some lawsuits concerning illegal practices on paying out mechanical licenses, so how effective these systems will be in the future is in question (Jacobsen 2017).

The financial viability of music streaming services is an important area of discussion. There is insufficient evidence to prove that Apple Music and Spotify, the two major interactive streaming services, use profitable business models. Apple Music is a subsidiary of Apple, and therefore information is not available on the streaming services' finances. Apple's CEO Tim Cook said in an interview with *Fast Company* that Apple is "…not in [music streaming] for the money." Some observers, including Bobby Owsinoski from *Forbes*, have stated that Apple considers Apple Music a loss leader. Apple's main objective is to keep users within their interface and make their mobile operating system an all-encompassing experience (Owsinoski 2017). In June 2019, it was reported that Apple Music had 60 million current paying subscribers, although the company later confirmed this number also included people who were on free trial subscriptions. It may be concluded that Apple Music's role as a loss leader has been effective. However, this does not mean that music streaming currently has a viable business model.

Spotify, the other major streaming service, strictly does business in music streaming. However, Spotify's financial reporting has shown a very concerning trend in the music streaming industry. Spotify has recorded net losses every single year between 2008 and 2018, and it continues to tell investors that these loses are due to attempts to increase membership (Spotify 2020, 30). Between 2016 and 2017, Spotify recorded a net operating income of almost one billion dollars. In 2019, Spotify saw its first positive net operating income, but only in the first two quarters. Spotify had a net operating loss overall in 2019, and firms such as Bernstein Bank and Wells Fargo both believe the company is underperforming (Cohen 2020). Therefore, given the performance of both Apple Music and Spotify, it is clear that the long-term viability of music streaming services is in question. The importance of sustainable online revenue cannot be understated, especially as concerts and live events are being cancelled in the wake of the COVID-19 pandemic. Overall, live performances are the largest revenue stream for musical artists. A study by the Music Industry Research Association showed that 80% of artist revenue came from live shows and performances (Krueger et al. 2018). It can be expected that the use of big data and analytics will grow in importance as businesses and individuals look to maximize profits and achieve sustainability in an evolving consumer landscape.

Generally speaking, the two ways a business can increase operating profits are to increase sales or reduce costs. Streaming services are already under fire for their payout statistics. Streaming services offer little insight into the mathematics behind their per song payout. Multiple sources (The Trichodist, Soundcharts, etc.) will report different per-stream payouts for the same period. Regardless, artists have noticed that even as revenue for Spotify and other services have increased, payouts have decreased. According to The Trichodist, artists would need approximately 333,334 Spotify streams every month to make minimum wage, based on the Federal minimum wage of $7.25 and a 40-hour workweek ("2019-2020 Streaming Price Bible…" 2020). If an artist sold physical CDs and made a net profit of ten dollars per CD (Christman 11, 2017), they would only need to sell 147 units to make minimum wage. To put this into perspective, an individual would have to listen to a ten-track album 229 times to equal the time spent in a streaming service to make the artist the same amount. Streaming services run the risk of dissuading artists from using their services if these numbers get any lower. However, SoundExchange reported that in 2018 there were 51 million paying customers of the music streaming business (Glanz 2018). Therefore, looking at how to increase sales and optimize products seems to be the only solution.

Literature Review

Many studies have been conducted on measuring musical elements; however, most focus on subjective elements and are not related to the song's financial value. A number of studies on how specific song elements affect a song's popularity or value state there is no clear determinant of what makes a song popular. Salganik and Dodes suggest that popular trends may be due to the cultural phenomenon that is beyond the ability to predict (2016). Jonah Berger and Grant Packard suggest that songs with lyrics that are atypical of the genre tend to be the most popular (2018). Their study was done on 1,879 high-charting songs between the years of 2014 and 2016 and focused on buzzwords and phrases, which attempted to remove the subjectivity of interpreting a song's theme.

Similarly, in 2014 an analysis in the *Journal of Advertising Research* was able to predict if a song would make the Billboard Hot 100 chart with 73.4% accuracy (Hernard and Rossetti 2014). The study showed that the most common themes in the Billboard Hot 100 songs from 1950 to 2009 were loss, desire, aspiration, breakup, pain, inspiration, and nostalgia. Breakup songs were found to be the most prevalent theme throughout every decade. It is difficult to make business decisions based on interpreting lyrical themes due to the subjectivity involved. To address this, my study focuses on making objective observations about song elements that would allow the music industry to make decisions based on the content of their product.

Many elements can be identified in songs. Some of these include song length, number of choruses, lyric content, and tempo. Many other factors have been covered in other studies with specific focuses. For example, a paper published in *Royal Society Open*

Science analyzed pop songs that charted in the United Kingdom between 1985 and 2015 and put them in categories depending on the song's mood. It was found that songs have become sadder in terms of content, yet the instrumentals were more danceable (Interiano et al. 2018). In another study entitled "What Has America Been Singing About?" researchers suggested that music has become more materialistic, whereas older pop music was more romantic and sexual in nature (Christenson 2018). A study by Michael Tauburg found that streaming services like Spotify are reinventing classic song titles, with newer songs either having 1 or 2 word titles, or as many as 7 or more word titles, with less relevance to the song's subject matter ("Spotify Is Killing Song Titles" 2018). The major element of these studies, however, is a personal assessment by the author on what makes music "materialistic" or "sad" in nature. This highlights the major difficulty in music analysis: capturing the subjective nature of the art.

One of the most thorough studies on the topic is "Instrumentational Complexity of Music Genres and Why Simplicity Sells" by Gamaliel Percino, Peter Klimek and Stefan Thurner published in 2014 by PLOS One. By using the Discogs database of Amazon sales rankings, they attempt to see how the complexity of instrumentation affected a song's popularity. While "instrumental complexity" is a very subjective idea at the surface, the study strictly defined this through information found on the Discogs database. The authors assumed that the instrumentational complexity of a style "is related to the set of specialized skills that are typically required of musicians to play that style" and therefore only took into account how many and what variety of instruments were played by contributors of the project (Percino et al. 2014, 3). They found that

> As a style increases its number of albums, i.e. attracts a growing number of artists, its variety also increases. At the same time the style's uniformity becomes smaller, i.e. a unique stylistic and complex expression pattern emerges. Album sales numbers of a style, however, typically increase with decreasing complexity (Percino et al. 2014, 13).

Unlike other studies, the authors were confident their model could accurately predict popular music. However, their methodology does assume that open source data about the subjective topic of instrumentation is accurate. The ability to apply this in a business setting confidently remains in question.

Thesis Statement

The purpose of this study is to analyze trends in a specific set of structural elements in American popular music to determine how they contribute to the song's commercial value (i.e., its "popularity"), how these relationships evolve through time, and how they change within different forms of consumption. Focusing on the years between 2015 and 2018, this study will use data from BuzzAngle to assess the value of elements for the industry's most popular genres and assess the impact each has on song value, as measured by streaming data. (11-12) in the digital age of music. Furthermore, by focusing on elements of songs that are quantitative, one can determine whether the use of big data and trend analysis can be used effectively in the music industry to determine the possible value of specific song structures and therefore lead to making impactful business decisions. While subjectivity plagues the usefulness of many musical studies in a business sense, this study aims to determine whether quantitative elements can be of use to a company and the artist.

Hypotheses

1. The length of the song will be related to song value (Ciampaglia et al, 2015).
    a) The relationship between song value and the length of the song will vary across genres.
    b) The relationship between the length of the song and specific sales data (streams, programmed streams, etc.) will vary due to different consumption mediums.
2. The length of the song's intro will be related to song value (Frank 2009).
    a) The relationship between song value and the length of the song's intro will vary across genres.
    b) The relationship between the length of the song's intro and specific sales data (streams, programmed streams, etc.) will vary due to different consumption mediums.
3. The number of times the song title occurs within the lyrics will show a weak relationship with song value (Tough 2017).
    a) The strength of the relationship between song value and the number of times the song title occurs within the lyrics will vary across genres.
    b) The relationship between the number of times the song title occurs within the lyrics and specific sales data (streams, programmed streams, etc.) will vary due to different consumption mediums.
4. The length to the first chorus will be related to song value (Murphy 2011).

a) The relationship between song value and the length to the first chorus of the song will vary across genres.

b) The relationship between the length to the first chorus and specific sales data (streams, programmed streams, etc.) will vary due to different consumption mediums.

The above hypotheses are based on previous studies, insight on consumption habits or guides to music writing technique. Hypothesis 1 follows from the study "The Production of Information in the Attention Economy," which used internet traffic to test how people's attention span for product and information is getting smaller in the digital age (Ciampaglia et al, 2015).

In his 2009 book *Futurehit.DNA*, Jay Frank states that the digital revolution is pushing songs to have shorter intros to appeal to their consumers (38). Based on the Frank study, I propose Hypothesis 2.

For Hypothesis 3, I test the findings in the study "An Analysis of Common Songwriting and Production Practices in 2014-2015 Billboard Hot 100 Songs" by David Tough (2017). He analyzed the relationship between the number of times a song's title appeared and its success on the Billboard Hot 100 chart. He compared this number to peak date as well as the trend direction of the song by its charting number to calculate an index number, which he used to define success. He found there was "a weak negative non-significant relationship" between a song's success and the number of times the song used its title in the lyrics (102).

In his book *Murphy's Laws of Songwriting: The Book*, Ralph Murphy suggests keeping the length to the song's first chorus short and that successful songs follow this trend. He states that the song's chorus and catchy hook or phrase should happen before the 60 second mark of the song (2011). In this study, I test a relationship between the length to the song's first chorus and value in Hypothesis 4.

