Mendel University in Brno
Faculty of Business and Economics

Determinants of success of music production

Bachelor thesis

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Brno 2016

Acknowledgement

I am deeply grateful to Ing. Bc. Martin Machay, Ph.D. without whom this work would never see the light of the day. I would also like to thank Ing. Vladimír Hajko, Ph.D. whose suggestions about the econometric model were truly invaluable.

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In Brno on May 16, 2016 ______________________________

Abstrakt

Charvát, D. Determinanty úspěšnosti hudební produkce. Bakalářská práce. Brno: Mendelova Univerzita v Brně, 2015.
Tato bakalářská práce se zaměřuje na hledání aspektů, které mohou mít značný vliv na současné hudební preference. Celkově 755 pozorovaných písní pochází z elektronické databáze hudebních žebříčků British Official Singles Chart Top 40 za období 2013 až 2015. Za využití analýzy přežití bylo zkoumáno 29 různých charakteristik hudebních skladeb a 14 z nich bylo považováno za významné na 10% hladině významnosti. Výsledky naznačují, že úspěchu lze dosáhnout do jisté míry za pomoci faktorů, které nemají pouze náhodný charakter. Pop a elektronické žánry se jeví jako nejpopulárnější žánry posledních let. Stejně tak počáteční popularita a hudební doprovody filmů, her a reklam se zdají být významnými determinanty úspěšnosti. Naopak elektronické klávesy, klavír a výrazný audio engineering mají zřejmě negativní vliv na délku pobytu na hudebním žebříčku. To samé platí i pro narůstající průměrnou délku slov písňového textu.

Klíčová slova

Hudební preference, vlivné hudební faktory, populární hudba, analýza přežití

Abstract

Charvát, D. Determinants of success of music production. Bachelor thesis. Brno: Mendel University, 2015.
The bachelor thesis examines factors that may considerably affect contemporary music preferences. A total of 755 songs were acquired from an online database British Singles Chart Top 40 in the period from 2013 to 2015. Afterwards, overall 29 music characteristics were examined through a survival analysis and 14 were considered significant at a 10 % significance level. The outcomes suggest that the success may be achieved through factors of a non-random character to a certain degree. It seems that pop and electronic are the most popular genres of recent years. Soundtrack songs and initial popularity are significant determinants of success as well. On the other hand, electronic keyboards, piano and heavy audio engineering appear to have a negative effect on the survivability on chart. The same is true for an increasing average length of words of lyrics.

Keywords

Music preferences, influential music factors, popular music, survival analysis

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1 Introduction and aim of the thesis

1.1 Introduction

> *„Vocal or instrumental sounds (or both) combined in such a way as to produce beauty of form, harmony, and expression of emotion."* *(Oxford Dictionaries, 2015)*

Listening to music enhances life of many. For some it is a mean of relaxation and relief, for others a way to maintain their focus and for many a mean of showing off their lifestyle.

Throughout the history music has, like most of human products, gradually developed and its current form is considerably different from creations of ancient times. This fact is related not only to invention of new musical instruments and modernization of those already existing, but also to ever changing taste of musicians and their listeners. Although music genres have been changing, the goal of composers has remained the same – compose a famous song.

Even though many have tried to create a globally renowned song, there are only handful of truly worldwide famous songs which people are fond of listening to for decades. A question then arises: what makes a musical piece famous and how come so few authors have achieved long lasting popularity? In other words, what are the determinants of success of music production?

Every song differs in many factors like genre, length, language, tempo or instruments used which variedly influence eventual success. Therefore, artists, record producers and music publishers, for whom music is often both pleasure and livelihood, are steadily searching for an answer for the aforementioned question and they try to mix musical factors in such a way that would result in a hit song.

1.2 Aim of the thesis

The Aim of the thesis is to determine musical factors that influence success of music production among their listeners. The research question discussed herein is what the determinants of success of music production are. Moreover, the proposed research question is related to a hypothesis that success is achieved through factors of a non-random character.

The theoretical part defines basic musical aspects with an accompanying description. The following section discusses aspects that are influencing music preferences supported by an overview of conducted research on the topic of music preferences. The final part suggests various means of measurement of success and highlights the significance of understanding the concept of preferences in music consumption.

In the practical part I will observe selected physical and so called "behind-the-scene" characteristics of music and compare their ability to explain music preference variance. The data set consists of songs that appeared on the Official Singles Chart Top 40 (2015). To quantify musical piece's success a scale will adopted in which points will be assigned to every song accordingly to its weekly ranking on chart. The next section contains an application of a duration analysis and a presentation of the results. Lastly, a reduced model is included which aims at testing the relevance of the acquired outcomes.

2 Aspects of music

Music is a broad concept with room for many perspectives. It may be looked upon from the perspective of physics and then considered as melodic vibration in form of mechanical waves. For artists, music is a form of self-expression and an art of harmony. As far as the listeners are concerned, it serves numerous purposes such as mean of relaxation, psychological arousal or mood regulation. Several authors over the years have examined the relationship between various aspects of music and their effect on the music consumers with regard to their personal characteristics.

The first section lists several music characteristics with an accompanying description. That is followed by an overview of studies that examined music preferences with respect to the personality of the listeners and also the effect of various physical properties of the stimulus. The next section includes an overview of potential reasons for an endless urge for new music production and how a specific musical piece becomes more popular than the others. Last two sections deal with possible means of measurement of success and why the understanding of mechanisms underlying music preferences could be significant.

2.1 Musical features

Listeners are generally able to distinguish various music characteristics. As a consequence, they choose which songs they will listen to repeatedly and which they will dismiss shortly. Some of the aspects are easy to differentiate such as loudness or tempo, other are somewhat more difficult like harmony or timbre. However, there is much more to the elements of music than meets the eye which is the reason why trained musicians recognize more features and appreciate rather complex music structures in comparison to a regular listener (Fung, 1996). That does not mean, however, that nonmusicians are not unconsciously affected by them.

As it is apparent from Figure 1, there is a great deal of sources of variation in music preferences. Preferences in general may be interpreted as a greater liking for one alternative over another or others (Oxford Dictionaries, 2015). The variation could be separated into three major sources of input information (LeBlanc et. al., 1988):

1. The Physical characteristics of the music itself
2. The influence of the cultural environment in which the listener lives
3. The Personal characteristics of listener

In my thesis I will summarize previous research that examined mainly physical characteristics of the music itself and personal characteristics of the listener. In the practical part, however, I will not focus on the personal characteristic as they cannot be objectively and conclusively measured. Before I proceed to the research, it is necessary to write out basic aspects of music theory that define a particular piece and differ one song from the other (About.com, 2016; Burger, 2013; Crossley-Holland, 2014).

Rhythm may be described as placement of sounds in time. It defines song's texture and describes how sounds and notes change throughout the piece. As this concept is difficult to measure on its own, it is commonly described by separate and more specific terms. Beat is one component which is characterized as distinct energy bursts in time. It is a recognizable periodic division of music in time. The pace of the periodic succession is called tempo. It is commonly expressed in beats per minute. Tempo is believed to be one of the key factors that influence music preferences and it had been examined either directly or indirectly in several studies (LeBlanc et. al., 1988).

A musical piece has a musical form which is created by repetition, contrast or variation. Even though a song may have constant melody throughout its full length, the contemporary music usually includes certain repetition in form of a chorus – a group of lines repeated after a verse.

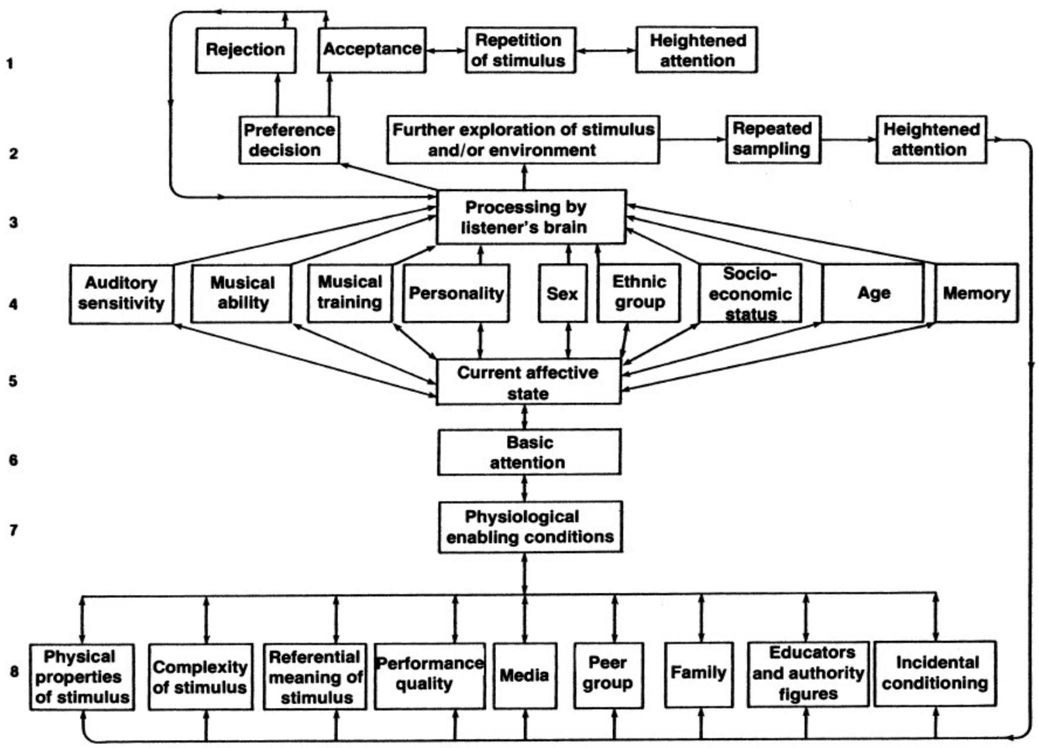

Figure 1: Sources of Variation in Music Preference (LeBlanc et. al., 1988, p. 158)

Closely related are lyrics of a given piece. Although songs may often possess a referential meaning, it is often perceived differently because of time progression, listener's characteristics and current affective state of the consumer. However, word intensity and emphasis on a given set of words may be objectively measured.

Another factor that explains variance in music preference are types and number of music instruments played on. LeBlanc (1981) examined the effect on the preferences when a song was either vocal or purely instrumental. Although the influence was not as significant as in comparison to genre or tempo, he indeed observed a relationship between performing medium and music preference.

