All Musicians are Equal, but Some Musicians are More Equal than Others

An Exploratory Research on the Differences and Similarities and Concentration of Consumption of the Top Hits on Music Streaming Services

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ABSTRACT

In the last years music streaming services have taken over as the main mode of consumption for music, and even though they have noticeably contributed to the increase of profitability of the industry as a whole, it is still uncertain whether they facilitate the emergence of a more diversified and idiosyncratic musical environment or whether there is a tendency for market size and earnings to be skewed towards the most popular artists. This study intends to answer the following questions: what are the differences and similarities between the Top 100 most popular songs on YouTube, Spotify and Apple Music; and how evenly distributed is the consumption of the most popular artists and songs on these music streaming services? Using a dataset of the most popular songs for YouTube, Spotify and Apple Music collected from Kworb.net an online public database that aggregates data regarding the music industry in conjunction with variables operationalized and collected from the author, the paper will initially present some descriptive statistics and frequencies of the different characteristics of the songs and artists present within the Top Charts. The results find that there are mostly shared characteristics, especially in terms of the proportion of solo artists and bands, and that of song featurings, between Spotify and Apple Music, which also present the largest amount of overlapping songs within the Top100 charts, whereas YouTube was the most different from the others in terms of language, genre, and artist's country of origin; which could indicate a larger market size and user base. The Second section of this paper will present an index of the most popular artists calculated by looking at the individual song rankings on each platform, finding a high concentration of songs and of rankings for the Top 10 artists. The final section of the paper will present the Gini Coefficient, an index of inequality of distribution of resources, for the popularity of the Top100 and Top2500 songs of each platform, as well as that for all the artists present on the various Top100 charts. The results show that whereas on the Top100 songs, the index of popularity is pretty equally distributed, this is quite different when looking at the Top2500 songs and the most popular artists, indicating that there is a high concentration of superstar artists.

Keywords: *Music Streaming, Top Charts, Concentration, Diversity, Superstar Effect*

Preface

The way in which online media have shaped the dynamics of the music industry has been a matter that has captured my interest for quite a long time. This curiosity stems from my passion for music and my witnessing of the changing environment regarding the dynamics of promotion, distribution and consumption of music, as well as how people now discover new songs and artists. I'm thankful to Dr. Handke for allowing me to further pursue this interest in an academic context. I would also like to thank my parents for supporting me throughout all my academic life and for keeping me focused on my objectives; my brother, my girlfriend and all my friends in Rome, Rotterdam, or wherever in the world they might be, for keeping me motivated and serene during the last two years.

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1. Introduction

Music streaming services have been an established reality within the music industry for several years now, and not only they are the preferred platform for listening to music, but since 2016 they are also the biggest contributor to the music industry, with 8.9 billion USD generated only in 2018 (IFPI 2019). This shift in consumption has clearly benefited musicians in terms of being able to communicate to a global audience at almost no cost, as well as increasing the possibility to new emerging artists to emerge and reach the top charts. Furthermore, thanks to features such as music recommendation systems and shareable playlists, the choices and possibilities for consumers and artists are virtually unlimited. Despite so, it is still contested whether online music streaming services actually do increase the diversity of music consumed or whether they have magnified the perception of what Sherwin Rosen (1981) defines the Superstar Effect, in which "[R]elatively small numbers of people earn enormous amounts of money and dominate the activities in which they engage" (Rosen 1981,p.845) and in which there is a tendency for market size and earnings to be skewed towards the most talented artists.

Evidence from the IFPI Global Music Report, which creates a list of the most popular artists for each year; shows that since 2015 more one third of the artists have appeared more than once (IFPI 2016-2019), this is quite a high number, and possibly in favour of the argument that music streaming services perhaps increases the concentration of popular artists and reduces the diversity of music listened by users. Whether or not this is true, it may be possible that different music streaming services present different degrees of concentration or diversity in the most popular songs and artists; and this is why there are different views on the matter. In the recent years most of the cross-platform studies conducted have either concentrated on hits within national borders (Liikkanen 2014); the interaction between countries (Gomez-Herrera et al. 2014; Kim et al. 2017); the survival of hit songs over time (Im et al. 2018); or the converging tastes for international hits (George and Peukert 2014); however, no large-scale cross-platform analysis of worldwide hits has ever been made.