Methodology

The value of a financial investment is simply the present value of all future expected cash flows. However, valuing a song is less clear cut. The study considers a variety of measures of song value. In addition, I gather data on specific song elements to determine what drives value.

The first phase of the study was collecting the raw data and creating a database of songs to analyze. The songs analyzed were the top five songs per chart at the end of each month between the years of 2015 and 2018. These songs were collected from Billboard Pro, the official database for Billboard chart occurrences. According to a study by BuzzAngle in 2017, the four most popular genres of music by album consumption are Hip-Hop/R&B, Country, Rock, and Pop (11-12). Since the focus of this study is on a song's profitability, I will focus on these four genres. Specifically, Pop music was analyzed through the Adult Contemporary chart, Hip-Hop and R&B music was analyzed through the Hot R&B/Hip-Hop chart, Country was analyzed through the Hot Country Songs chart, and Rock music was analyzed through the Mainstream Rock chart. In addition, a fifth category of the Billboard 100 was analyzed, which accounts for each month's most popular songs without considering the genre. This allows insight into which genres are seen as most popular by consumers as well as whether or not the most popular songs are derived from the genre or elements within a song.

After the list of songs was finalized, I analyzed each song individually based on four elements. One methodological limitation of the study is the subjective nature of analyzing music. Specific details such as chord progressions or tempo proved too and interpretive to offer clean data to analyze profitability. To address this, the four elements of this study were chosen due to their quantitative nature, making cross-analysis easier. While not entirely objective, the elements studied are less interpretive than others that could have been chosen. The elements analyzed are the length of the song, the length of the intro, the length to the first chorus, and the number of times the song title occurs within the lyrics. All encoding was done by listening to each song individually.

The four song elements will be followed for the entirety of the study. The length of song will be defined as the time when the music begins to the time when there is no additional music being played. This includes fade-outs but does not include echoes or delays. The length of intro will be defined as the time from the start of the song to the first downbeat of the next structural element, such as verse or chorus. If a vocalist begins singing before the first beat of the verse, for example, the length of the intro will still be measured as extending to the first downbeat of the verse. This approach will also be used to determine the length of the chorus. For the number of times the song's title occurs in the lyrics, variations from the title will not be counted. Lastly, to add consistency, the original album release of the song will be the one used in the study. Songs that are structurally altered through video streams were not counted.

To record these elements, I programmed a stopwatch with JavaScript that started and stopped the time upon clicking the mouse. For consistency, all songs were listened to using Apple Music and to avoid latency issues, all songs were downloaded through the streaming service. To ensure accuracy, each song was listened through three times and the average value for each element, length of intro ("LOIA"), length to first chorus ("LTFC") and length of song ("LOSA"), were used in the regression analysis. A fourth listen of the song was to note the number of times the song's title appeared in the chorus ("NOST") which was measured by identifying each occurrence, and cross-referencing the number by searching through the song's lyrics on Genius.com.

To validate my plan and my personal analysis, I analyzed 10 songs that were also analyzed by Hit Songs Deconstructed, a database that does song analysis and is used at universities for reference purposes. After comparing the results of their research with my own analysis, and discounting two unclear data inconsistencies within Hit Song's Deconstructed's analysis, the two data groups were 100% synonymous after discounting differences in methodology (see Appendix A). In the case of the one inconsistency analyzing the song "Do I Wanna Know" by the Arctic Monkeys, I noted that the song title was included six times within the song, whereas Hit Songs Deconstructed said it occurred five times, with one partial occurrence. The difference is due to the fact that for this study, I do not include partial occurrences.

One aspect of this study was to see how well songs performed relative to their time on each of our selected charts. Billboard Pro's database provides a database that includes charting appearances. This data shows the charting position of each song every week. From there, I recorded the number of weeks the song was "on the chart" and "off the chart." Each song's time off the chart was divided into pre and post charting appearances. Before charting appearances were the number of weeks before the song's first appearance on the subsequent chart. After chart appearances are every week the song was off the chart after the song had its first appearance on the chart.

After recording these elements, I cross referenced each song to BuzzAngle's sales database. BuzzAngle provides "… complete access of every single music consumption transaction in its finest detail" ("Our Platform" 2020). Similar to Nielsen, this database provided sales information for each song of the database. From this database, I was able to get weekly data for each song in three categories: interactive online streams, and digital sales and radio spins. These will be referred to as "audio streams", "song sales" and "spins." Specific limitations of these three categories are provided in the Abbreviations & Definitions section. These three categories were split into three categories of charting appearances: On-Chart, Off-Chart Before, and Off-Chart After. I recorded the sales data from the song's release date until the end of the sample period studied, August 30th, 2019. A cut-off date was chosen when data collection began, as songs can sell infinitely beyond their release date. From the initial recording of 1,200 chart occurrences, the number of songs used in the final database was 356. However, for the sake of regression analysis, songs that appeared on multiple charts were recorded twice for genre-specific analysis. Including duplicate songs because of chart reoccurrences, the database contained 417 songs. This breakdown of the sample studied is shown in Table 1.

Year		Genres
2015-2018	Song Count	Total
	Chart Appearances	1200
	Songs Removed, Repeats	803
	Songs Removed With Bad Data	41
	Total Songs for Study (No Duplicates)	356
Breakdown by Genre		
	Billboard Hot 100	89
	Country	99
	Hip-Hop/R&B	76
	Mainstream Rock	102
	Pop/Contemporary	51
	Total	417

Note:
Songs that appeared on multiple chart were counted once during the regression analysis of all songs
However, these songs are added back when doing individual regressions per genre

Table 1: Song Breakdown of Observations for Regression

Next, I calculated several values from this database. I calculated the total and weekly averages of audio streams, song sales, and spins while they were on-chart, before they were on the chart, and after they were on the chart. I also calculated the maximum number of weeks the song consecutively charted. Other elements that were recorded were the peak charting number (1, 2, 3, etc.) and the first date in which the song reached its peak charting number. These were used as control variables. Other control variables include "Multiple Charts" and "Multiple Songs From the Same Album." "Multiple charts" denotes when a song appears on multiple charts simultaneously. A "1" on the database signified if this was true, and a "0" denotes if this is false. "Multiple Songs From The Same Album" denotes when multiple songs from the same album were charting simultaneously, and the same process was used to signify this on the database as the "Multiple Chart" value. To make sure the data sample was of high quality, songs were removed if all data was not available. The criteria for having an incomplete dataset consisted of any missing information in the song's sales figures and charting time or the lack of an official version on streaming services. A list of songs studied is provided in Appendix B.

Results

The first step was completing univariate analysis on the song database. This included calculating the mean, median, standard deviation and the minimum and maximum for each of the four song elements ("LOIA," "LOSA," "LTFCA," and "NOST"). The univariate results are shown in Table 2 for the entire sample and for each genre.

All Songs	Observations	Mean	Median	Std. Dev	Min	Max
NOST	356	10.23	8	10.5	0	110
LTFCA	350	44.26	41.86	23.67	0	241.26
LOIA	356	12.1	12.33	11.1	0	99.43
LOSA	356	218.84	215.35	42.28	123.7	508.34
Billboard Hot 100	**Observations**	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
NOST	89	13.14	9	16.29	0	110
LTFCA	88	41.28	39.46	31.11	0	241.26
LOIA	89	10.9	10.15	7.64	0	39.46
LOSA	89	217.22	215	42	123.7	342.54
Country	**Observations**	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
NOST	99	9.19	8	5.61	2	38
LTFCA	99	41.76	40.86	11.54	0	76.38
LOIA	99	12.99	12.62	5.75	0	29.13
LOSA	99	205.26	200.19	30.74	134.44	332.84
Hip-Hop/R&B	**Observations**	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
NOST	76	10.45	6.5	12.44	0	78
LTFCA	74	39.52	29.56	36.34	0	36.41
LOIA	74	13.95	12.16	9.06	0	44.85
LOSA	76	217.75	216.75	43.81	123.7	342.54
Mainstream Rock	**Observations**	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
NOST	102	8.72	7	7.85	0	44
LTFCA	101	52.64	51.31	21.02	0	135.03
LOIA	102	19.33	16.3	15.95	0	99.43
LOSA	102	234.43	229.1	52.55	168.59	508.34
Pop/Contemporary	**Observations**	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
NOST	51	11.82	9	9.8	0	55
LTFCA	48	42.21	40.34	19.42	0	75.88
LOIA	51	8.73	7.89	6.63	0	23.42
LOSA	51	220.83	220.38	31.16	161.61	300.61

Table 2: Univariate Analysis of Song Elements

Across the whole database, the average song mentioned the title in the lyrics 10.23 times, with a 12.1 second intro, 44.26 seconds to the first chorus, and an overall length of 218.84 seconds. On average, songs that appeared on the Billboard Hot 100 list mentioned the title in the lyrics more than any other genre with 13.14 occurrences. Mainstream Rock showed the fewest mentions of the title in the lyrics on average (8.72 occurrences) with the smallest standard deviation of 7.85 occurrences. Mainstream Rock also had the longest time to first chorus on average with 52.64. My analysis showed that in comparison to other genres, Hip-Hop/R&B had the highest number of songs that began with the chorus and subsequently had the lowest average length to first chorus with 39.52 seconds. Pop/Contemporary songs had the shortest average intro with 8.73 seconds (and the smallest standard deviation of 6.63 seconds) with Mainstream Rock averaging the longest intros with 19.33 seconds. Pop/Contemporary charts are based heavily on radio play, and this may explain the desire for a short introduction. Country songs averaged the lowest total length of songs with 205.23 seconds, with Mainstream Rock averaging the longest songs with 234.43 seconds. The extreme nature of Mainstream Rock's elements may explain why the sales of the genre were lowest of the group, perhaps serving a niche market. Differences in observation among elements in the same genre can be explained through Tobit regression censoring.