A familiarity with the production is one of the key factors that contributes to its popularity and preference among public (Fung, 1996; Strobl, Tucker, 2000). Any song could quickly become appealing and well-known for number of reasons. One of them is the initial fame of an artist, which may quickly attract a large number of consumers (Adler, 2006). The familiarity of the given musical piece may be supported by a frequent repetition on the radio (Boyle, Hosterman, Ramsey, 1981) or, nowadays, through music streaming services, especially among young people.

Songs are frequently composed for a movie and if a particular production becomes popular, its popularity is likely to have a positive impact on the survivability of a given song on a music chart (Strobl, Tucker, 2000).

Sex of a singer may affect timbre, pitch, or vibrato. As such it is an important factor that might have an effect on the perceived performance quality.

The aforementioned list of aspects of music is by no means exhaustive nor is intended to be. The aim is to identify various physical properties of a musical piece that may be objectively measured and at the same time may contribute to explaining variance in music preferences and thus help reveal determinants of success of music production.

2.2 In search of music preferences

2.2.1 The relation to personality

Music has become essential to many individuals all around the world. One hears it in shopping centers, on TV, at the restaurant or simply on the street. It serves various purposes such as relaxation, self-awareness, comfort, psychological arousal, social relatedness, mood regulation or as a multipurpose marketing technique (Freire, Santos, 2013; Schäfer, Sedlmeier, Städtler, Huron, 2013). People also believe that music preferences reveal substantial information about their character qualities and depict their and others' personality (Rentfrow, Gosling, 2003).

Music is likely to be even more important for young people than for older generations. Young Americans listen to music frequently in various situations and consider it to be one of their main leisure time activities (Renfrow, Gosling, 2003). Japanese college students spend as much as 1.8 hours of their daytime listening to music (Brown, 2012).

Despite its undisputable importance, the topic of music preferences in general is yet to be deeply examined and general music theory to be established. As pointed out by Rentfrow and Gosling (2003), only seven articles concerning music were published in the leading social and personality journals between years 1965 and 2002. Since then various authors have reported significant research findings that shed more light on the topic of music preferences and how they are shaped.

In one of the profound studies Renfrow and Gosling (2003) suggested that the choice of music is likely to be closely related to personality, physiological arousal and social identity. At first they identified four major dimensions of music preferences: Reflective & Complex (classical, jazz, folk and blues), Intense & Rebellious (rock, alternative, heavy metal), Upbeat & Conventional (country, pop, religious, soundtracks), Energetic & Rhythmic (rap, soul, electronica). Afterwards they were able to trace a connection between music preferences and personality, self-views and cognitive ability. Their findings were supported by a study focused on Dutch adolescents (Delsing et al, 2008) in which four music-preference dimensions associated with several personality characteristics emerged. Those factors were labeled Rock (rock, heavy metal/hardrock, punk/hardcore/grunge, and gothic), Elite (jazz, classical and gospel music), Urban (hip-hop/rap, soul/R&B) and Pop/Dance (trance/techno, top 40/charts). Another study implied existence of five factors (Rentfrow, Golberg, Levitin, 2011) labeled Mellow (pop, soft-rock, soul/R&B), Urban (rap, electronica), Sophisticated (classical, operatic, jazz, world), Intense (heavy metal, punk, rock), Campestral (country, rock-n-roll, pop genres). Similarly, in a study focusing on German young adults, Schäfer and Sedlmeier (2009) concluded that music preferences could be grouped into six factor. They were labeled Sophisticated (classical, jazz, blues, swing), Electronic (techno, trance, house, dance), Rock (rock, punk, metal, alternative, gothic, ska), Rap (rap, hip hop, reggae), Pop (pop, soul, r&b, gospel) and Beat, folk & country (beat, folk, country, rock 'n' roll). To examine whether similar results would surface outside Euro-American Borders, Brown (2012) conducted research based on the original study of Rentfrow and Gosling (2003). Even though the Upbeat dimension was represented only by pop, he traced likewise four dimensions of music preference.

Although neither their methods nor results were not identical, it has been proven that there is indeed a certain relation between personality and music genres. But there are other aspects that define a song besides genre. People are social beings and thus seek emotion flow. Moreover, they are also strongly influenced by their feelings. One particular feature of music is the ability to transmit some kind of emotion (Guimaraes, Mesquita, Silva, 2015) and as such it satisfies human social needs. Among the emotions it may evoke are happiness, sadness or enthusiasm. It can also feel energetic, clever, simple or boastful (Rentfrow, Gosling, 2003). Last but not least, because the number of all possible combinations of instruments and voices is infinite, it is natural that the same song may be appealing to an individual while played on a certain instrument and sung by one artist, but tuneless in different settings. This may be further affected by listener's current affective state, peer group and other socio-psychological aspects. All that supports the importance of individual's personality in relation to music appreciation. Therefore, in any research it is vital not to focus solely on music genres, but remember that music preferences are also driven significantly by certain other musical characteristics as well as listener's personality.

2.2.2 Physical properties of a musical piece

A number of theories exists about why is a certain composition preferred to another. Some speculate that certain pop music songs are preferred because they are often played and promoted, from another standpoint it is argued that young people perceive certain recordings as reflections of contemporary youth values or values they wish to identify with. Other say that the preferred songs have better composition and thus perceived as “better” (Boyle, Hosterman, Ramsey, 1981).

According to LeBlanc (1981), as much as 28 % of preference variation may be explained by style (genre), tempo and medium. Genres themselves possibly explain 23 % of the variation. Genre is often one the factors analyzed in studies targeted at music preference and/or relationship to personality (e. g. Rentfrow, Gosling, 2003; Delsing et al, 2008). Faster tempo seems to be generally preferred to slower (LeBlanc, 1981, LeBlanc et. al., 1988, Fung, 1996). Boyle, Hosterman and Ramsey (1981) propose that structural factors such as melody, rhythm, lyrics or instruments are generally more important than the others.

2.2.3 Steadiness of music preferences

Human preferences are unstable and ever changing, they are unique to every individual and music is not an exception (Delsing et al, 2008). However, that does not predetermine that a song can attract only a single person. If that was the scenario, there would not be any star (Adler, 1985) and the market would be vastly fragmented. Whether artists attract groups of consumers because of genre, vocalist, instruments, rhythm or tempo, the reality is that a certain song is generally enjoyed by many. The question is how many individuals it may appeal to and how a certain choice turns out to be stable over time. It is especially important to artists and people involved in the music industry to know whether the adjustment of their production is needed considering for example gender, age, region or social status of their fan base. Rentfrow, Goldberg and Levitin (2011) came to a conclusion that “even though there are significant sex and age differences in preferences for specific pieces of music, the factors underlying music preferences are invariant to gender and age effects.” The factors also appear to be generalizable across populations and geographic region (Rentfrow, Gosling, 2003).

Another matter of interest is the time stability. Based on 706 internet participants, music preferences seem to be stable at least over a short period of 5 months (Rentfrow, Goldberg, Levitin, 2011). Also young people, who are devoted listeners, appear to have fairly stable music preferences at early adolescence (12-15) and that becomes increasingly stable as they grow older (16-19). However, at certain a point in time it is not uncommon that music preferences may change (Guimaraes, Mesquita, Silva, 2015).

2.3 Emergence of a new “hit” song

As proposed in the subsection 2.2.3, music preferences exhibit decent stability across time. But as it will be discussed in the practical part of this thesis, not a single piece manages to remain on a music chart forever. What creates such inconstancy and why does even the most popular musical piece at the given time falls out of the limelight eventually? Because the song doesn’t change, reason underlying this process has to be on the consumer’s side. Earl and Pots (2012) argue that one of the reasons why new tastes for cultural production arises is because our mind is designed to focus on novelty. Once a cultural piece becomes uninteresting and tiresome, people will seek novelty and based on their needs they may experiment with new styles, instruments or melody. Such effect occurs due to diminishing marginal utility. The marginal utility that one derives from listening to the same musical piece declines with repeated exposure. Upon reaching a point of low or negative marginal utility, the individual is motivated to seek a new hit. Initially a song might be almost unknown, but dependent on various factors (fame of an artist being one of the most eminent), it will be more frequently played and discussed which will lead to a decrease in consumption costs and make finding discussants easier and thus widens the fan base further. This process continues and it may reach a point where the frequency of plays exceeds other production and it snowballs into a “hit” song (Adler, 1985, 2006). The tricky question is how much novelty consumers seek. If products are too progressive and complex, potential consumers may fail to give attention to them and they dismiss the new product. However, the opposite scenario holds risks as well. Standing still or offering too little novelty may result in being outcompeted and the audience could shift to more progressive producers. Artists are left to seek the balance between extremism and conservatism in order to maintain or expand their audience (Earl and Pots, 2012). As far as the music charts are concerned, the desire for novelty elucidates why songs come and go frequently.

Even though novelty clarifies the eagerness for new production, it gives no explanation how and why is a specific song chosen to make it all the way to the top. Adler (1985, 2006) argues that even if all individuals could have equal artistic talents, not all individuals would be artists. The implication is that all the individuals could not accumulate equal fan base, even if they were able to compose identical songs. In his theoretical framework he considers the main determinant of stardom effect to be luck. Initially a group of consumers with similar tastes devote their time to an ostensibly randomly chosen musical piece. As more admires appear, the cost of searching for knowledgeable discussants decrease and its popularity will snowball as discussed in the previous paragraph. Once renowned and well-known, the word-of-mouth effect supports its popularity for an indeterminate period of time. As people share and discuss a specific popular piece, its popularity tends to increase. This fact has a negative impact on a diversity and underlines the Pareto’s 80/20 distribution of creative industry where 80% of the total revenue is accumulated only by 20 % of supply (Berlin, Bernard, Fürst, 2015). In order to endorse other than the “hit” song, it has to be sufficiently appealing at relatively small search costs.

Another view is offered by Rosen (1981) in his study The Economic of Superstars. He supports the idea that the most well-known artists have a bigger market share. However, he proposes that not luck, but talent is the most significant factor of success. Even a small advantage in talent may be multiplied (snowball) into higher earnings and a greater market share. This is mainly due to the fact that lesser talent is a poor substitute for greater talent and consumers are willing to spend more money on famous artists. Besides talent, technology is assumed to significantly affect condition on the market. One of the effects of technological improvement is decrease in costs of production and transmission which increases profit of the most talented even further. However, as the total amount of money that consumers are willing to spend on art increases and costs decrease, new artists have a chance to gain a foothold on the market. Who succeeds depends on many variables, luck being only one of them.