This study intends to answer the following questions: what are the differences and similarities between the Top 100 most popular songs on YouTube, Spotify and Apple Music; and how evenly distributed is the consumption of the most popular artists and songs on these music streaming services. To do so, the research will draw from data gathered online from Kworb.net, an online public database that aggregates data regarding the music industry. The data is comprised of 9559 songs, 2500 for YouTube, 2657 for Apple Music, and 4402 for Spotify, which includes the song name and the total amount of streams since the launch of the service. This dataset has never been previously used for research and it will be used in both sections of the paper in order to provide insights regarding the most listened songs on each platform.

To answer the research questions, the paper will initially present some descriptive statistics and frequencies of the different characteristics of the songs that make up the 100 most popular songs on each platform, based on data retrieved from Musicbrainz.com, an online music database. Following this, an index of popularity based on the rankings on each platform will be constructed in order to visualize the degree of concentration of the artists and songs present in the sample. Finally, the data will be expressed through a Lorenz Curve, after which the Gini Coefficient will be calculated. The Lorenz Curve depicts the cumulative percentage of popularity of the most popular songs, whereas the Gini Coefficient represents the deviation of the Lorenz Curve to the Line of Equality that ranges from 0 to 1. A large Gini Coefficient (closer to 1) indicates a Superstar market dominated by the hits, while a small Gini Coefficient shows a Long Tail market characterized by the long tail (Zhong 2012, p.13).

The research is relevant for the following reasons: first, by looking at the characteristics of the Top 100 hits of each platforms it may be possible to gather new insights regarding the most attractive features of the various streaming services, and possibly point out their relative strengths and weaknesses, such as the sizes of the catalogues or the diversity in terms of demand and supply, as well as set the foundations for future comparative studies. Secondly, by establishing the degree of diversity of the most popular songs, as well as the degree of concentration of superstar artists on the top charts of these music streaming service and how much evenly distributed the views or popularity, it may be possible to establish whether online music streaming services could increase the perception of the Superstar Effect.

The paper is structured as follows: the first section will introduce the previous studies, as well as concepts such as the economic significance of music streaming services, the different business models, and their role in the perception of the superstar effect. The following section will provide a description of the different platforms, explaining their characteristics, and their role within the music streaming industry. The methods section will begin with an operationalization of the variables that will be used in the research, as well as explain the data selection and collection. Following the results section, the paper will present the results and an analysis of the studies, as well as their limitations and managerial implications.

2. Literature review

2.1. Superstar Effect

Sherwin Rosen (1981) introduced the concept of the Superstar Effect as a way to express when [S]mall differences in talent become magnified in larger earnings differences, with greater magnification of the earnings-talent gradient increases sharply near the top of the curve"(p.846, cited in Hamlen 1991, p.729). However, this definition is quite problematic for experience goods such as songs, whose quality may vary significantly depending on the listener. Despite so, many attempts have been made in order to provide some possible measures of quality or talent. For example, Hamlen (1991) does so by measuring the relationship between record sales and voice quality for singers in the period between 1955 and 1987. The results of this research conclude that although consumers of popular music do recognize quality, the degree of proportionality between record sales and quality is uncertain. These results may be explained by many factors: first, it is possible that some artists are appreciated by other qualities that go beyond the voice range, such as musical ability or songwriting. Furthermore, one must also take in consideration those music genres in which voice quality is not as important as with other genres, like in the case of Rap and Hip Hop music. Another factor to take in consideration for this research is the fact that the study was conducted prior to the rise of digital music services as the preferred method for listening to music; and although this aspect may not seem to be vital for demonstrating the existence of a superstar effect in the music industry, the fact that digital technologies has magnified this effect may provide some more concrete proof of the superstar effect.