Next, a Tobit regression method was chosen due to the nature of the database and the sales value. Tobit regressions are the best option because the measure of value is limited to values greater than or equal to zero. A number of regressions were run to predict sales, streams and radio spins based on the four song elements for the songs in the database. Due to the large numerical values of sales, streams, and radio spins (our dependent variables), each value was scaled by a million. The regressions were completed by genre and for the total sample and for three measures of value. In addition, models were also estimated for totals as well as pre-charting and post charting values. Additional independent variables were added when calculating the regression over the period of time from the song's release. These include the song's peak charting number ("P"), the song's longest consecutive run on the chart ("MCWOC"), if the song was appearing on multiple charts simultaneously ("MCS"), and if multiple songs were charting from the same album ("MSFSA"). Due to the vast number of regressions, I focus on important findings throughout, and my explanations for what I learned. The results are divided based on the hypotheses made about each element and highlight significant values that support a working model, as well as the importance of which time segment of data is focused on. The regression results not discussed in the text are provided in Appendix C.

Tobit regression analysis does not have an equivalent to R-squared, which is seen in OLS regressions. This is mathematically impossible with multinomial regressions. In OLS regression, the sum of squared regressions and sum of squared errors will always equal the sum of squared total. This is not the case when the regressions are non-linear. There are a number of pseudo R-squared equations that attempt to calculate a goodness-of-fit statistic. Stata, the software used for this study calculates McFadden's pseudo R-squared valued. A relationship between the R-squared of OLS regressions and McFadden's pseudo R-squared can be found in the book *Urban Travel Demand: A Behavioral Analysis* by Tom Domencich and Daniel L. McFadden (124). McFadden's pseudo R-squared is calculated as equaling one minus the constant-only log likelihood divided by the full model log-likelihood.

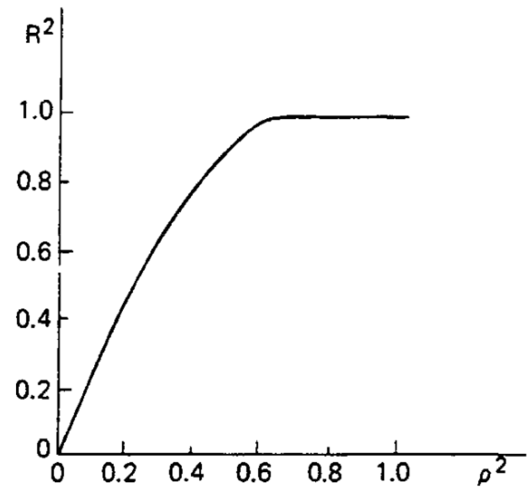

Figure 1: Relationship between Traditional R-squared and McFadden's pseudo R-squared

From this, it can be understood that larger pseudo R-squared values indicate a stronger fit for the model, where smaller values do not. Negative values are also possible in McFadden's pseudo R-squared for continuous or mixed continuous regressions such as Tobit (Sribney 2020).

Total vs. Before Charting vs. After Charting

Billboard Hot 100 - Streams

	Total	Before Charting	After Charting
NOST	3.113	3.067 ***	-0.213
	(1.38)	(2.76)	(-0.79)
LTFCA	-0.975	0.952	-0.039
	(0.16)	(1.66)	(-0.28)
LOIA	-1.321	-5.199 **	-0.305
	(0.36)	(-2.13)	(-0.52)
LOSA	-0.063	1.011 **	0.019
	(0.21)	(2.31)	(0.18)
MCWOC	8.67		
	(1.74)		
P	-20.573		
	(-4.39)		
MCS	424.511		
	(-0.53)		
MSFSA	-43.218		
	(0.49)		
CONSTANT	122.448	86.720	48.294
	(3.17)	(0.85)	(1.95)
PSEUDO R-SQR	0.0385	0.0131	0.0011
NUMBER OF OBSERVATIONS	88		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table 3: Regression Analysis: Billboard Hot 100 - Streams

The initial regression analysis was completed over the length of time between the song's release until the end of the sample period, August 30th, 2019. However, it became obvious very quickly that a significant predictor of song value would not be found in total values or after charting data. Once a song is on the chart, it is popular. Hence, there is a redundancy to using the time on the chart to indicate value. By the time a song has left the chart, many outside factors may be involved it what influences value. Referencing Billboard Hot 100 streams in Table 3, NOST ($p > .007$), LOIA ($p > .036$) and LOSA ($p > .024$) were all significant predictors. Longer songs with short introductions that used the title of the song extensively throughout the lyrics correlated to a higher value. Restricting the regressions to pre-charting data shows the strongest method of valuing a song through these elements.

Length of Song's Intro

All Songs - Streams

	Total	Before Charting	After Charting
NOST	3.113 ***	0.001 ****	-0.016
	(2.15)	(3.72)	(-0.09)
LTFCA	-0.975	0.0004	-0.067
	(-1.37)	(0.29)	(-0.78)
LOIA	-1.321	-0.004 ***	-0.469
	(-0.82)	(-3.23)	(-2.44)
LOSA	-0.063	0.0003	0.039
	(-0.16)	(1.41)	(0.82)
MCWOC	8.67 ****		
	(6.43)		
P	-20.573		
	(-1.79)		
MCS	424.511 ****		
	(10.43)		
MSFSA	-43.218		
	(-1.36)		
CONSTANT	122.448	0.035	19.983
	-(1.24)	(2.36)	(1.97)
PSEUDO R-SQR	0.0385	0.0057	0.0027
NUMBER OF OBSERVATIONS	350		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table 4: Regression Analysis: All Songs - Streams

All Songs - Sales

	Total	Before Charting	After Charting
NOST	0.007	0.0003	0.001
	(0.09)	(0.02)	(1.47)
LTFCA	-0.050	-0.009	0.0004
	(-1.26)	(-0.91)	(0.92)
LOIA	0.099	-0.062 ***	-0.004 ****
	(-1.10)	(-2.85)	(-4.07)
LOSA	-0.003	0.037 ****	0.007
	(-0.16)	(6.84)	(1.58)
MCWOC	-0.055		
	(-0.72)		
P	-0.674		
	(-1.04)		
MCS	5.582 **		
	(2.43)		
MSFSA	-1.460		
	(-.82)		
CONSTANT	5.987	-6.423	-0.05
	(1.08)	(-5.60)	(0.77)
PSEUDO R-SQR	0.0033	0.0226	-0.0721
NUMBER OF OBSERVATIONS	350		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table 5: Regression Analysis: All Songs - Sales

Hypothesis 2 predicted that the length of a song's introduction would have a significant relationship to value. Of the four song elements chosen, the length of the song's intro shows significance in several places. Referencing Table 4 and Table 5, LOIA is significantly related to STOB ($p > 0.005$, with a pseudo R-squared of 2.26%) and STTOB ($p > 0.001$, with a pseudo R-squared of 0.57%) for all songs included in the database. In both cases, songs with short introductions result in higher streaming and sales numbers. If we increase the LOIA by 1 standard deviation, we see decrease of 6.88 in the number of streams as measured by STOB. This is much more effective than for streams, which sees a minute decrease of 0.044 in the number of streams as measured by STTOB. However, the effectiveness changes dramatically depending on the genre. Referencing Table 3, Billboard Hot 100 songs saw a 39.72 decrease in the number of streams for every 1 standard deviation increase in LOIA ($p > .05$, with a pseudo R-squared of 1.31%).

Length of Song

Country - Sales

	Total	Before Charting	After Charting
NOST	-0.006	-0.002	0.0006
	(-0.97)	(-0.61)	(0.54)
LTFCA	0.0005	0.001	-0.00003 *
	(0.15)	(0.71)	(-0.04)
LOIA	-0.002	-0.00006	-0.0003 ***
	(-0.28)	(-0.02)	(-0.21)
LOSA	0.0006	0.001 **	-0.0003 **
	(0.46)	(2.03)	(-1.07)
MCWOC	0.009 ***		
	(3.01)		
P	-0.167 ****		
	(-5.73)		
MCS	-0.466 *		
	(-1.92)		
MSFSA	0.008		
	(0.11)		
CONSTANT	0.737	-0.072	-0.041
	(2.54)	(-0.73)	(2.18)
PSEUDO R-SQR	0.3711	-0.0812	-0.0094
NUMBER OF OBSERVATIONS	99		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table 6: Regression Analysis: Country - Sales

Country - Streams	Total	Before Charting	After Charting
NOST	-0.006	2.555	0.196
	(1.61)	(1.39)	(0.90)
LTFCA	0.0005	0.709	-0.004
	(-0.27)	(0.64)	(-0.03)
LOIA	-0.002 **	-2.641	-0.249
	(-2.45)	(-1.31)	(-1.02)
LOSA	0.001	0.862 **	-0.057
	(0.32)	(2.28)	(-1.27)
MCWOC	6.420 ****		
	(6.14)		
P	-52.07 ****		
	(-5.51)		
MCS	-164.350 **		
	(-2.09)		
MSFSA	-12.41		
	(-0.50)		
CONSTANT	205.016	-35.57	18.920
	(2.18)	(72.840)	(2.20)
PSEUDO R-SQR	0.0513	0.0075	0.0073
NUMBER OF OBSERVATIONS	99		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table 7: Regression Analysis: Country - Streams

Hypothesis 2 predicted that the length of a song would have a significant relationship to value. Results for the Country genre are consistent with Hypothesis 2. Referencing Table 6 and Table 7, LOSA is significantly related to STOB ($p > .045$, with a pseudo R-squared of 8.12%) and STTOB ($p > .025$, with a pseudo R-squared of 0.75%) for all Country songs included in the database. In both cases, the longer songs have higher streaming and sales numbers. A 1 standard deviation change in LOSA results in an increase of 26.50 in the number of streams as measured by STTOB. Length of song showed far less effect on sales in the Country genre, showing only a 0.03 increase of 0.044 in the number of sales as measured by STOB. This can also be for songs that appeared on the Billboard Hot 100. Referencing Table 3, if we increase LOSA by 1 standard deviation, we see an increase of 42.46 in the number of streams as measured by STTOB ($p > .05$, with a pseudo R-squared of 1.31%). We can reject the null hypothesis in these instances.