One way or the other, the lack of information about the market puts consumers into inefficient position by not satisfying their needs fully. Because it is both economically and technologically implausible to compose a song for every consumer that would maximize their utility, artists are encouraged to focus on production that would minimize the luck factor required to address broad audience and at the same time maximize their market share and profit.

2.4 Measurement of success

In order to search for determinants of success of music production, a mechanism for measuring success has to be designed. Success of an artist is generally measured in the total quantity of albums sold (Strobl, Tucker, 2000). If the measurement aims only at newly released album, charts display only the total quantity of the specific album sold. Total revenue may be similarly used as an indicator of success. Both techniques are unfortunately somewhat clumsy when measuring popularity of a single song. Although with the development of internet services purchase of a single song has become more common, many individuals could buy a whole album even though they may be mainly interested in a single musical piece only.

Throughout the late 20th century and the 21st century new tools of tracking popularity appeared and with it new possibilities how to record success on charts such as frequency of streaming, social network activity concerning the musical piece, illegal and legal downloads etc. (Legrand, 2014). Therefore, it is possible to measure songs’ success on multiple fronts. It may be of interest how often is a song played on the radio, downloaded, mentioned on a social network (such as Twitter or Facebook), how many people attend artist’s concert etc. It is also usually possible to review charts for any country worldwide.

2.5 Significance of music preferences

Understanding the mechanism which affects music preferences may be of use to various interested parties. As artists compose musical pieces for living, it is essential to them to appeal to their audience. Individuals and groups sharing similar musical interests differ in various aspects such as gender, age, nationality, level of education, tradition and so on (Leshkova, Islam, 2012). As it is more difficult than ever before to find homogenous preference groups, composing a "hit" song that would attract a worldwide audience has become equally difficult. On the other hand, such conditions open new possibilities for wider spectrum of artists, because they may target a specific group and claim their share on the market. As suggested by Filimon, López-Sintas and Padrós-Reig (2009), young generations seek the way how to express their own identity and distinguish themselves from their predecessors. That being said, both stable and aspiring artists are encouraged to understand ever-changing needs of their fans. Otherwise they may not be able to build up their fan base, because number of artists who can be popular at any one time is limited – not all talented artists can be successful (Adler, 2006). This thesis may help understand music preferences of the contemporary audience.

Understanding music preferences may also prove important to music publishers and to executive and music producers. It requires considerable financial and time investments to develop a new artist (Strobl, Tucker, 2000). Therefore, it is in their best own interest to recognize relevant music factors that may stood them in good stead.

Last but not least, revealing relevant factors of music preferences would improve algorithms used by various internet services for music streaming. With more profound knowledge of music preferences the algorithms would recommend appealing songs with better accuracy. Various companies have developed data mining algorithms with the aim of planning marketing campaigns, geo-locating fan engagement and developing engines for music discovery and recommendation (Legrand, 2014). All results concerning music preference may contribute to the improvement of such algorithms.

3 Methodology

The overview of several studies aimed at music preferences has laid the basis for the following analysis of relevant properties of a stimulus that may have an impact on music preferences in the contemporary music industry. An introduction and description of the data set is followed by a presentation of examined variables which are further separated into two groups: physical and behind-the-scenes properties. The last section introduces the model used herein as well as a discussion about its suitability for the purpose of the analysis.

3.1 Data set

The theoretical part outlined the conducted research on the topic of music preference and its relationship to various physical characteristics of music itself and personal characteristics of listeners. In accordance with the aim of the thesis, I will focus on the physical characteristics such as performing medium, tempo or word repetition and also on "behind-the-scenes" factors. These include impulses that are not apparent during the consumption of music itself, but may greatly affect song's reception. There are countless different measuring methods of success which result in a vast range of differing charts. For the purpose of the following examination, I will use publicly accessible database British Official Singles Chart Top 40 (2015) which releases weekly a new chart of the 40 most successful songs based on sales of downloads, CDs, vinyl and audio streams. These data offer various advantages. Not only is the database free for anyone to review, but it also stores previously released charts. Moreover, as it is weekly updated, it should quite precisely capture shifts in preferences. Although Britons may differ in music preferences to a certain degree, the British market should be sufficiently large and thus presumably reflect general music preferences with satisfactory accuracy.

The maximal amount of time that a given song may remain on chart is not restricted, its durability on chart is solely dependent on its popularity. The data set covers breakthrough of songs across a period of three years from 6th of January 2013 to 31st of December 2015. Any song that exceeds the proposed period remains observed until it drops out of the chart. As the list is released weekly, the entrance period covers 155 weeks. Throughout the observation, 844 unique songs appeared on chart. Points were assigned to every piece accordingly to its weekly ranking. In order to prevent bias caused by songs that might enter the chart only because of an irrelevant event specific only to the United Kingdom and not truly reflect current global tendencies, the following model will take only songs that acquired more than 10 points into account. That leaves 755 unique musical pieces for further examination. As an example, Table 1 displays ten songs that acquired the most points throughout the examined period and ten songs that acquired the least.

3.2 Identification of influential factors

The first step was to identify variables that could affect music preferences. Based on the review of previously conducted research covered in the previous sections and certain alteration by the author, the practical part will examine following characteristics of music using a survival analysis. Table 2 and Table 3 contain summary statistics of all dependent variables as well as of the independent variable.

Table 1: Songs with the most and the least acquired points

Title	**Points**	**Title**	**Points**
Thinking out loud	1 353	PYD	11
Happy	1 224	Alive	11
All of me	1 208	Wasting my young years	10
Uptown funk	1 056	Love me so	10
Let it go	1 008	It’s raining men	10
Stay with me	1 004	Forever now	10
Budapest	1 950	Wait for me	10
Take me to church	1 940	Bad day	10
What do you mean	1 906	High school	10
Wake me up	1 865	Mark my words	10

3.2.1 Physical properties

Physical properties are fundamental to every composition. Its quality indicates how appealing the song is going to be. Physical properties include factors that are recognizable and distinctive during the performance and thus play a vital role in music preferences and song’s subsequent popularity.

Genre is generally an important variable in music preference studies. In order to compare its relevance to other factors, I will use several dummy variables each representing a different genre. For a full list see appendix B.

Based on results acquired by LeBlanc (1981) and his co-authors Colman, McRary, Sherrill and Malin (1988), *tempo* seems to be a notable determinant as well. They concluded that faster tempo seems to be preferred to slower. It is worth an inquiry whether this assumption is valid with regard to the contemporary music.

Both musical and lyrical repetition may emphasize a certain referential meaning or improve the final production to reflect the composer’s conception. Lyrics were acquired from an online lyrics database and then examined in an online word counter tool in order to acquire an average word and sentence length. The former is labeled *AvgWord* and the latter *AvgSentence*. The same tool was used to determine the ratio of the most reoccurring word to the total word count. The proportion was labeled *RelWordFrequency*. Lastly, the total count of chorus repetition was identified and will be referred to as *ChorusRepetition*.

Several additional sets of dummy variables will be included in the research. First of them is sex of a singer (Male = 1, Female = 0). It will be referenced to as *Male*.

As many performances are a joint cooperation of singers of both sexes, another dummy variable labeled *Duet* is adopted which acquires value of one if singers of both sexes are distinctively and continuously present (Both = 1), zero if all singers are only either male or female (One = 0).

Last but not least, the music instruments are often the most distinctive part of a composition. Several music instruments (listed in appendix A) are examined in the model as dummy variables. In order for a variable to acquire a value of one, it has to be distinctively perceivable throughout most of the verses and/or chorus (distinctive = 1). This precaution assumes that listeners prefer certain songs because they enjoy sound of a specific instrument. Such approach, however, is not capable of recognizing preferences that occur due to a compact combination of several instruments. Such mixture could result into an enjoyable composition, even though the listeners might not be able to differ instruments from one another.

Table 2: Summary statistics –non-binary variables

Variable	Mean	Minimum	Maximum	Std. Dev.
Points	188,60	10,00	1 353,00	206,86
AvgWord	3,90	2,90	6,10	0,33
AvgSentence	6,63	2,60	11,00	1,42
ChorusRepetition	2,92	1,00	5,00	0,62
RelWordFrequency	0,17	0,05	10,90	0,40
Tempo	113,94	40,00	176,00	22,14
Writers	3,76	1,00	22,00	2,37
Label	1,64	1,00	5,00	0,80
WoC	114,51	0	1 067,00	143,63

3.2.2 Behind-the-scene properties

A musical piece is by no means conjured within few minutes by the composer alone nor is released and promoted by the artist alone. There are numerous mechanisms, strategies and hard work hidden behind every composition. Although they might not always be apparent to the listeners, their proper execution substantially increases song's positive reception and contributes extensively to its popularity. Hence these factors should be examined simultaneously with the physical properties. This group of factors will be referred to as “behind-the-scene” properties.

Firstly, it will be inspected whether a song was a part of a soundtrack originally composed for a movie, a video game or a commercial (Yes = 1, No = 0). It will be simply referred to as *Soundtrack*.

Table 3: Summary statistic – Binary variables

Variable	True [1]	False [0]	Proportion [%]
Male	386	365	51,13
Duet	97	654	12,85
Drums	311	444	41,19
BeatDrums	420	335	55,63
Keyboard	436	319	57,75
Piano	66	689	8,74
Engineered	196	559	25,96
Strings	110	645	14,57
Wind	80	675	10,60
Electronic	294	461	38,94
Jazz	6	749	0,79
Reggae	7	748	0,93
Blues	6	749	0,79
FunkSoul	43	712	5,70
Rock	114	641	15,10
FolkWorldCountry	26	729	3,44
HipHop	122	633	16,16
Pop	425	330	56,29
Soundtrack	40	715	5,30
Christmas	71	684	9,40
Summer	184	571	24,37

Music preferences could also be affected by the season of the year. Winter time is usually associated with calm and relaxing mood further deepened by Christmas songs while summer songs are commonly vivid and ecstatic. In order to examine the importance of a release time, another two variables labeled S*ummer* and *Christmas* will be adopted.

As discussed in previous sections, initial popularity is essential and increases artist's chances to breach the chart. In my thesis the initial popularity will be expressed as a sum of weeks that all artist's songs other than the observed spent on chart before the examined recording entered the top 40. Such variable will be called *WoC*.

Specialization and division of labor has been evolving since prehistoric times and music industry does not break the rule. Commonly some contribute to lyrics, some to composition while others are responsible for the final polishing and adjustments. It is therefore a point of interest to examine whether the total number of persons involved in the creation may affect subsequent reception. For this reason, another variable called *Writers* will be adopted.