Strachan (2013) uses the Lorenz Curve and Gini coefficient to analyze the concentration of superstars within digital music in the period between 2004 and 2008, and their results show that the period between 2005 and 2007 was characterized by higher levels of concentration, while starting from 2007 the industry was facing a democratization of the distribution of sales. According to the author, this is a clear superstar effect, regardless of the slight decline in concentration observed in the final two years(Strachan 2013, p.181). This is made even more evident by the author when removing the top selling artist from their model, which ended up in lower levels of concentration. However, these results focus more on the modes of consumption rather than the characteristics of the songs present on the charts. Im et al. (2018) attempt to do so by analysing the survival period of songs on the Top 100 weekly streaming charts in South Korea between 2011 and 2014, and by looking at different factors which may contribute to an extended stay on the charts. Their results suggest that being the title track of an album is the most critical factor for songs' survival on the charts. These findings are quite interesting as they suggest that it is not a difference in quality that may explain the emergence of superstars, but rather the visibility gained by being the title track of the album; although it is worth noting that in some cases a song may be chosen to be the title track for its perceived increased quality with respect to the other songs on the album.

In contrast to the view that music streaming services amplify the extent of the superstar effect, Datta et al. (2018) study how the adoption of music streaming affects listening behaviour, using panel data on individual consumers' listening histories across platforms over 2.5 years. Their findings suggest that consumers play more and more diverse music following the adoption of both free and subscription-based music streaming services, resulting in a 16% drop in superstar consumption (p.15), and indicating that music streaming services act as a tool of discovery for new music even though the effect attenuates through the years. The authors attribute this increased diversity to the price reduction of costs in assessing the quality of streaming music as opposed to the previous download model, which required users to purchase the song before evaluating its quality. Other justifications provided by Datta et al. (2018) include the presence of playlists as a way to increase diversity as well as platform-specific features, such as the recommendation systems.

The challenges encountered with music recommendation systems have rapidly grown in the years of transition from downloading to streaming music. These are, among others, the cold start problem, which is defined as when a new user registers to the system or a new item is added to the catalogue and the system does not have sufficient data associated with these items/users; the challenge of automatic generation of playlists, and the challenge of holistically evaluating music recommender systems.(Schedl et al. 2018). Such problems make it so that in the case of new or unsubscribed users, the services might have to rely on general listening trends rather than the individual's preferences, increasing the chance that more popular songs will be played. However, as it is pointed out by Levy and Bosteels (2014) on their study on the effect of music recommendation system on consumption of long tail music on listeners of the streaming service Last.fm, music recommendation systems do not display a popularity bias and also do not affect significantly their listening habits. Bauer's (2018) analysis on music recommendation system research papers concludes that issues such as the cold start problem and popularity bias do indeed affect non-superstar artists, however, by knowing how those mechanisms function and some support it could be possible for also less popular artists to overcome these issues.

The extent of the superstar effect in the digital music industry is not only present when looking at songs or artists, but also in the case of record labels, often referred as 'majors'. As explained by Kask & Öberg (2019) this increase in the presence of majors is unexpected, this is because when rapid technological shifts occur, old forms of businesses are often replaced by new entries (p.443), which did not happen with the transition to music streaming services. Even though the excessive presence of majors may be seen as a negative aspect decreasing diversity in provision by the music streaming services, it is exactly this reason why streaming services have managed to survive and to emerge as the primary mode of music consumption. Music streaming services have been present within the music industry for a long time, however, they were severely limited by the licensing deals with record labels, allowing only label-owned services to provide streaming services. This changed with the introduction of Spotify that, thanks to the innovative decision of creating alliances with major labels and share part of their revenues (Kask and Öberg 2019) they managed to generate an extensive musical catalogue. This is not the case for all streaming services; for example, YouTube was often overlooked by record labels, and it wasn't until the acquisition by Google for $1.65 billion in 2006 (Kim 2012) that record labels decided to request compensation for the spread of their copyrighted material.