Number of Times Title of Song Appears in Lyrics

Billboard Hot 100 - Sales

	Total	Before Charting	After Charting
NOST	0.007	0.002 *	0.001
	(1.01)	(1.69)	(0.99)
LTFCA	0.006	0.001 **	0.001 *
	(1.57)	(2.06)	(1.97)
LOIA	-0.047 ***	-0.007 ***	-0.008 ***
	(-2.84)	(-2.70)	(-2.90)
LOSA	0.005	0.001 **	0.001 **
	(1.90)	(2.44)	(2.19)
MCWOC	0.045 ****		
	(4.49)		
P	-0.175 *		
	(-1.97)		
MCS	0.065		
	(0.23)		
MSFSA	-0.086		
	(-0.32)		
CONSTANT	-0.608	-0.057	-0.041
	(-0.76)	(-0.49)	(-0.34)
PSEUDO R-SQR	0.1142	-0.5511	-0.5627
NUMBER OF OBSERVATIONS	88		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table 8: Regression Analysis: Billboard Hot 100 - Sales

Hypothesis 3 predicted that the number of times the title of a song appears in the lyrics would not have a strong relationship with the song's value. Although this remained true across all songs, songs on the Billboard Hot 100 chart showed a significant relationship between sales and streams and NOST. Referencing Table 3 and Table 8, NOST is significantly related to STOB (p > .017, with a pseudo R-squared of -55.11%) and STTOB (p > .024, with a pseudo R-squared of 1.31%) for all songs in the database in Billboard Hot 100. For every 1 standard deviation increase in NOST, there is a 49.96 increase in the number of streams as measured by STTOB. In contrast, the impact on STOB is only a 0.03 increase for each 1 standard deviation in NOST. According to this model, the number of times the title of a song appears in lyrics does have a relationship with value.

Length to the Song's First Chorus

Mainstream Rock - Sales

	Total	Before Charting	After Charting
NOST	-0.074	-0.030	-0.0002
	(-0.93)	(-0.37)	(-1.21)
LTFCA	-0.0870 **	-0.087 **	-0.00002
	(-2.14)	(-2.07)	(-0.21)
LOIA	-0.147 **	-0.123 **	0.00007
	(-2.14)	(-2.16)	(-0.58)
LOSA	0.105 ****	0.097 ****	-4.50E-06
	(-2.64)	(6.69)	(-0.15)
MCWOC	0.025		
	(0.17)		
P	-0.445		
	(-0.83)		
MCS	Omitted		
MSFSA	3.131 **		
	(2.47)		
CONSTANT	-16.914	-14.583	0.013
	(-3.52)	(-4.53)	(1.97)
PSEUDO R-SQR	0.0651	0.019	-0.0795
NUMBER OF OBSERVATIONS	101		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table 9: Regression Analysis: Mainstream Rock - Sales

Hypothesis 4 predicted that the length of a song's first chorus would have a significant relationship to value. Of the four song elements chosen, the length to the song's first chorus shows the least significance over the span of genre's selected. However, an interesting relationship is found in Mainstream Rock. MCS was removed from the calculations on Mainstream Rock to due collinearity. Referencing Table 9, LTFC is significantly related to STOB ($p > .041$, with a pseudo R-squared of 1.9%) for all songs included in the database from the Mainstream Rock genre. The faster a song arrived at the chorus section, the more valuable it was seeming to be connected with sales numbers in the Mainstream Rock genre. For every 1 standard deviation increase in LTFC, there is a decrease of 1.83 in the number of sales as measured by STOB. This is more effective than songs across all genres, which did not show significance for this element. According to the database, the songs with the longest time to the first chorus were mainly in the Mainstream Rock genre, which makes these findings surprising.

The critical value of $p > .05$ was used in my analysis. However, because multiple tests were conducted, adjusting the alpha level may be a necessary step for future tests. Multiple methods of to correct alpha levels exist, including the Bonferroni correction. Bonferroni's correction divides the alpha level by the number of tests conducted. In this case, regressions were calculated on five genres, as well as the five genres collectively, over three time periods. This would make the critical value, by Bonferroni's correction, $p > .0028$, or $p > .01$ if discounting time periods. This would eliminate the majority of significances found throughout the regressions. However, due to the complexity and number of regressions calculated and the conservative nature of such correction methodologies, we assumed all the tests were independent of each other for this study to avoid substantial occurrences of false positives. Future studies, however, may benefit from some form of correction.

Discussion

The results of how songwriting elements affect a song's value were surprising. Some elements proved to be more effective at creating value. For example, the length of song was more effective at predicting value than length to the song's first chorus across all genres. Some genres were more impacted by certain elements than others. For example, Mainstream Rock songs were more valuable when they had shorter choruses compared to other genres. Billboard Hot 100 songs were more valuable when they had shorter introductions and the title of the track was used in the lyrics frequently. However, the four factors analyzed do not offer a straightforward answer to predicting a song's value. To create simple, quantitative elements of songs that could be analyzed automatically, the model does not provide a surefire way of answering the question of what drives value. This perhaps could be expected in the digital age. So many influences can affect a song's value. These include popularity through viral means (including memes and other social media posts), movie placements, and non-quantitative artistic elements. Trying to quantify these factors remains difficult, and these findings are similar to other studies. For example, the 2018 study by Minna Reiman and Philippa Ornell attempted to use machine learning with algorithms such as Gaussian Naïve Bayes and Support Vector Machine to predict whether songs would reach the Billboard Hot 100 list. Their model was only able to predict songs with 60% accuracy (Reiman and Ornell, 2018).

A key element of my hypotheses was that the value would vary depending on consumption medium. This turned out to be true, as the elements overall showed to be valuable indicators in streaming numbers but not sales number. This may be due to the demographics that are purchasing music versus those who are streaming services. However, streaming is the most valuable medium to predict, as nearly 80% of music consumption in 2019 was via paid streaming services (Nicolaou 2020).

In 2014, a viral video by Sir Mashalot emerged that showed six chart-topping songs could be laced together seamlessly through minor editing in Pro Tools. These six songs were “Sure Be Cool If You Did” by Blake Shelton, “Drunk on You” by Luke Bryan, “Chillin’ It” by Cole Swindell, “Close Your Eyes” by Parmalee, “This is How We Roll” by Florida Georgia Line, and “Ready, Set, Roll” by Chase Rice (“Sir Mashalot…” 2014). At the surface, certain genres are more prone to following formulaic song structures than others. However, my regression analysis only found significance in the length of country songs in streams before charting and streams before charting. This may suggest that using seconds instead of bars in studies on song structure may not be effective. However, that analysis is subjective, and the use of quantitative and non-subjective data collection becomes more difficult. Until a more sophisticated computer-based listening methodology is created, human subjectivity may always be necessary for studies such as this.

However, for songwriters, these elements are not to be completely dismissed. The strongest correlations were found within songs on the Billboard Hot 100, which is a good indicator of what is popular among listeners at the time. Specifically, short songs with titles that are repeated without the lyrics were linked to an increase in value through streams. These factors may be considered when attempting to write songs to receive widespread popularity.

Of all consumption mediums, radio spins had very few correlations throughout the study. Unlike streaming and direct sales, the consumer has little choice in deciding what they are consuming. As covered in a 2019 *Rolling Stones* article, despite formal investigations in 2004, the practice of payola and “pay-to-play” is still rampant within the industry (Leight 2020). While these allegations are far from proven, it does beg the question of the usefulness of including radio spins in studies to determine the value of a song.

Another important discussion is the difficulty of collecting clean data related to music sales, charting data and information on song elements. As I experienced over the course of this study, the data available on music is not easy to obtain nor extremely accurate upon review. Individual labels and companies are in charge of reporting data. Some songs, specific to certain labels, had large amounts of missing sales data. Billboard has made third party collection of their data illegal under copyright infringement. Outside of large established labels that have access to this data, the process remains tedious. With advances in technology, the access and accuracy of data should continue to improve, so that independent labels and lower-level artists may have the ability to use this data to the advantage of their careers.

Conclusion

This paper shows one example of how big data and analytics can be used to predict song value. As companies continue to implement the use of big data and analytics throughout the business world, it only seems certain that it will attempt to automate all facets of the business. This includes A&R jobs at major labels and music conglomerates. Although my model does not show any groundbreaking relationships between my chosen elements, it does highlight the possibilities involved with creating a model that could predict song value. In a market that is rewarding sustainable online revenue in the face of pandemic, the use of big data and analytics to maximize these profits in foreseeable future is vital. With the continued growth of these technologies, it may one day be possible to find a science within the art of music.

Works Cited

"2019-2020 Streaming Price Bible: YouTube Is STILL The #1 Problem To Solve." The Trichordist, March 5, 2020. https://thetrichordist.com/2020/03/05/2019-2020-streaming-price-bible-youtube-is-still-the-1-problem-to-solve/.

Berger, Jonah, and Grant Packard. "Are Atypical Things More Popular?" *Psychological Science* 29, no. 7 (July 2018): 1178–84. doi:10.1177/0956797618759465.