Once the production is finished, a worldwide distribution and indigenous advertising follows. An artist has commonly a contract with one or more well-established record labels which are responsible for logistic and advertising. In theory, when more companies back up an artist, their production should reach out to more potential consumers. In order to test the assumption a variable called *Label* will be included.

3.3 Model

In order to search for significant factors of music success, I will use a survival model which may be also used for an estimation of endurance capabilities of a song on a music chart. Generally, a survival analysis observes certain units which are constantly at risk of experiencing a predefined event throughout time. An event in this context represents a change in state after which the unit is no longer observed. The whole process is sometimes referred to as a "failure time process", because the change of state is often equivalent to deterioration. Conclusions arising from the survival analysis help to answer a question: "What is the risk that a certain event occurs at the given time?" (Bhat, 2007; Pornchaiwiseskul, 2016).

The survival analysis estimates probability density distribution (f) throughout time and identifies relevant variables that affect the probability of a change in state and duration before the change occurs, respectively (Cottrell, Luchetti, 2016). Survival models are able to recognize that the likelihood of changing in state depends on the length of elapsed time since start of the duration (Bhat, 2007). The model is further broken down into two functions.

First is called a survival function (S) which estimates a probability that a state lasts at least as long as t. In other words, it quantifies the probability that a state will not change until specific point in time (Cottrell, Luchetti, 2016).

A hazard function (λ) in its essence characterizes a risk of a change in state. It quantifies the likelihood that the state will change shortly given that it persisted until time t. The result of the hazard function is a rate of occurrence (also called hazard ratio). It is equal to the density of event at t divided by the probability of surviving to that duration without experiencing the event. Following formula is a universal expression of the hazard function

$$\lambda(t, X, \theta) = \frac{f(\mathrm{t}, \mathrm{X}, \theta)}{S(\mathrm{t}, \mathrm{X}, \theta)}$$

where t is the length of time in the state in question, X is a matrix of covariates and θ is a vector of parameters (Cottrell, Luchetti, 2016).

Although the dependent variable is generally a unit of time, it will be somewhat transformed herein. As discussed in section 3.1, the dependent variable represents points that a given musical piece accumulated over time. Consider that every song would achieve μ points in average per week during its time on chart. It is therefore possible to acquire duration in weeks by dividing points by μ. Such approach holds a significant advantage. Imagine a situation when a certain song barely squeezes into the chart for two weeks and ends consecutively on the 35th position. Another song becomes a huge hit because it was played in the background of a viral video and as a result it breaks into top 5 for one week. However, the video is available on various video portals for anyone to watch for free. As a result, people choose to watch it and listen to the accompanying music this way. Therefore, the song drops out of the chart the following week. If weeks on charts were used as a dependent variable, the former would be seemingly more popular. Hence points as a transformed expression of time may be more appropriate in mapping determinants of music success.

There are several distribution assumptions for the hazard rate which differ in the baseline hazard, duration dependency possibilities and function forms. In order to fit the survival model, four parametrical approaches will be considered. Firstly, an exponential probability distribution holds hazard rate constant. That would imply that the duration is not related to the time elapsed since the beginning (Bhat, 2007). This assumption does not fit well the ranking progression of a recording on chart. Due to shifting music preferences, eagerness for novelty and release of new songs, the risk of dropping out is certainly dependent on time spent on chart.

The need for varying risk ratio is partially addressed by the Weibull probability distribution which allows hazard rate to be monotonically increasingly or decreasingly duration dependent. The simplified formula for the hazard function in Weibull's probability distribution may be written as:

$$\lambda(t) = \alpha\gamma^{\alpha}t^{\alpha-1}$$

Without going further into details, if $\alpha > 1$, then there is positive duration dependence, meaning that the more time since the start elapses, the more likely it is that the state will change soon. For $\alpha < 1$, the effect is opposite (Bhat, 2007). Related to the model discussed herein, the Weibull method would propose that a song is either in a bigger or smaller risk to drop out of the chart with rising number of points in its bank. Common logic suggests that the risk increases over time – it is more likely to fade away as the time passes.

However, songs on chart usually follow more variable course of events. When a certain musical piece wins its time in the limelight, it generally remains fairly popular for some time. Unless it becomes a global hit, the urge for novelty shifts focus of music consumers elsewhere and the song fades away. Only few songs remain on chart for a long time and thus accumulate lots of points. However, if they do, the risk of them fading away decreases relatively to the period when most of the songs drop out. Hence monotonic progress of the hazard rate is an inappropriate form.

Both log-logistic and log-normal probability distribution allow the hazard ratio to vary throughout its progress in other than monotonic way (Cottrell, Luchetti, 2016). In order to opt for a model that would be more appropriate in this case, one may compare information criterions of the candidates. In a survival model where the dependent variable are total number of acquired points and the explanatory variables are represented by factors reviewed in section 3.2, all information criterions, especially log-likelihood, suggest that the log-normal distribution offers a better fit (Overview of results in appendix C and D). Although the log-likelihood does not differ greatly in comparison to the Weibull distribution, the log-normal distribution fits the initial assumption better. Hence unless otherwise stated, all results presented in this work will be based on the log-normal distribution.

The log-normal model is an accelerated time failure model (AFT) which allows for a comprehensible interpretation. If the coefficients of AFT models are exponentiated and then one is subtracted, it is possible to interpret the outcomes as a percentage change in the dependent variable per change in unit of the given explanatory variable while keeping all other covariates constant (Rodríguez, 2007).

Lastly, it is necessary to briefly discuss one additional precondition that is vital for a credible survival analysis. In practice, researchers are often challenged with a problem of a limited observation period. This means that for some units of interest the examined state had started prior to the examination or had not ended before the last observation. In order to account for the incomplete states, survival analysis models include dummy variables for right-censoring or left-censoring (Cottrell, Luchetti, 2016). Eight songs still remained on chart at the time of the survival analysis and were capable of accumulating more points. Thus a dummy variable *OnChart* was accepted which implements right-censoring on the given songs.

3.3.1 Survival analysis vs. OLS regression

Before I proceed to the results, it would be appropriate to clarify the reason for choosing the survival analysis over an ordinary least square regression. It would be possible to examine the relationships using OLS while holding *Points* as an independent variable. The interpretation would be straightforward – marginal effect of the explanatory variable would lead to an increase (decrease) in accumulated points accordingly to the value of the given coefficient. Nevertheless, as Pornchaiwiseskul (2016) points out, there are almost always specific problems with usage of OLS on duration data. Common issue is that OLS assumes that the entries are normally distributed. That is, however, hardly ever true for the duration data which have tendency to be more thickly distributed towards its lower boundary. Another problem arises when OLS estimates negative predicted values. Time data by their nature must always be positive. Although there were only eight censored observations in the discussed survival model, it is another specific requirement that OLS has difficulties dealing with. Furthermore, survival analysis is capable of accommodating independent variables that change value over time. All the aforementioned features of duration data are true for the examined data set and thus the OLS method is not appropriate.

4 Results

The following chapter provides results of the survival analysis. For the full outcome of the survival model see appendix D. The Kaplan-Meier survival estimate (Figure 2) captures distribution of songs based on the number of points they accumulated. The initial steep slope clearly reflects that most of the songs drop out of the chart quite soon. Only 8,9 % of recordings obtained at least 500 points.

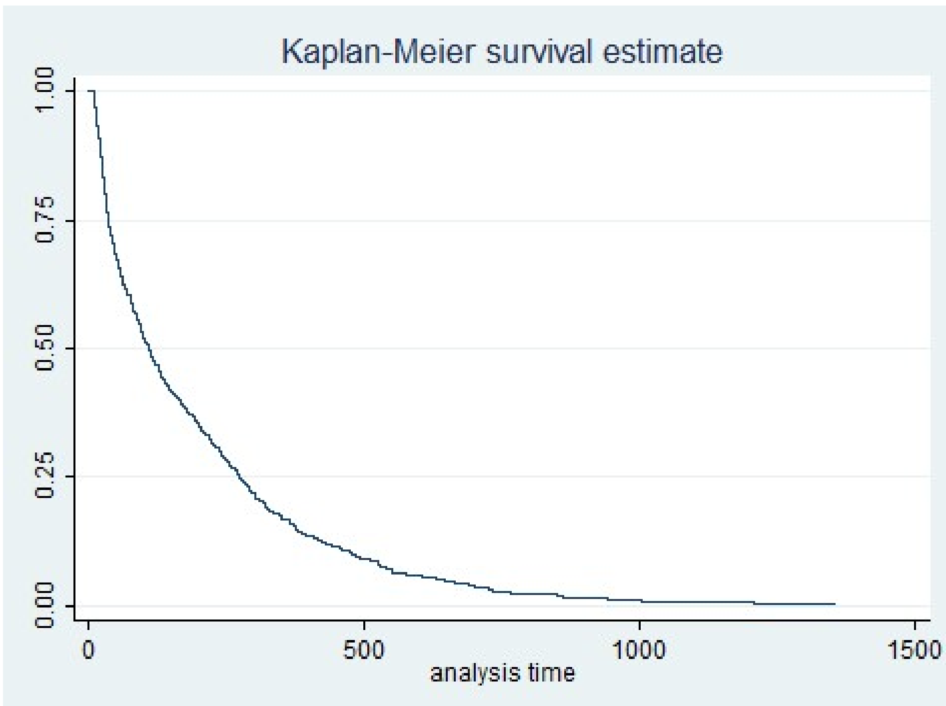

Figure 2: Kaplan-Meier survival estimate

The parametric survival analysis estimates which factors affect the total point count positively and which negatively. Positive values of coefficients lead to decrease in the hazard ratio, negative values increase it. In other words, if a variable has a positive coefficient, it decreases the risk of dropping out of the chart shortly after accumulating certain amount points. A negative coefficient decreases the chance of accumulating additional points.

For a better understanding the coefficients will be exponentiated which allows for an interpretation in terms of time ratios. The obtained value may then be interpreted as a percentage change in the dependent variable per change in unit of the given explanatory variable while keeping all other covariates constant (Rodríguez, 2007).

4.1 Physical properties

Table 4: Survival analysis (selected variables – physical properties)

Variable	coefficient	Exp(β_i) – 1	std. error	z	p-value	
Male	0,016951	1,710 %	0,098774	0,171612	0,863742	
Duet	-0,072476	-6,991 %	0,144039	-0,503172	0,614843	
AvgWord	-0,261416	-23,004 %	0,129743	-2,014883	0,043917	**
AvgSentence	-0,016775	-1,664 %	0,031768	-0,528054	0,597462	
ChorusRepetition	0,071623	7,425 %	0,070561	1,015046	0,310084	
RelWordFrequency	0,133803	14,317 %	0,105210	1,271764	0,203457	
Drums	0,291076	33,787 %	0,160391	1,814785	0,069557	*
BeatDrums	0,261334	29,866 %	0,167310	1,561977	0,118293	
Keyboard	-0,334972	-28,464 %	0,094533	-3,543447	0,000395	***
Piano	-0,803797	-55,237 %	0,168653	-4,765986	0,000002	***
Engineered	-0,236907	-21,094 %	0,111770	-2,119602	0,034040	**
Strings	-0,053255	-5,186 %	0,129445	-0,411412	0,680770	
Wind	0,023668	2,395 %	0,147115	0,160878	0,872189	
Electronic	0,310774	36,448 %	0,114075	2,724288	0,006444	***
Jazz	-0,849369	-57,232 %	0,483414	-1,757023	0,078914	*
Reggae	0,199863	22,124 %	0,441439	0,452754	0,650726	
Blues	0,898605	145,617 %	0,485573	1,850609	0,064226	*
FunkSoul	0,539238	71,470 %	0,190506	2,830551	0,004647	***
Rock	-0,329769	-28,091 %	0,136676	-2,412783	0,015831	**
FolkWorldCountry	0,277169	31,939 %	0,240696	1,151532	0,249513	
HipHop	0,036795	3,748 %	0,133696	0,275214	0,783152	
Pop	0,258523	29,502 %	0,100406	2,574785	0,010030	**
Tempo	0,000323	0,032 %	0,002064	0,156612	0,875551	

4.1.1 Genre, tempo, instruments

One of the goals was to test LeBlanc's proposal (1981, 1988) that genre, tempo and performing medium are substantial determinants of music preferences. According to the outcomes, as much as 23 % preference variation was explained by genre, 26 % by genre and tempo and 28 % by genre, tempo and performing medium. Although the survival model provides results in a different form, the qualitative interpretation and comparison of the outcomes is plausible. The survival analysis suggests that the song's genre indeed is an important factor. However, it seems that not every genre is a determinant of success at the same time. As a reminder – positive values increase the chance of accumulating more points, negative values increase the risk of dropping out of the chart soon.

To begin let's focus on genre itself. Table 4 reveals that *blues* ends up as a surprising winner. The coefficient has a value of 0,899, thus the exponentiated value is a notable 145,62 % difference in comparison to songs that are not considered blues. It is also significant at a 10% significance level. Despite that, interpret-ing the value as a decisive factor of success might turn out to be misleading. Closer examination of the data set reveals that only six songs throughout the observed period were labeled blues. Although those songs managed to gain notable popularity, it would be too hasty to conclude that the blues genre is a safe choice. The scarce occurrence in the data set would, however, suggest that blues songs had been less likely to enter the chart. Therefore, it appears that blues songs are less popular than some other genres which are present in the data set more often. Nevertheless, it might be true that if a blues song appears on chart and attracts notable attention, it also tends to remain on it for a long period of time. A larger data set that would include a larger collection of blues songs is required to examine the influence thoroughly.

Funk / Soul with the relative effect of 71,47 % appears to be a potent determinant of success at a 5% significance level. The outcome is more robust in comparison to blues as the genre is represented by 43 musical pieces. It is important, however, to be cautious with conclusions again. The list of genres (see appendix B) and the classification of songs is based on a music database Discogs (2016). Their judging system allows songs to belong to more than one genre. As a consequence, only very few songs that are considered to be members of Funk / Soul genre belong only to a single genre. Roughly half of them are considered to be representatives of pop at the same time which appears to be a very significant factor of success too. However, pop appears in the data set far more often and hence its relevance seems to be undeniable. It might be the case that Funk / Soul reduces the risk of losing popularity quickly only because it is tightly related to other positive factors. The results suggest that leaning towards the discussed genre is generally a good choice. Despite that, a further research that would examine a larger data set is required in order to test the relevance.

On the other hand, *electronic* and *pop* genres are not only significant popularity factors, but their relevance is also supported by p-values and the data set. Out of 755 examined songs 621 are labeled either pop, electro or both. Based on the survival analysis, pop songs accumulate 29,5 % more points in comparison to songs that aren't considered to be pop. In case of the electronic genre, the relative impact is 36,45 %. Large and positive effect of both factors and their regular appearance on chart hint that these two genres are influential factors of success in the contemporary music industry at least in Great Britain.

The other group of variables are the risk factors. These are genres that could potentially decrease the chance to attract greater attention. The biggest risk is related to *jazz*. With a relative negative effect of 57,23 %, artists opting for this genre are rather unlikely to become greatly popular. Even though the parameter is significant at the extended 10% significance level, the identical robustness issues as with the aforementioned positive factors arise. The problem with such conclusions is that jazz had been represented only by six songs over the course of three years. That is, however, argument on its own. Because jazz songs break into the chart so rarely and barely accumulate couple dozen points, it appears that jazz songs are far from being a mainstream genre of recent years.

Rock is a great example of shifting preferences. Rock and its variations enjoyed major attention from 1940' to 1970'. Nowadays, however, its popularity has been long declining and the survival model confirms the trend. Although many of the 114 rock songs managed to gain impressive number of points, the majority of them only remained on chart only for a while and then fade away. According to the survival model, rock songs accumulate in average 28,09 % less points in comparison to non-rock songs. Even though it is still a fairly popular genre and many rock songs enter the chart, its fame is somewhat dull and short-lasting. On the other hand, the fact that 15 % of songs on chart were rock songs proves that the genre is relatively more popular than blues or folk, word and country which were represented only scarcely. Qualitative interpretation of the survival model lacks essential robustness to provide clear answers about effect of less numerous genres.

Remaining genres seem to have a negligible effect on the recording's success. With reference to *Reggae* and *Folk, World & Country,* weaker demand for such songs is further supported by the scarce appearance in the data set. Hip Hop outcome requires a different interpretation. The large p-value suggest that whether a hip hop song becomes greatly popular or not depends on factors other than the choice of genre. However, the genre itself appears to be quite popular as 122 out of 755 songs were labeled Hip Hop. That is the third most frequently observed genre in the data set.

To sum it up, genres themselves seem to be strong determinants of music success as proposed in LeBlanc's study (1981). This is apparent from the survival model, where six genre variables are significant at a 10% significance level. The overall positive effect on the hazard ratio, in other words decreasing risk of dropping out early of the chart, reflects Figure 3.

Another LeBlanc's (1981, 1988) outcome was a proposition that faster tempo is relatively more popular than slower tempo. The *tempo* of the examined songs has a mean of 114 BPM which is in the middle between moderately slow and moderately fast tempo groups based on a qualification in LeBlanc's study (1988). Relative greater popularity of fast paced songs in contemporary music is therefore somewhat unclear. Consequently, tempo is considered insignificant in the survival model. The p-value is immense and thus the effect on hazard rate seems to be non-existent. Therefore, the survival analysis conducted on the herein examined data set could not support the hypothesis about preference for faster tempo.

The last proposed factor at the beginning of this subsection were instruments and their alteration. It seems that a necessary feature of almost every popular song are *drums* or a repetitive beat (*BeatDrums*) in the background. Only 42 songs went against the flow. In case of drums, the survival model supports the proposition with a relative positive effect of 33,79 % at a 10% significance level. The outcome for the repetitive beat with a p-value of 0,12 is less conclusive. Although having a distinctive beat in the composition appears to be a good choice, 17 out of those 42 differing songs gained more than 100 points and one ended up third overall. Even though it may be a risky move, it is obvious that music consumers do enjoy variety to a certain degree and that going off the beaten track may occasionally turn out to be a wise decision.

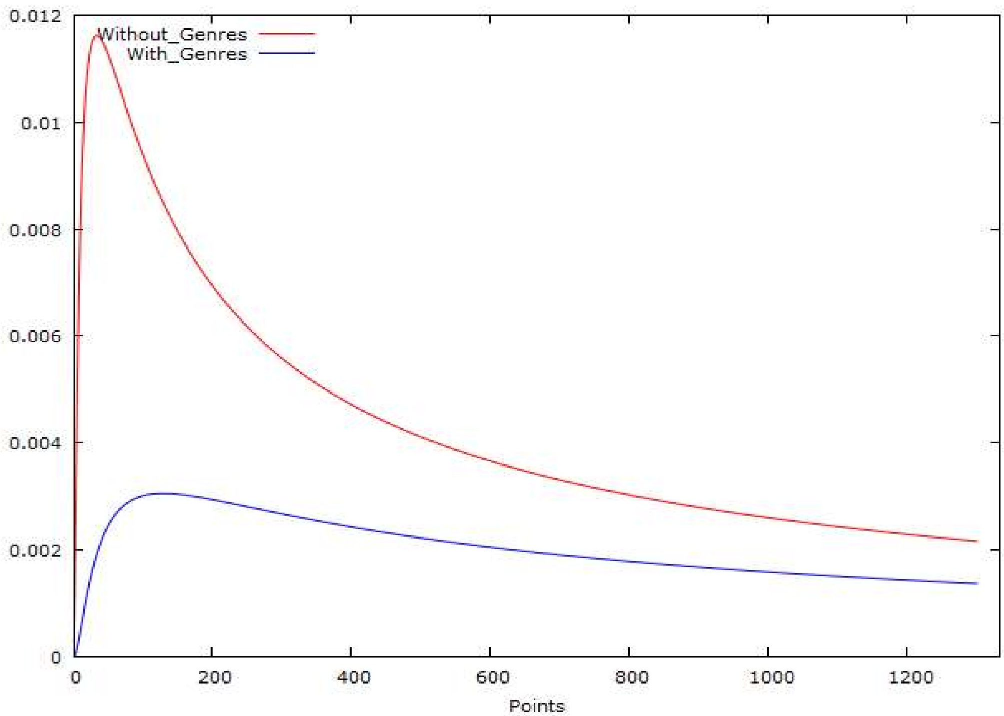

Figure 3: Impact of genres on hazard rate

Electronic *keyboards* have a negative relative effect on the popularity potential. Songs that incorporate electronic keyboards in the composition accumulate in average 28,46 % less points that the recordings that don't use it. The outcome further supports the assumption about urge for originality. As the electronic keyboards were used in 1/3 of the examined songs, it is beyond any doubt that electronic keyboards are a popular choice of both artists and their fans. However, the large negative value suggests that even though such songs manage to break into the chart regularly, they remain there only for a couple of weeks and then drop out. This chain of events may be occurring due to the human need for novelty as discussed in section 2.3. The idea is that people focus on new production once their current playlist doesn't satisfy their cultural needs anymore. A new song that is similar to those previously popular may gain attention for a while, but due to its limited innovation potential it quickly fades away as well. Songs that differ greatly from the mainstream production - that is when artists do not play on electronic keyboards for example - may be able to maintain attention of consumers for a longer period of time.