BuzzAngle Music. *BuzzAngle Music 2017 Report US*, 2017. https://www.buzzanglemusic.com/wp-content/uploads/BuzzAngle-Music-2017-US-Report.pdf. 28 December 2018.

Christenson, Peter G., et al. "What Has America Been Singing about? Trends in Themes in the U.S. Top-40 Songs: 1960–2010." *Psychology of Music*, (January 2018) pp. 1-19. *EBSCOhost*, doi:10.1177/0305735617748205.

Christman, Ed. "Life at the Margins." *Billboard*, 14 Apr. 2007, pp. 11.

Ciampaglia, G. L., Flammini, A., & Menczer, F. (2015). *The production of information in the attention economy*. Scientific Reports, 5(9452). doi:10.1038/srep09452

Cohen, Colin. "Bernstein Initiates Coverage of Spotify, Starts at 'Underperform'." *Digital Music News*, 13 Jan. 2020, www.digitalmusicnews.com/2020/01/13/bernstein-initiates-coverage-spotify/.

Davidson, Miriam, and Kiya Heartwood. *Songwriting: An Easy Beginning Method*. Alfred Pblishing Co., 1997.

Domencich, Thomas A., and Daniel McFadden. *Urban Travel Demand: A Behavioral Analysis*. Amsterdam: North-Holland Pub. Co., 1975.

Frank, Jay L. *Futurehit.DNA*. Nashville: Futurehit Press, 2009.

Friedlander, Joshua. "News and Notes on 2017 RIAA Revenue Statistics." *RIAA*, last modified March 22, 2018, www.riaa.com/wp-content/uploads/2018/03/RIAA-Year-End-2017-News-and-Notes.pdf.

Glanz, William. "Report: Streaming Has 51 Million Paying Customers in U.S." SoundExchange, October 18, 2018. https://www.soundexchange.com/2018/09/13/report-streaming-has-51-million-paying-customers-in-u-s/.

Grover, Varun, et al. “Creating Strategic Business Value from Big Data Analytics: A Research Framework.” *Journal of Management Information Systems* 35, no. 2 (2018) pp. 388–423. *EBSCOhost*, doi:10.1080/07421222.2018.1451951.

Henard, David H, and Christian L Rossetti. “All You Need Is Love? Communication Insights From Pop Music’s Number-One Hits.” *Journal of Advertising Research* 54 (June 1, 2014): 53–66. https://doi.org/10.2501/JAR-54-2-178-191.

Interiano, Myra et al. "Musical Trends And Predictability Of Success In Contemporary Songs In And Out Of The Top Charts". *Royal Society Open Science* 5, no. 5 (2018) p. 171-274. *The Royal Society*, doi:10.1098/rsos.171274

International Federation of the Phonographic Industry (IFPI). "Music streaming revenue worldwide from 2005 to 2018 (in billion U.S. dollars)." Chart. April 2, 2019. Statista. Accessed December 12, 2019. https://www.statista.com/statistics/587216/music-streaming-revenue/

Introducing Sony's 360 Reality Audio | The Future of Music. *YouTube*. YouTube, 2019. https://www.youtube.com/watch?v=h4ZbhQgE9_k.

Jacobson, Erin M. “Spotify May Have To Pay Songwriters $345 Million.” Forbes. Forbes Magazine, July 19, 2017. https://www.forbes.com/sites/legalentertainment/2017/07/19/spotify-may-have-to-pay-songwriters-345-million/#4d79c25c193d.

Krueger, Alan B., et al. “Inaugural Music Industry Research Association (MIRA) Survey of Musicians.” 22 June 2018, https://img1.wsimg.com/blobby/go/53aaa2d4-793a-4400-b6c9-95d6618809f9/downloads/1cgjrbs3b_761615.pdf.

Leight, Elias. “Want to Get on the Radio? Have $50,000?” Rolling Stone, January 16, 2020. https://www.rollingstone.com/music/music-features/radio-stations-hit-pay-for-play-867825/.

“Marketing & Sales Big Data, Analytics, and the Future of Marketing & Sales.” McKinsey & Company, March 2015, https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Marketing%20and%20Sales/Our%20Insights/EBook%20Big%20data%20analytics%20and%20the%20future%20of%20marketing%20sales/Big-Data-eBook.ashx

“Methodology.” *BuzzAngle Music*, 2020, www.buzzanglemusic.com/charts/methodology/.

Middleton, Richard, et al. “Pop.” *Grove Music Online*. (January 2001) pp. 1-54. Accessed 9 Jan. 2019, www.oxfordmusiconline-.com.ezproxy.mtsu.edu/grovemusic/view/10.1093/gmo/9781561592630.001.0001/omo-9781561592630-e-0000046845

Murphy, Ralph. Murphy's Laws of Songwriting: The Book. Nashville, Tennessee: Murphy Music Consulting, 2011.

Nicolaou, Anna. "US Music Sales Set 13-Year Record After Streaming Surge." Financial Times. Financial Times, February 25, 2020. https://www.ft.com/content/448e544a-57e1-11ea-a528-dd0f971febbc.

Olivet, Dean, et al. "Chartmania!! I Broke Down Every Song That Reached the Billboard Top 5 in 2017." *Soundfly*, 11 Jan. 2018, flypaper.soundfly.com/write/chartmania-breaking-down-billboard-top-40-songs-2017/.

"Our Platform." BuzzAngle Music, 2020. https://www.buzzanglemusic.com/platform/.

Owsinski, Bobby. "This Is Why Spotify Is Beating Apple Music." Forbes. Forbes Magazine, September 16, 2017. https://www.forbes.com/sites/bobbyowsinski/2017/09/16/spotify-apple-music/#503f01a3170b.

Percino G, Klimek P, Thurner S (2014) Instrumentational Complexity of Music Genres and Why Simplicity Sells. pp. 1-16. PLOS ONE 9(12): e115255. https://doi.org/10.1371/journal.pone.0115255

"Ralph Murphy Lecture - How to be Successful at Songwriting." Filmed [July 2011]. YouTube video, 1:48:45. Posted [July 2011]. http://youtu.be/8wBOUJ5Mbrk.

Reiman, M., & Örnell, P. (2018). Predicting Hit Songs with Machine Learning (Dissertation). http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-229705

Reimer, Bennett & Palmer, Anthony J. & Regelski, Thomas A. & Bowman, Wayne D. "Why Do Humans Value Music?" *Philosophy of Music Education Review* 10, no. 1 (2002): pp. 41-41. *Project MUSE*, muse.jhu.edu/article/408670.

Recording Industry Association of America (RIAA). (2016). U.S. sales database. Undefined: RIAA.

Rosenblatt, Bill. "Vinyl Is Bigger Than We Thought. Much Bigger." Forbes. Forbes Magazine, March 29, 2019. https://www.forbes.com/sites/billrosenblatt/2018/09/18/vinyl-is-bigger-than-we-thought-much-bigger/#3926d2eb1c9c.

Salganik, M. J., Dodds, P. S., Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. Science, 311, 854–856.

Schneider, Marc. "Warner Music Group Hires Chief Information Officer, Adds New Data Role." Billboard. Prometheus Global Media, LLC, December 14, 2016.

https://www.billboard.com/articles/business/7624487/warner-music-group-ralph-munsen-vinnie-freda.

Schreiber, David, and Alison Rieple. “Uncovering the Influences on Decision Making in the Popular Music Industry; Intuition, Networks and the Desire for Symbolic Capital.” *Creative Industries Journal* 11, no. 3 (2018): pp. 245–262. *EBSCOhost*, doi:10.1080/17510694.2018.1490146.

Sribney, William. “Pseudo-R2 for Tobit .” Stata. StataCorp. 2020. Accessed March 22, 2020. https://www.stata.com/support/faqs/statistics/pseudo-r2/.

“Sir Mashalot: Mind-Blowing SIX Song Country Mashup” Sir Mashalot, published on November 4th, 2014, YouTube video, 03:55, https://www.youtube.com/watch?v=FY8SwIvxj8o.

Spotify. "Annual Report for 2019." Spotify (2019): 1-238. Spotify. February 12, 2020. https://s22.q4cdn.com/540910603/files/doc_financials/quarterly/2019/601c445e-1d37-4938-b854-e5344850c3f9.pdf

Starr, Larry, and Christopher Alan Waterman. *American Popular Music: from Minstrelsy to MP3*. Oxford University Press, 2018.

Tagg, Philip. “Analysing Popular Music: Theory, Method and Practice.” *Popular Music*, vol. 2 (1982): pp. 37–67. *JSTOR*, www.jstor.org/stable/852975.

Tauberg, Michael. “Spotify Is Killing Song Titles.” *Medium*, last modified March 23, 2018, www.medium.com/@michaeltauberg/spotify-is-killing-song-titles-5f48b7827653.

Tough, David T. "An Analysis of Common Songwriting and Production Practices in 2014-2015 Billboard Hot 100 Songs." MEIEA Journal 17, no. 1 (2017): 79-120. Academic OneFile (accessed February 25, 2019). https://link.galegroup.com/apps/doc/A520582346/AONE?u=tel_middleten&sid=AONE&xid=9a3d9620.

Webster, James. *Haydn's "Farewell" Symphony and the Idea of Classical Style: Through-Composition and Cyclic Integration in His Instrumental Music*. Cambridge Univ. Press, 2004.

“What Are Pseudo R-Squareds?” UCLA. IDRE Stats, October 20, 2011. https://stats.idre.ucla.edu/other/mult-pkg/faq/general/faq-what-are-pseudo-r-squareds/.