So called audio engineering is a common technique used in the contemporary music industry. Almost every artist has his or hers recording altered to a certain degree. However, in the proposed model, the *Engineered* variable represents songs that have either voices or instruments altered in such a way that it doesn't sound like a voice or the original instrument anymore. 196 songs undergone such a heavy alteration which suggests that it is a common and fairly popular practice. Nevertheless, distinctive audio engineering appears to suffer the same fate as songs that have electronic keyboards incorporated in the composition. It seems that heavy alteration of the final production may reduce the popularity potential by as much as 21,09 % in comparison to songs that don't use this technique so distinctively. Because the final alteration could be perceived as too similar to that in other songs, such recordings may quickly lose their momentum.

Artists who choose *piano* as an accompaniment are likely to fade away relatively quickly. Out of the 66 observed songs only 16 of them managed to acquire more than 100 points and none had more than 250 points. The relative negative effect of distinctive usage of piano is 55,24 %. In the observed period, the songs that had pianos in the composition neither broke into the chart often nor did they become greatly successful.

Last two examined instruments were various *wind* and *string* instruments excluding guitar and bass. The former were used in 80 observed recordings while the latter were used in 110. Both variables obtained a large p-value and were considered insignificant. Although artists use wind and string instruments commonly, it seems that they have a negligible effect on the reception.

The overall effect of genres and instruments on the hazard rate is reflected in Figure 4. Tempo was because of its insignificancy excluded. A large gap between lines representing the hazard functions with inclusion of genres and instruments factors and without them exhibits their considerable importance.

4.1.2 Other physical properties

The remaining physical properties examined in the survival model seem to have a lesser impact on the survival time on chart than genre, tempo and instruments used in the composition. The sole exception is an average word length (*AvgWord*) which captures lyrics complexity in a certain way. Songs that use extensively short repeating phrases (yeah, hey, la, oh…) generally have shorter words in average. On the other hand, songs that avoid such repetition tend to focus more on a referential meaning of lyrics. Therefore, the objective of this variable is to observe whether listeners enjoy repetitive lyrical structure which is easier to remember and sing along. In the model, *AvgWord* has a coefficient of -0,262. It means that with an increasing length of words songs are in greater risk of dropping out of the chart shortly. More specifically, an additional letter decreases the point accumulation potential by 23 %. In other words, the shorter average length of words that is often related to short repetitive phrases especially in a chorus seems to be preferred to a more complex structure.

Other variables that focus on the lyrical structure have a large p-values and don't seem to have a significant impact. The variable labeled *AvgSentence* reflects average number of words in a sentence. Especially for fast-paced songs with a large total word count such outcome is unsurprising. In many recordings sentences follow in quick succession and pauses between them are barely perceptible.

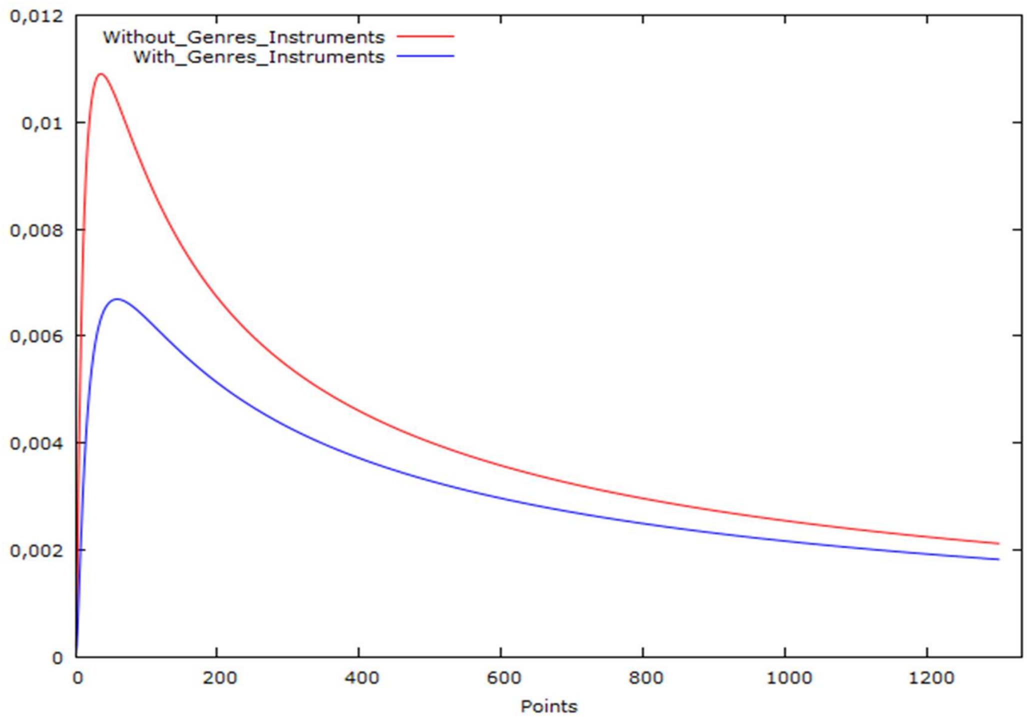

Figure 4: Impact of genres and instruments on hazard rate

Another variable that deals with the lyrical structure is *RelWordFrequency* which represents ratio of the most frequently occurring word in lyrics to the overall word count. The emphasis on a specific word appears to be insignificant. Though it is possible that a variable that would measure repetition of a specific phrase rather than a single word could yield different results. The mean value of 17 % suggests that lyrics are often build on a specific repetitive word which could also be part of a longer phrase.

Lastly, a number of chorus repetitions (*ChorusRepetition*) seems to be irrelevant as well. However, such conclusion might be questioned when applied on the data set. The majority of the examined songs have their chorus repeated thrice. The monotony could puzzle the survival analysis because such structure is used by both successful and unsuccessful songs. We may conclude that three choruses are a common practice. Nevertheless, it is uncertain whether a different count has any major impact on music preferences.

Last two variables examined the impact of sex of singers on the popularity. It appears to be irrelevant whether all singers are *male* or female as well as whether vocalists consist of both males and females or not. In fact, the ratio between male and female singers was almost equal.

4.2 Behind-the-scene properties

Table 5: Survival analysis (selected variables – behind-the-scene properties)

Variable	coefficient	Exp(βi) – 1	std. error	z	p-value
Soundtrack	0,391545	47,926 %	0,190093	2,059749	0,039423 **
Writers	0,014329	1,443 %	0,019575	0,732005	0,464166
Label	0,112601	11,919 %	0,054958	2,048854	0,040476 **
WeeksOnChart	0,000542	0,054 %	0,000324	1,675712	0,093795 *
Christmas	-0,019769	-1,957 %	0,147206	-0,134293	0,893171
Summer	-0,065745	-6,363 %	0,100635	-0,653297	0,513565

As discussed in subsection 3.2.2, behind-the-scene properties are factors that may be invisible and ostensibly unperceivable by listeners, but play in fact a vital role in recording's acceptation by the market. Appropriate promotion, productive cooperation and initial popularity – all these and many other factors that are not present in the musical piece itself may be a decisive factor of success as well as a cause of failure.

Commercials, video games and movie *soundtracks* and especially their main theme song appear to be strong performers on chart. Based on the survival model, being a soundtrack song increases the amount of obtained points by noteworthy 47,93 %. If a certain song is tied to a memorable scene of a successful movie, it often becomes, as a consequence, highly favorable. Although the survival model suggests that soundtrack songs are appealing, it is by no mean a guarantee of success. A successful movie increases awareness about the song and thus reduces amount of luck required to snowball into a hit song. Nevertheless, a poor quality song is unlikely to become popular despite being commercialized by the movie. On the other hand, a song that has a potential to appeal to great masses in combination with movie's success has a great chance to become fans' favorite.

Initial popularity decreases marginal cost of seeking new enjoyable musical pieces through word-of-mouth effect and already established fan base. As a consequence, new songs and albums released by famous and well-known artists are immediately played, judged and discussed by a respectable number of people and the awareness usually continues to further increase. In the survival model, the initial popularity is reflected by a total number of weeks that all artist's songs other than the examined spent on chart prior to its break through (WoC). According to the model, the preceding number of weeks on chart could strengthen song's survival capabilities. Every additional preceding week on chart increases the number of points by 0,0054 %. That means that a new recording released by an artist that had already spent 100 weeks on chart has a potential of accumulating 5,4 % more points than a newcomer. There could be two explanations for the relatively small effect. The chosen method might be inappropriate in capturing initial popularity of an artist. Preferences are subjective and difficult to measure which is why an effort for numerical quantification is condemned to be more or less inaccurate. Secondly, the model specification offers alternative interpretation. It seems that unknown artists have almost an equal opportunity to break into the music chart. In other words, music market may hold only small barriers to entry. Therefore, even newcomers have a reasonable chance to attract major attention and become superstars.

Record *labels* are responsible for promotion, marketing, distribution and often coordinate production and manufacture as well. The question related to this factor is whether increasing number of record labels could lead to more effective promotion and broaden the consumer base or it is better to cooperate only with few companies and avoid any possible communication and collaboration issues. The survival model leans toward the former. Every additional record label that participates in promotion and other related services increases the amount of obtained points by additional 11,92 %. Record labels may focus only on a certain region or a target group. That is why using service of various companies that have a different strategy should outweigh any cost and communication obstacles and lead to a greater net profit.

On the other hand, the number of *writers* that contribute to the final production seems to have a negligible effect on the song's subsequent perception. Nevertheless, a song is seldom composed by a single person. Based on the data set, 3,76 persons in average contribute to the musical composition. Larger number of people involved in the process may lead to a productive distribution of work and utilization of their skills in an effective way. It is naturally undesirable to reach a point of overload. If too many contributors were involved in the production, it could lead to a painful and chaotic cooperation.