Appendices

Appendix A

Data Collection Comparison – Hit Song's Deconstructed vs. Personal Analysis

	Hit Song's Deconstructed				Personal Analysis			
Song Title	Song Length	Length of Intro	Title of Song in Chorus	Length to First Chorus	Song Length	Length of Intro	Title of Song in Chorus	Length to First Chorus
Don't Let me Down - The Chainsmokers ft. Daya	3:23	0:12	26	0:36	3:23	0:12	26	0:36
Meant to Be - Rexha	2:41	0:06	17	0:31	2:41	0:06	17	0:31
Starboy - The Weeknd	3:42	0:15	8	0:56	3:42	0:15	8	0:56
We Don't Talk Anymore - Charlie Puth	CNIR	0:00	19	0:00	3:33	0:00	19	0:00
Body Like a Back Road - Sam Hunt	2:40	0:12	4	0:31	2:40	0:12	4	0:31
Do I Wanna Know - Artic Monkeys	4:31	0:29	5, 1 partial	1:36	4:31	0:29	6	1:36
Happy - Pharrell Williams	3:51	0:02	56	0:26	3:51	0:02	56	0:26
Wrecking Ball - Miley Cyrus	3:40	0:08	5	0:42	3:40	0:08	5	0:42
Roar - Katy Perry	3:43	0:05	16	0:48	3:43	0:05	16	0:48
Cruise - Florida Georgia Line	CNIR	0:07	9	0:00	3:30	0:00	9	0:00

Table A.1: Data Collection Comparison – Hit Song's Deconstructed vs. Personal Analysis

Note: This chart presents a comparison between my analysis and that of Hit Song's Deconstructed, a database used in universities and studying in-depth song analysis. Due to the possible subjectivity of music analysis, it is important to show the similarities and or differences between my analysis and that of other published sources. The abbreviation "CNIR" means that the report had conflict information

Appendix B

Songs Analyzed in Study

Song Title	Artist Title	Billboard Hot 100	Country	Hip-Hop/R&B	Mainstream Rock	Pop/Contemporary
679	Fetty Wap	x		x		
1-800-273-8255	Logic	x		x		
2 Phones	Kevin Gates			x		
24K Magic	Bruno Mars	x		x		
7 Years	Lukas Graham	x				
7 Years	Lukas Graham					x
7/11	Beyonce			x		
A Guy With a Girl	Blake Shelton		x			
Ain't Worth The Whiskey	Cole Swindell		x			
Amen	Halestorm				x	
American Dreams	Papa Roach				x	
Angels Fall	Breaking Benjamin				x	
Any Ol' Barstool	Jason Aldean		x			
Apocalyptic	Halestorm				x	
Asking For It	Shinedown				x	
Atlas, Rise!	Metallica				x	
Attention	Charlie Puth	x				
Baby, It's Cold Outside	Brett Eldredge					x
Backroad Song	Granger Smith		x			
Bad and Boujee	Migos	x		x		
Bad At Love	Halsey	x				
Bad Blood	Taylor Swift	x				
Bang Bang	Green Day				x	
Bank Account	21 Savage			x		
Believer	Imagine Dragons	x				
Bent To Fly	Slash				x	
Betray and Degrade	Seether				x	
Better Man	Little Big Town		x			
Better Now	Post Malone	x		x		
Better Now	Post Malone					
Black	Dierks Bentley		x			
Black Beatles	Rae Sremmurd	x		x		
Black Rose	Volbeat				x	
Blank Space	Taylor Swift	x				x
Bloodfeather	Highly Suspect					x
Blue Ain't Your Color	Keith Urban		x			
Bodak Yellow (Money Moves)	Cardi B	x		x		
Body Like a Back Road	Sam Hunt		x			
Boo'd Up	Ella Mai	x		x		
Born For Greatness	Papa Roach				x	
Bounce Back	Big Sean			x		
Break Up In A Samll Town	Sam Hunt		x			
Break Up in the End	Cole Swindell		x			
Break Up With Him	Old Dominion		x			
Broccoli	D.R.A.M.			x		
Broken Halos	Chris Stapleton		x			
Burning House	Cam		x			
Buy Me A Boat	Chris Janson		x			
Came Here to Forget	Blake Shelton		x			
Can't Feel My Face	The Weeknd	x		x		
Can't Feel My Face	The Weeknd					
Can't Stop the Feeling!	Justin Timberlake	x				x
Candy Cane Lane	Sia					x
Cheap Thrills	Sia	x				x
Cheerleader	OMI	x				
Christmas Eve	Kelly Clarkson					x
Church Bells	Carrie Underwood		x			
Closer	The Chainsmokers	x				
Cold Water	Major Lazer	x				
Coming For You	The Offspring				x	
Congregation	Foo Fighters				x	
Controlla	Drake			x		
Cozy Little Christmas	Katy Perry					x
Crash And Burn	Thomas Rhett		x			
Craving You	Thomas Rhett		x			
Crazy	From Ashes to New				x	
Cut The Cord	Shinedown				x	
Dance Macabre	Ghost				x	
Dark Necessities	Red Hot Chili Peppers				x	
Deja Vu	J. Cole			x		
Delicate	Taylor Swift					x
Despacito	Luis Fonsi & Daddy Yankee	x				
Devil	Shinedown				x	
Die A Happy Man	Thomas Rhett		x			
Different for Girls	Dierks Bentley		x			
Dirt on My Boots	Jon Pardi		x			
Dirty Laundry	Carrie Underwood		x			
Don't	Bryson Tiller			x		
Don't Let Me Down	The Chainsmokers	x				
Don't Mind	Kent Jones			x		
Don't Wanna Know	Maroon 5					x
Down in the DM	Yo Gotti			x		
Drinkin' Problem	Midland		x			
Drinking Class	Lee Brice		x			
Drip Too Hard	Lil Baby & Gunna			x		
Drunk On Your Love	Brett Eldredge		x			
Earned It (Fifty Shades Of Grey)	The Weeknd	x		x		
Ex's & Oh's	Elle King					x
Face Everything And Rise	Papa Roach				x	
Failure	Breaking Benjamin				x	
Fake Love	Drake			x		
Fast	Luke Bryan		x			
Feel Invincible	Skillet				x	

Table B.1: Songs Analyzed in Study – Complete List

Feel It Still	Portugal. The Man	x				
FEFE	6ix9ine	x		x		
Fight Song	Rachel Platten					x
Figure It Out	Royal Blood				x	
Finesse	Bruno Mars	x		x		
Five More Minutes	Scotty McCreery		x			
Follow Me Down	The Pretty Reckless				x	
Footsteps	Pop Evil				x	
Freaky Friday	Lil Dicky			x		
From the Ground Up	Dan + Shay		x			
G.D.F.R.	Flo Rida			x		
Get Along	Kenny Chesney		x			
Get Up	Shinedown				x	
Ghost	Badflower				x	
Girl Crush	Little Big Town		x			
Girls Like You	Maroon 5	x				x
Go To War	Nothing More				x	
God, Your Mama, and Me	Florida Georgia Line		x			
God's Plan	Drake	x		x		
Gone Away	Five Finger Death Punch				x	
Gonna	Blake Shelton		x			
Greatest Love Story	LANCO		x			
Gucci Gang	Lil Pump	x		x		
H.O.L.Y.	Florida Georgia Line		x			
Hallelujah	Pentatonix					x
Happy Song	Bring Me The Horizon				x	
Hardwired	Metallica				x	
Havana	Camila Cabello	x				x
Have Yourself a Merry Little Christmas	John Legend					x
Head Over Boots	Jon Pardi		x			
Hear Me Now	Bad Wolves				x	
Heartbeat	Carrie Underwood		x			
Heartbeat Song	Kelly Clarkson					x
Heathens	twenty one pilots	x				
Heaven	Kane Brown		x			
Heavy Is The Head	Zac Brown Band				x	
Hello	Adele	x				x
Help	Papa Roach				x	
Here	Alessia Cara			x		
Here's To The Heartache	Nothing More				x	
Home Alone Tonight	Luke Bryan		x			
Homegrown	Zac Brown Band		x			
Honey, I'm Good	Andy Grammer					x
Hotel Key	Old Dominion		x			
Hotline Bling	Drake	x		x		
House Party	Sam Hunt		x			
How Did You Love	Shinedown				x	
Human Race	Three Days Grace				x	
Humble and Kind	Tim McGraw		x			
Humble.	Kendrick Lamar	x		x		
Huntin', Fishin', & Lovin' Every Day	Luke Bryan		x			
Hurricane	Luke Combs		x			
I Am Machine	Three Days Grace				x	
I Am The Fire	Halestorm				x	
I Apologize	Five Finger Death Punch				x	
I Don't F**k With You	Big Sean			x		
I Don't Mind	Usher			x		
I Don't Wanna Live Forever (Fifty Shades Darker)	Zayn & Taylor Swift	x				
I Got The Boy	Jana Kramer		x			
I Know Somebody	LOCASH		x			
I Like It	Cardi B	x		x		
I Only Lie When I Love You	Royal Blood				x	
I Took a Pill in Ibiza	Mike Posner	x				
I'm Coming Over	Chris Young		x			
I'm Not The Only One	Sam Smith					x
I'm the One	DJ Khaled	x		x		
If Only For Now	Pop Evil				x	
In Case You Didn't Know	Brett Young		x			
In My Feelings	Drake	x		x		
In The Dark	3 Doors Down				x	
In The Night	The Weeknd			x		
Infra-Red	Three Days Grace				x	
iSpy	KYLE			x		
It Don't Hurt Like It Used To	Billy Currington		x			
Jekyll And Hyde	Five Finger Death Punch				x	
John Cougar, John Deere, John 3:16	Keith Urban		x			
Judas	Fozzy				x	
Juju on that Beat (TZ Anthem)	Zay Hilfigerrr & Zayion McCall			x		
Jumpman	Drake			x		
Just Like Fire	P!nk					x
Kick The Dust Up	Luke Bryan		x			
Kill4me	Marilyn Manson				x	
Killshot	Eminem	x		x		
Let Me Love You	DJ Snake	x				
Let You Down	Seether				x	
Lights Come On	Jason Aldean		x			
Lights Out	Royal Blood				x	
Like I Loved You	Brett Young		x			
Like I'm Gonna Lose You	Meghan Trainor					x
Little Monster	Royal Blood				x	
Little One	Highly Suspect				x	
Little Red Wagon	Miranda Lambert		x			
Lonely Tonight	Blake Shelton		x			
Look Alive	BlocBoy JB	x		x		
Look What You Made Me Do	Taylor Swift	x				
Lose It	Kane Brown		x			