Last two variables examined the impact of a release time. The assumption is that lively and ecstatic songs are generally related to *summer* while calm and cozy songs are repeatedly replayed during *Christmas*. Hence their time on chart might be limited as a result. At the same time their thematic concept could boost their chances during the particular season. Because of large p-values, the release time seems to be irrelevant. However, it is likely that the chosen method is incapable of capturing the true relationship. In order to find preference relationships between so called summer songs and seasonally changing music taste it would be necessary to construct a model that would examine the recordings in every season separately. The issue with modeling preference relationships for Christmas songs is that the chosen method does not takes possibility of reoccurring on chart into account. Furthermore, herein chosen objective factors are because of their nature unfit for capturing mainly subjective stimulus.

4.3 Reduced model

The fully specified model included factors that turned out be insignificant. Furthermore, it also consisted of music genres that were only scarcely represented in the data set such as Blues or Jazz. In order to verify the outcomes of the survival analysis, it is appropriate to construct a reduced model.

Firstly, the insignificant variables that don't belong to a bigger group were omitted. Those were *Male, Duet, AvgSentence, ChorusRepetition, RelWordFrequency* from the physical properties group and *Writers, Christmas, Summer* from the behind-the-scenes properties group. While several genre and instrument variables were also insignificant, they remained in the model as they belong to a group of related music aspects.

Secondly, the scarcely represented genres were omitted. Namely those were Blues (6 occurrences), Reggae (7), Jazz (6).

Table 6 contains results obtained from the reduced survival model as well as the outcomes of the fully specified model for the corresponding variables. All of the listed variables maintained the same positive/negative effect on the hazard rate. Additionally, neither of the coefficients differed by more than |0,1| in comparison to the fully specified model. Such outcome would suggest that the significant variables are robust enough and thus are potential determinants of success of music production rather than just random outcomes. The results are also consistent with the hypothesis that music success is achieved to a certain degree by factors of a non-random character.

Table 6: Survival analysis (reduced)

Variable	Coefficient (full)	Coefficient (reduced)	std. error	z	p-value	
const	4,984731	5,142436	0,539020	9,540336	0,000000	***
AvgWord	-0,261416	-0,257472	0,126794	-2,030636	0,042292	**
Drums	0,291076	0,277780	0,160705	1,728501	0,083898	*
BeatDrums	0,261334	0,253252	0,166438	1,521598	0,128110	
Keyboard	-0,334972	-0,352141	0,093987	-3,746693	0,000179	***
Piano	-0,803797	-0,839956	0,166144	-5,055597	0,000000	***
Engineered	-0,236907	-0,240296	0,111282	-2,159348	0,030823	**
Strings	-0,053255	-0,054302	0,129003	-0,420938	0,673800	
Wind	0,023668	0,000478	0,144997	0,003299	0,997368	
Electronic	0,310774	0,326358	0,111328	2,931507	0,003373	***
FunkSoul	0,539238	0,546600	0,188642	2,897550	0,003761	***
Rock	-0,329769	-0,293181	0,134002	-2,187879	0,028678	**
FolkWorldCountry	0,277169	0,289205	0,235271	1,229244	0,218980	
HipHop	0,036795	0,064373	0,128925	0,499304	0,617565	
Pop	0,258523	0,276922	0,098387	2,814610	0,004884	
Soundtrack	0,391545	0,382938	0,190119	2,014202	0,043988	**
Label	0,112601	0,122597	0,054151	2,263964	0,023576	**
WoC	0,000542	0,000571	0,000309	1,845738	0,064930	*
sigma	1,133920	1,142178	0,029727	38,422649	0,000000	

5 Conclusion

Human preferences have been a subject of research for several decades. Even though much have been uncovered since, the topic still keeps many answers hidden. The concept of music preferences is yet to be thoroughly examined and is in fact little known about the underlying principles on which individual musical preferences are based (Rentfrow, Goldberg, Levitin, 2011).

This thesis examined music preferences in the contemporary music industry and sought answers for the research question: “What are the determinants of success of music production?” The analysis was based on performance of songs on British Official Singles Chart Top 40 (2015) during years 2013 – 2015. Each song accumulated certain number of points accordingly to its ranking and length of stay on chart. In the end, 755 unique songs were fitting for a further examination.

Overall 29 attributes were identified for every recording and were divided into two groups. First group of factors was labeled physical properties. These are the characteristics that are perceivable and distinctive in the composition itself. The other group is referred to as behind-the-scene properties. Their objective is to examine the impact of choice of strategy, cooperation and evaluate the starting position of a given musical piece. In essence, these attributes may not be apparent to music fans, but their proper execution is vital for a subsequent success.

I used a survival analysis in order to determine relevant factors of success. It enables an estimation of a probability distribution throughout time and identifies relevant variables that affect the probability of a change in state and duration before the change occurs, respectively. (Cottrell, Luchetti, 2016). The model is further broken down into two functions. First is often referred to as a survival function which estimates the likelihood of remaining in the same state until time t. The other is called a hazard function and its objective is to estimate the likelihood of change in state shortly after t. Although the survival model requires independent variable to be a certain expression of time, it may be utilized to examine point distribution in this work due to the nature of the independent variable. Points were assigned to every song accordingly to its weekly position on chart. If the final results were divided by μ which would correspond to points songs accumulated in average per week, the independent variable would be then expressed in weeks. Thus points are only a different expression of time.

While the survival model estimates what separates modestly popular songs and music hits on chart, the frequency of occurrence of a given factor reveals more about aspects of music that are, nowadays, more appealing in general. That might differ from the outcomes of the survival analysis. That is true for Blues genre which was represented only by six songs throughout the examined period. This suggests that blues songs are not as popular as other more frequent genres. On the other hand, if a blues song appears on chart, it obtains in average 145,62 % more points than if it wasn’t labeled so.

Overall 14 examined attributes were found significant at a 10 % significance level. Therefore, it appears that Adler‘s proposition (1985, 2006) that success is mostly a product of luck is inaccurate. At least on the British market the determinants of success seem to be to a certain degree of a non-random character.

In the first group that involved physical properties, *drums* appear to be of greatest significance with relative effect of 33,79 %. It is a vital component of the majority of the examined songs and many of them have become greatly successful. Nowadays, *pop* and *electro* genres dominate the British music chart based on the model and the actual number of pop and electro songs that entered the chart. Although other genres were present too, their popularity were far less eminent.

Distinctive usage of *piano*, electronic *keyboards* and strong audio *engineering* negatively contribute to song's survival on chart. Usage of piano decreases the number of points obtained by 55,37 %, electronic keyboards by 28,58 % and heavy alteration by 21,07 %. In the case of piano it appears that such songs are simply not appealing enough to become regularly greatly popular. The negative effect of usage of electronic keyboards and distinctive audio engineering may occur because of similarity of the final production. As it offers only limited novelty, it might be the reason why such songs are able to attract attention only for a short period of time.

What seems to be strongly influential is an easy lyrical structure. Short words and possibly simple sentences appear to be preferable to a complex lyrical structure. Every additional letter decreases the total point count by 23,08 %. I assume that explanation lies in an easy learning process and an opportunity to quickly sing along. Short words and phrases are easy to remember which allows for singing with the vocalist basically after first replay. That makes the experience more vivid and fulfilling.

In the second group of variables *soundtrack* songs come out as a winner. In the observed data set recordings that were part of a soundtrack obtained in average 47,93 % more points. It appears that successful movies are a great form of promotion and quality songs in quality movies are likely to become popular.

Promotion is essential for subsequent success. Every additional record *label* increases the average number of obtained points by additional 11,92 %. It would mean that an increasing number of record labels that are tied with a given song broadens the artist's fan base. Different companies focus on different regions and target groups. That is why utilizing service of several record labels could extend the effect of promotion.

This work's aim was to contribute to the understanding of music preferences and to identify several factors that may have an impact on musical pieces' success. The discussed set of potentially influential factors is by no means exhaustive nor definite. Neither do the final results have an ambition to represent an unmistakable manual for success. The achieved outcomes may, however, offer guidance to artists and music publishers as well as music streaming services. A better understanding of impulses that influence decisions and music preferences would help artists to compose songs that would be perceived as generally more appealing. It would also assist music publishers and music agents with managerial decisions. Additionally, it could offer a deeper insight into music preferences of the 2nd decade of the 21st century and serve as a starting point for a continuous research. There are several issues and drawbacks that remain unresolved and several questions unanswered.

There are other methods that deal with survivability and the hazard rate. The outcomes were acquired through a parametric model, specifically one using a log-normal probability distribution. The problem with such approach is that it requires initial assumptions about the distribution of the survival times (Pornchaiwiseskul, 2016). Semiparametric and non-parametric models remove the need for the distributional assumptions. Therefore, it is desirable to apply alternative methods in order to test robustness of the results. Furthermore, the chosen method does not take possible multiple occurrence on chart into account which is an issue especially with regards to the Christmas songs.

The data set was based on a British music chart. Although Great Britain due to its size presumably reflects well global shifts in music preferences, it may possess certain features that are unique and limited only to its inhabitants. Therefore, research conducted under different settings is needed to test robustness of herein achieved outcomes. It would also be desirable to seek determinants of success on different music charts and ranking systems. There are countless unique measuring methods like replay count on streaming services, illegal downloads, concert attendance and so on.

Furthermore, the songs on the British Official Singles Chart Top 40 are mostly the most popular songs of the presence which are often simply labeled pop. A possible consequence is that the outcomes could be biased because of that. A similar research conducted separately on individual sets of genres could prevent the potential bias.

A data set spanning across three years may fail to capture the overall picture of the contemporary music preferences. It would require a longer period of time to ensure that the results are not biased by a random short-lasting trend in music taste.

Lastly, the proposed model has taken into account only songs that managed to get into the chart and examined their popularity in comparison to other recordings on chart. In essence, such approach divides successful songs from those greatly successful. It doesn't, however, answer the question what factors determine that a song attracts enough attention to become one of the forty most popular songs at least for the given week.