Table B.1: Songs Analyzed in Study – Complete List (Continued)

Love Me Like You Do	Ellie Goulding	x				x
Love Me Like You Mean It	Kelsea Ballerini		x			
Love On the Brain	Rihanna	x		x		
Love Yourself	Justin Bieber	x				x
Loving You Easy	Zac Brown Band		x			
Lucid Dreams	Juice WRLD	x		x		
Luv	Tory Lanez			x		
Lydia	Highly Suspect				x	
Make Me Wanna	Thomas Rhett		x			
Make You Miss Me	Sam Hunt		x			
Maps	Maroon 5					x
Marry Me	Thomas Rhett		x			
Mask Off	Future			x		
May We All	Florida Georgia Line		x			
Meant to Be	Bebe Rexha & Florida Georgia Line	x	x			x
Mercy	Brett Young		x			
Middle of a Memory	Cole Swindell		x			
Million Reasons	Lady Gaga	x				
Mo Bamba	Sheck Wes			x		
Monster	Starset				x	
My Church	Maren Morris		x			
My Girl	Dylan Scott		x			
My House	Flo Rida	x				
My Name Is Human	Highly Suspect				x	
My Nemesis	Five Finger Death Punch				x	
My Way	Fetty Wap			x		
Nearly Forgot My Broken Heart	Chris Cornell				x	
Needed Me	Rihanna			x		
Never Again	Breaking Benjamin				x	
Nice For What	Drake	x		x		
No Limit	G-Eazy			x		
No Type	Rae Sremmurd			x		
Now That We're Dead	Metallica				x	
Oh My God	The Pretty Reckless				x	
One Call Away	Charlie Puth					x
One Dance	Drake	x		x		
One Number Away	Luke Combs		x			
Only	Nicki Minaj			x		
Open Your Eyes	Disturbed				x	
Panda	Desiigner	x		x		
Perfect	Ed Sheeran	x				x
Peter Pan	Kelsea Ballerini		x			
Photograph	Ed Sheeran					x
Pillowtalk	Zayn	x				
Psycho	Post Malone	x		x		
Rats	Ghost				x	
Reapers	Muse				x	
Record Year	Eric Church		x			
Red Cold River	Breaking Benjamin				x	
Rise	Sixx: A.M.				x	
Rotting In Vain	Korn				x	
Run	Foo Fighters				x	
Rx (Medicate)	Theory Of A Deadman				x	
Sad!	XXXTENTACION	x		x		
Safari Song	Greta Van Fleet				x	
Same Damn Life	Seether				x	
Same Old Love	Selena Gomez	x				
Sangria	Blake Shelton		x			
Santa's Coming For Us	Sia					x
Say You Won't Let Go	James Arthur					x
Scars To Your Beautiful	Alessia Cara					x
Seal The Deal	Volbeat				x	
See You Again	Wiz Khalifa	x		x		
Seein' Red	Dustin Lynch		x			
Setting the World on Fire	Kenny Chesney		x			
Shake It Off	Taylor Swift	x				x
Sham Pain	Five Finger Death Punch				x	
Shape of You	Ed Sheeran	x				x
She Got the Best of Me	Luke Combs		x			
Show Yourself	Mastodon				x	
Shut Up + Dance	WALK THE MOON	x				x
Sicko Mode	Travis Scott	x		x		
Side to Side	Ariana Grande	x				
Sign of the Times	Harry Styles	x				
Simple	Florida Georgia Line		x			
Sleep Without You	Brett Young		x			
Small Town Boy	Dustin Lynch		x			
Smoke Break	Carrie Underwood		x			
Somebody	Natalie La Rose			x		
Something From Nothing	Foo Fighters				x	
Something In The Water	Carrie Underwood		x			
Something Just Like This	The Chainsmokers	x				x
Somewhere on a Beach	Dierks Bentley		x			
Song #3	Stone Sour				x	
Sorry	Justin Bieber	x				
Speechless	Dan + Shay		x			
Spit Out The Bone	Metallica				x	
Square Hammer	Ghost				x	
Starboy	The Weeknd	x		x		
State Of My Head	Shinedown				x	
Stay A Little Longer	Brothers Osborne		x			
Stay With Me	Sam Smith					x
Still Breathing	Green Day				x	
Stitches	Shawn Mendes	x				x
Stressed Out	twenty one pilots	x				
Strip It Down	Luke Bryan		x			

Table B.1: Songs Analyzed in Study – Complete List (Continued)

Style	Taylor Swift					x
Sucker for Pain	Lil Wayne, Wiz Khalifa & Imagine Dragons			x		
Sugar	Maroon 5	x				x
Sun Daze	Florida Georgia Line		x			
Sunflower (Spider-Man: Into The Spider-Verse)	Post Malone & Swae Lee	x		x		
T-Shirt	Thomas Rhett		x			
Take It All	Pop Evil				x	
Take Me	Korn				x	
Take Me Down	The Pretty Reckless				x	
Take Your Time	Sam Hunt		x			
Talladega	Eric Church		x			
Tennessee Whiskey	Chris Stapleton		x			
Tequila	Dan + Shay		x			
Thank U, Next	Ariana Grande	x				
The Devil's Bleeding Crown	Volbeat				x	
The Fighter	Keith Urban		x			
The Hills	The Weeknd	x		x		
The Light	Disturbed				x	
The Line	Foo Fighters				x	
The Middle	Zedd, Maren Morris & Grey	x				x
The Mountain	Three Days Grace				x	
The Sky is a Neighborhood	Foo Fighters				x	
The Stage	Avenged Sevenfold				x	
The Vengeful One	Disturbed				x	
The Violence	Rise Against				x	
There's Nothing Holdin' Me Back	Shawn Mendes					x
Think a Little Less	Michael Ray		x			
Think of You	Chris Young		x			
Thinking Out Loud	Ed Sheeran	x				x
This Christmas	Seal					x
This is America	Childish Gambino	x		x		
This is What You Came For	Calvin Harris	x				
Throne	Bring Me The Horizon				x	
Thunder	Imagine Dragons	x				
Too Good	Drake			x		
Too Good at Goodbyes	Sam Smith	x				
Torn in Two	Breaking Benjamin				x	
Trap Queen	Fetty Wap	x		x		
Treat You Better	Shawn Mendes					x
Trouble	Five Finger Death Punch				x	
Truffle Butter	Nicki Minaj			x		
Try	Colbie Caillat					x
Tunnel Vision	Kodak Black			x		
Uncomfortable	Halestorm				x	
Unforgettable	French Montana	x		x		
Unforgettable	Thomas Rhett		x			
Up Down	Morgan Wallen		x			
Uptown Funk!	Mark Ronson	x				x
Used to This	Future			x		
Wake Up in The Sky	Gucci Mane			x		
Waking Lions	Pop Evil				x	
Wanna Be That Song	Brett Eldgride		x			
Want To Want Me	Jason DeRulo	x				
Wash It All Away	Five Finger Death Punch				x	
Water Under the Bridge	Adele					x
Ways To Get High	Pop Evil				x	
What About Us	P!nk					x
What Do You Mean?	Justin Bieber	x				
What Ifs	Kane Brown		x			
What It Is	Jonathan Davis				x	
When It Rains It Pours	Luke Combs		x			
When Legends Rise	Godsmack				x	
When The Curtain Falls	Greta Van Fleet				x	
Wild Thoughts	DJ Khaled	x		x		
Wildest Dreams	Taylor Swift					x
Without Me	Halsey	x				
Work	Rihanna	x		x		
Wrong Side Of Heaven	Five Finger Death Punch				x	
XO Tour Llif3	Lil Uzi Vert			x		
You Make It Easy	Jason Aldean		x			
Yours	Russell Dickerson		x			
ZEZE	Kodak Black	x		x		
Zombie	Bad Wolves				x	

Table B.1: Songs Analyzed in Study – Complete List (Continued)

Appendix C

Regression Results – Separated by Genre and Consumption Type

All Songs – Radio

	Total	Before Charting	After Charting
NOST	-2.014 ***	-0.880 *	-0.019
	(-2.79)	(-1.95)	(-0.49)
LTFCA	-0.503	-0.221	0.014
	(-1.42)	(-0.99)	(-0.71)
LOIA	0.761	-0.148	-0.017
	(0.95)	(-0.30)	(-0.41)
LOSA	-0.159	-0.021	-0.007
	(-0.81)	(-0.17)	(-0.68)
MCWOC	1.431 **		
	(2.12)		
P	10.887		
	(1.89)		
MCS	54.970 ***		
	(2.70)		
MSFSA	-11.875		
	(-0.75)		
CONSTANT	26.134	44.178	1.946
	(0.53)	(1.68)	(-0.86)
PSEUDO R-SQR	0.0061	0.0012	0.0006
NUMBER OF OBSERVATIONS	350		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.1: Regression Analysis: All Songs - Radio

Billboard Hot 100 – Radio

	Total	Before Charting	After Charting
NOST	-2.596	-1.074	-0.047
	(-1.71)	(-1.16)	(-0.61)
LTFCA	-0.599 *	-0.110	0.037
	(-0.78)	(-0.23)	(-0.93)
LOIA	0.221	-0.700	-0.088
	(0.06)	(-0.34)	(-0.52)
LOSA	-0.280	0.047	-0.012
	(-0.48)	(0.13)	(-0.39)
MCWOC	3.750 *		
	(1.77)		
P	17.274		
	(0.93)		
MCS	28.426		
	(0.48)		
MSFSA	-28.584		
	(-0.51)		
CONSTANT	6.714	51.437	0.630
	(0.04)	(0.60)	(7.140)
PSEUDO R-SQR	0.006	0.0014	0.0026
NUMBER OF OBSERVATIONS	88		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.2: Regression Analysis: Billboard Hot 100 - Radio

Country – Radio

	Total	Before Charting	After Charting
NOST	-0.006	-1.789	-0.049
	(1.60)	(1.31)	(0.09)
LTFCA	0.0005	0.718	-0.012
	(0.96)	(0.79)	(0.06)
LOIA	-0.002 *	-2.036	-0.001
	(1.82)	(1.44)	(0.10)
LOSA	0.0006	0.0972	-0.027
	(0.33)	(0.27)	(0.02)
MCWOC	0.844		
	(0.81)		
P	-6.676		
	(7.28)		
MCS	-93.168		
	(60.50)		
MSFSA	17.656		
	(19.06)		
CONSTANT	41.380	14.452	6.946
	(72.47)	(52.08)	(3.61)
PSEUDO R-SQR	0.0072	0.0042	0.0063
NUMBER OF OBSERVATIONS	99		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.3: Regression Analysis: Billboard Hot 100 - Streams

Hip-Hop/R&B – Sales

	Total	Before Charting	After Charting
NOST	-0.084	0.0002	0.002
	(-0.28)	(0.12)	(1.29)
LTFCA	-0.1060	0.0006	0.0003
	(-0.94)	(1.08)	(0.53)
LOIA	-0.708	-0.0006	-0.004 **
	(1.66)	(-0.26)	(-2.01)
LOSA	-0.181	0.0003	0.0002
	(-2.04)	(0.71)	(0.51)
MCWOC	-0.495		
	(-0.67)		
P	-2.85		
	(-0.93)		
MCS	8.73		
	(0.99)		
MSFSA	-6.630		
	(-0.79)		
CONSTANT	56.546	0.073	0.09
	(1.86)	(0.70)	(0.94)
PSEUDO R-SQR	0.0112	-0.0251	-0.0795
NUMBER OF OBSERVATIONS	74		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.4: Regression Analysis: Hip-Hop/R&B - Sales

Hip-Hop/R&B – Radio

	Total	Before Charting	After Charting
NOST	-3.876	-2.032 **	-0.023
	(-2.06)	(-2.12)	(-0.16)
LTFCA	-1.4250	-0.710 **	0.035
	(-2.04)	(-2.06)	(0.71)
LOIA	1.997 *	1.219	-0.128
	(0.75)	(0.89)	(-0.65)
LOSA	-0.480	-0.298	0.017
	(-0.87)	(-1.06)	(0.41)
MCWOC	3.831		
	(0.83)		
P	30.577		
	(1.60)		
MCS	99.341		
	(1.82)		
MSFSA	-97.427		
	(-1.86)		
CONSTANT	49.354	126.852	-0.712
	(0.26)	(1.94)	(-0.08)
PSEUDO R-SQR	0.0146	0.0085	0.0015
NUMBER OF OBSERVATIONS	74		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.5: Regression Analysis: Hip-Hop/R&B – Radio

Hip-Hop/R&B – Streams

	Total	Before Charting	After Charting
NOST	-1.641	2.444	-0.439
	(-0.71)	(1.58)	(-0.94)
LTFCA	-0.6910	0.613	-0.097
	(-0.80)	(1.11)	(-0.59)
LOIA	5.749 *	0.495	-0.826
	(1.75)	(0.22)	(-1.24)
LOSA	-0.495	0.435 **	0.010
	(-0.73)	(0.96)	(0.08)
MCWOC	8.134		
	(1.43)		
P	-114.386 ****		
	(-4.84)		
MCS	24.949		
	(0.37)		
MSFSA	75.425		
	(1.17)		
CONSTANT	773.697	166.569	63.477
	(3.32)	(1.58)	(1.990)
PSEUDO R-SQR	0.036	0.0044	0.0041
NUMBER OF OBSERVATIONS	74		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.6: Regression Analysis: Hip-Hop/R&B – Streams

Mainstream Rock – Radio

	Total		Before Charting		After Charting
NOST	0.189	**	0.202	*	-0.004
	(2.15)		(2.87)		(-0.88)
LTFCA	0.0450		0.051		0.001
	(1.01)		(1.39)		(0.59)
LOIA	-0.069		-0.220		0.001
	(-1.11)		(-0.44)		(0.35)
LOSA	0.046	***	0.015		0.0003
	(2.91)		(1.16)		(0.41)
MCWOC	-0.197				
	(-1.21)				
P	-0.193				
	(-0.33)				
MCS	Omitted				
MSFSA	1.363				
	(0.97)				
CONSTANT	-7.238		-5.892		-0.107
	(-1.36)		(-2.09)		(-0.61)
PSEUDO R-SQR	0.0259		0.019		0.0485
NUMBER OF OBSERVATIONS	101				
* p<.1, ** p<.05, *** p<.01, **** p<.001					

Table C.7: Regression Analysis: Mainstream Rock – Radio

Mainstream Rock – Streams

	Total	Before Charting	After Charting
NOST	-0.302	-0.435	0.007
	(-0.60)	(-0.87)	(0.21)
LTFCA	-0.231	-0.106	0.006
	(-0.90)	(-0.41)	(0.34)
LOIA	0.605	0.485	-0.011
	(1.73)	(1.38)	(-0.43)
LOSA	0.057	0.010	0.008
	(0.63)	(0.12)	(1.21)
MCWOC	2.496		
	(2.69)		
P	-3.088		
	(-0.92)		
MCS	Omitted		
MSFSA	5.775		
	(0.73)		
CONSTANT	-20.305	32.308	-0.103
	(-0.67)	(19.92)	(-0.07)
PSEUDO R-SQR	0.0148	0.004	0.0043
NUMBER OF OBSERVATIONS	101		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.8: Regression Analysis: Mainstream Rock – Streams

Pop/Contemporary – Sales

	Total	Before Charting	After Charting
NOST	-0.002	0.007 *	0.001
	(0.78)	(1.93)	(0.22)
LTFCA	-0.0870	-0.0004	-0.002
	(-0.51)	-(0.17)	(-0.39)
LOIA	-0.147	-0.0004 *	-0.010
	(-0.28)	(-.06)	(-1.05) ***
LOSA	0.105	0.003	0.007
	(2.02)	(1.95)	(2.76)
MCWOC	-0.002		
	(-0.18)		
P	-0.009		
	(-0.05)		
MCS	1.12 **		
	(2.59)		
MSFSA	0.425		
	(1.02)		
CONSTANT	-2.058	-0.423	0.013
	(-1.33)	(-1.61)	(-1.86)
PSEUDO R-SQR	0.0879	0.7863	0.1453
NUMBER OF OBSERVATIONS	48		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.9: Regression Analysis: Pop/Contemporary – Sales

Pop/Contemporary – Radio

	Total	Before Charting	After Charting
NOST	-0.759	-1.542	0.094
	(1.24)	(-0.73)	(0.36)
LTFCA	-0.3430	0.075	-0.039
	(-0.27)	(0.06)	(-0.24)
LOIA	1.557	0.416	-0.084
	(0.49)	(0.13)	(-0.21)
LOSA	0.082	0.362	0.048
	(0.11)	(0.46)	(0.51)
MCWOC	0.707		
	(0.53)		
P	-8.243		
	(-0.48)		
MCS	43.40		
	(1.05)		
MSFSA	50.097		
	(1.24)		
CONSTANT	-41.955	-52.921	-7.145
	(148.569)	(-0.35)	(-0.39)
PSEUDO R-SQR	0.0072	0.0015	0.0012
NUMBER OF OBSERVATIONS	48		
* p<.1, ** p<.05, *** p<.01, **** p<.001			

Table C.10: Regression Analysis: Pop/Contemporary – Radio

Pop/Contemporary – Streams

	Total		Before Charting	After Charting
NOST	0.465		1.286	-0.388
	(0.14)		(0.41)	(-0.53)
LTFCA	-2.1350		-1.092	0.260
	(-1.03)		(-0.57)	(0.57)
LOIA	2.357		1.616	-2.193
	(0.45)		(0.34)	(-1.96)
LOSA	3.342		3.124	0.195
	(2.66)		(2.72)	(0.71)
MCWOC	6.327			
	(2.91)			
P	-5.709			
	(-0.20)			
MCS	356.229	****		
	(5.23)			
MSFSA	180.515	***		
	(2.73)			
CONSTANT	-637.464		-412.343	-7.144
	(243.766)		(-1.87)	(0.39)
PSEUDO R-SQR	0.0707		0.0135	0.0106
NUMBER OF OBSERVATIONS	48			
* p<.1, ** p<.05, *** p<.01, **** p<.001				

Table C.11: Regression Analysis: Pop/Contemporary – Streams