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Appendix

A List of independent and explanatory variables

Variable Type	Variable	Description
Independent	Points	Sum of points a given song accumulated during its time on chart.
Explanatory	AvgWord	Average character count of words
Explanatory	AvgSentence	Average word count of sentences
Explanatory	ChorusRepetition	Total count of repetition of a certain and distinctive part of a given song
Explanatory	RelWordFrequency	Ratio of the most repeated word to overall word count
Explanatory	WoC	Sum of weeks artist's other songs spent on chart prior to examined song
Explanatory	Tempo	Song's tempo measured in beats per minute
Explanatory	Writers	Total count of persons contributing to composition
Explanatory	Label Count	Total count of record labels that participated in promoting and marketing
Explanatory (dummy)	Male	1 if singer is male, 0 otherwise
Explanatory (dummy)	Duet	1 if both male and female singers perform, 0 otherwise
Explanatory (dummy)	Soundtrack	1 if a song was composed for a movie/game/commercial, 0 otherwise
Explanatory (dummy)	Christmas	1 if released in December, 0 otherwise

Appendix A (continued)

Variable Type	Variable	Description
Explanatory (dummy)	Summer	1 if released in June/July/August, 0 otherwise
Explanatory (dummy)	Strings	1 if a string instrument other than guitar or bass was a distinctive part of composition, 0 otherwise
Explanatory (dummy)	Drums	1 if drums were a distinctive part their rhythm varied throughout composition, 0 otherwise
Explanatory (dummy)	BeatDrums	1 if drums were a distinctive part and their rhythm remained unchanged throughout composition, 0 otherwise
Explanatory (dummy)	Keyboard	1 if electronic keyboards were a distinctive part of composition, 0 otherwise
Explanatory (dummy)	Piano	1 if piano was a distinctive part of composition, 0 otherwise
Explanatory (dummy)	Wind	1 if wind instruments were a distinctive part of composition, 0 otherwise
Explanatory (dummy)	Engineered	1 if a song undergone significant engineering that resulted in otherwise unachievable effects, 0 otherwise
Explanatory (dummy)	Electronic	1 if labeled as Electronic, 0 otherwise
Explanatory (dummy)	Jazz	1 if labeled as Jazz, 0 otherwise
Explanatory (dummy)	Reggae	1 if labeled as Reggae, 0 otherwise
Explanatory (dummy)	Blues	1 if labeled as Blues, 0 otherwise
Explanatory (dummy)	FunkSoul	1 if labeled as Funk / Soul, 0 otherwise

Appendix A (continued)

Variable Type	**Variable**	**Description**
Explanatory (dummy)	Rock	1 if labeled as Rock, 0 otherwise
Explanatory (dummy)	FolkWorldCountry	1 if labeled as Folk, World & Country, 0 otherwise
Explanatory (dummy)	HipHop	1 if labeled as Hip Hop, 0 otherwise
Explanatory (dummy)	Pop	1 if labeled as Pop, 0 otherwise
Right-Censoring	OnChart	1 if the record was still on Chart during the survival analysis, 0 otherwise

B List of genres

Electronic	Electronic music is music that employs electronic musical instruments and electronic music technology in its production, an electronic musician being a musician who composes and/or performs such music.
Rock	Rock music is a genre of popular music that originated as "rock and roll" in the United States in the 1950s, and developed into a range of different styles in the 1960s and later, particularly in the United Kingdom and the United States.
Pop	Pop music (a term that originally derives from an abbreviation of "popular") is a genre of popular music, which originated in its modern form in the 1950s, deriving from rock and roll.
Folk, World & Country	This genre encompasses a few different styles of music, most of which are region-specific, such as Nordic, African, Bluegrass, and various location-specific forms of classical.
Jazz	Jazz is a genre of music that originated in African-American communities during the late 19th and early 20th century.
Funk / Soul	Funk is a music genre that originated in the mid to late 1960s when African-American musicians created a rhythmic, danceable new form of music through a mixture of soul music, jazz, and R&B.
Hip Hop	Hip hop music, also called hip-hop, rap music, or hip-hop music, is a music genre consisting of a stylized rhythmic music that commonly accompanies rapping, a rhythmic and rhyming speech that is chanted.
Reggae	Reggae is a music genre that originated in Jamaica in the late 1960s.
Blues	Blues is a musical form and genre that originated in African-American communities in the "Deep South" of the United States around the end of the 19th century.

Source: Discogs (2016)

C Survival analysis – log-normal distribution

Variable	coefficient	Exp(β_i) – 1	std. error	z	p-value	
const	4,984731	X	0,700437	7,116604	1,11e^{-12}	***
Male	**0,016951**	**1,710 %**	**0,098774**	**0,171612**	**0,863742**	
Duet	-0,072476	-6,991 %	0,144039	-0,503172	0,614843	
AvgWord	-0,261416	-23,004 %	0,129743	-2,014883	0,043917	**
AvgSentence	-0,016775	-1,664 %	0,031768	-0,528054	0,597462	
ChorusRepetition	**0,071623**	**7,425 %**	**0,070561**	**1,015046**	**0,310084**	
RelWordFrequency	**0,133803**	**14,317 %**	**0,105210**	**1,271764**	**0,203457**	
Drums	**0,291076**	**33,787 %**	**0,160391**	**1,814785**	**0,069557**	*
BeatDrums	**0,261334**	**29,866 %**	**0,167310**	**1,561977**	**0,118293**	
Keyboard	-0,334972	-28,464 %	0,094533	-3,543447	0,000395	***
Piano	-0,803797	-55,237 %	0,168653	-4,765986	0,000002	***
Engineered	-0,236907	-21,094 %	0,111770	-2,119602	0,034040	**
Strings	-0,053255	-5,186 %	0,129445	-0,411412	0,680770	
Wind	**0,023668**	**2,395 %**	**0,147115**	**0,160878**	**0,872189**	
Electronic	**0,310774**	**36,448 %**	**0,114075**	**2,724288**	**0,006444**	***
Jazz	-0,849369	-57,232 %	0,483414	-1,757023	0,078914	*
Reggae	**0,199863**	**22,124 %**	**0,441439**	**0,452754**	**0,650726**	
Blues	**0,898605**	**145,617 %**	**0,485573**	**1,850609**	**0,064226**	*
FunkSoul	**0,539238**	**71,470 %**	**0,190506**	**2,830551**	**0,004647**	***
Rock	-0,329769	-28,091 %	0,136676	-2,412783	0,015831	**
FolkWorldCountry	**0,277169**	**31,939 %**	**0,240696**	**1,151532**	**0,249513**	
HipHop	**0,036795**	**3,748 %**	**0,133696**	**0,275214**	**0,783152**	
Pop	**0,258523**	**29,502 %**	**0,100406**	**2,574785**	**0,010030**	**
Tempo	**0,000323**	**0,032 %**	**0,002064**	**0,156612**	**0,875551**	
Soundtrack	**0,391545**	**47,926 %**	**0,190093**	**2,059749**	**0,039423**	**
Writers	**0,014329**	**1,443 %**	**0,019575**	**0,732005**	**0,464166**	
Label	**0,112601**	**11,919 %**	**0,054958**	**2,048854**	**0,040476**	**
WeeksOnChart	**0,000542**	**0,054 %**	**0,000324**	**1,675712**	**0,093795**	*
Christmas	-0,019769	-1,957 %	0,147206	-0,134293	0,893171	
Summer	-0,065745	-6,363 %	0,100635	-0,653297	0,513565	
sigma	1,133920	X	0,029553			

Mean dependent var	189,340909	S.D. dependent var	207,378965
Chi-square(29)	95,193575	p-value	5,66e^{-09}
Log-likelihood	-1 152,836489	Akaike criterion	2 367,672979
Schwarz criterion	2 510,812471	Hannan-Quinn	2 422,834564

D Survival analysis – log-logistic distribution

Variable	coefficient	Exp(βᵢ) – 1	std. error	z	p-value	
const	5,097125	X	0,736948	6,916531	$1{,}11e^{-12}$	***
Male	**0,029397**	**2,983 %**	**0,103315**	**0,284538**	**0,775998**	
Duet	-0,054804	-5,333 %	0,151083	-0,362743	0,716797	
AvgWord	-0,282333	-24,598 %	0,134666	-2,096547	0,036034	**
AvgSentence	-0,012809	-1,273 %	0,034090	-0,375722	0,707123	
ChorusRepetition	**0,045150**	**4,618 %**	**0,076048**	**0,593701**	**0,552712**	
RelWordFrequency	**0,143778**	**15,463 %**	**0,091533**	**1,570773**	**0,116235**	
Drums	**0,329121**	**38,975 %**	**0,169647**	**1,940043**	**0,052375**	*
BeatDrums	**0,298270**	**34,753 %**	**0,177255**	**1,682718**	**0,092430**	*
Keyboard	-0,367417	-30,748 %	0,099920	-3,677109	0,000236	***
Piano	-0,839364	-56,801 %	0,171076	-4,906380	0,000001	***
Engineered	-0,285440	-24,832 %	0,118140	-2,416107	0,015687	**
Strings	-0,067718	-6,548 %	0,135797	-0,498671	0,618011	
Wind	**0,001641**	**0,164 %**	**0,147865**	**0,011101**	**0,991143**	
Electronic	**0,362849**	**43,742 %**	**0,119583**	**3,034283**	**0,002411**	***
Jazz	-0,861510	-57,748 %	0,505634	-1,703822	0,088414	*
Reggae	**0,238300**	**26,909 %**	**0,483862**	**0,492495**	**0,622369**	
Blues	**0,988061**	**168,602 %**	**0,585358**	**1,687961**	**0,091419**	*
FunkSoul	**0,535933**	**70,904 %**	**0,203179**	**2,637735**	**0,008346**	***
Rock	-0,418047	-34,167 %	0,144640	-2,890263	0,003849	***
FolkWorldCountry	**0,257876**	**29,418 %**	**0,263163**	**0,979911**	**0,327130**	
HipHop	**0,055203**	**5,675 %**	**0,139144**	**0,396732**	**0,691565**	
Pop	**0,274146**	**31,541 %**	**0,106330**	**2,578267**	**0,009930**	***
Tempo	**0,000128**	**0,013 %**	**0,002173**	**0,059077**	**0,952891**	
Soundtrack	**0,427945**	**53,410 %**	**0,198550**	**2,155350**	**0,031134**	**
Writers	**0,015040**	**1,515 %**	**0,020673**	**0,727515**	**0,466911**	
Label	**0,133903**	**14,328 %**	**0,059523**	**2,249608**	**0,024474**	**
WoC	**0,000637**	**0,064 %**	**0,000337**	**1,890580**	**0,058680**	*
Christmas	-0,060185	-5,841 %	0,154260	-0,390155	0,696422	
Summer	-0,065577	-6,347 %	0,106569	-0,615345	0,538327	
Sigma	0,673132	X	0,020217			

Mean dependent var	189,3409091	S.D. dependent var	207,3789645
Chi-square(29)	106,2822268	p-value	$9{,}44e^{-11}$
Log-likelihood	-1175,356698	Akaike criterion	2412,713396
Schwarz criterion	2555,852888	Hannan-Quinn	2467,874981