2.2. Consumer Preference for Music Streaming Services.

Many of the recent cross-platform analyses for streaming services in the recent years focused primarily on the different business models and how they affect both the revenue generated by the music streaming as well as consumer preference. For example, Kim et al. (2017) study the differences in consumer preference between two of the largest music streaming markets, USA and South Korea by conducing a conjoint analysis on the factors affecting consumer's marginal willingness to pay for streaming services. Their study finds differences in what consumers consider the most important characteristics of music streaming services, much of which depends on the current present market; with audiences more used to free services being more tolerant towards the presence of ads. The authors also suggest a convergence of preferred business models, with subscription-based or hybrid models eventually prevailing over ad-supported free services. According to these studies, the effect of music streaming platforms is overall positive for increasing revenue generated, as well as demonstrating the different outcomes in relation to geographical locations and current prevailing business models. Although this study demonstrates how the business model of a music streaming service may influence its ability to attract customers, especially in already consolidated markets, as it is also stated by the authors the

Other cross-platform researches include Liikkanen's (2014) study on the relative ranking of the most popular music across services, YouTube and Spotify, in Finland; finding high correlations of popularity between the two services. In particular, the author demonstrates a high, statistically significant correlation (Spearman $r=.74$, $p<0.5$)between YouTube and Spotify plays.(Liikkanen 2014, p.2). Despite so, as the research was focused on Finnish artists, and not on the global superstars, it is not possible to generalize on the relationship between musical hits across different platforms. Nevertheless, the results provide some interesting insights on some of the different characteristics of the two different platforms: there was less variation among Spotify than in YouTube hits, and both the standard deviation and range measures were bigger for YouTube than Spotify, demonstrating that there was more potential for hits to 'get bigger' on YouTube. Other insights provided by the author demonstrate that the share of mobile users was quite low for YouTube (around 11%), although there was a notable variation between artists, suggesting that there were quickly emerging differences due to different segments that have different viewing habits and devices.(p.3). Finally, despite the limited geographical range of the study, the research provided some important details regarding the two music streaming platforms: although YouTube is a video-first platform, the high correlation with the top hits on Spotify demonstrates that YouTube can be considered as much as a music service as Spotify is.

Gomez-Herrera et al. (2014) show how the shift from analogue to digital music distribution has substantially reduced trade costs and has enlargened the choice sets of music consumers around the world. Furthermore, with the expansion of the reach of these services and the artists present within, is also causing a shift away from domestic consumption. According to the authors, the most likely possibilities the changes in preferences of origin of repertoire and recent vintages of repertoires, which have grown more appealing to world consumers. Similar to this research, George & Peukert (2014) analyse the effect of YouTube on the market for music, focusing on converging national tastes. Their study focuses on the top 75 songs across two countries sharing the same language, Germany and Austria, and finds that YouTube reduces fixed entry costs for local artists but also lowers the cost of access to international superstars, and although the net impact of the YouTube platform is to widen the reach of international hits, the magnitude of estimated effects are modest, suggesting that YouTube will not drive out the market for local artists (p.19). However, as the authors also point out, a trend away from domestic music on the top charts does not mean fewer domestic songs are available or played in aggregate, it does however demonstrate a clear presence of superstars across different countries, most of which come from the United States.

2.3. Music Streaming Platform Business Models

As previously stated, a possible explanation for the popularity of music streaming services can be attributed to the diversity of business models available to consumers to reproduce content; with different platforms accommodating different necessities. Current business models now vary from ad-supported free services, subscription-based services as well as 'hybrid' models, which offer both options (Thomes 2013) Within the market there are various companies, some of which have music streaming as the initial intended business model such as Spotify, some which adapted their model in order to accommodate to the current trends such as Apple Music, and others which simply incorporated music streaming as a possible option, such as YouTube. The adoption of streaming by these companies is significant for the consolidation of streaming as the primary mode for music consumption, promotion, and distribution. Besides the payment model, these streaming services differ also in the catalogue, quality of the product, as well as auxiliary services offered. For example YouTube, offers the possibility of accompanying the recording with a video as well with the opportunity for users to access and upload content for free or at a very low cost; however, the quality of the musical recording is not always the best possible, and the presence of ads may affect the user experience. Furthermore, despite the large significance of websites such as YouTube for the worldwide spread of music, there have been several concerns regarding their profitability and their ability in encouraging consumption among more or less active users.

2.4. YouTube

YouTube was funded in 2005 as an online video-sharing platform in which users could share original content among each other. Thanks to its rapid rise in popularity, YouTube managed to attract a wide range of audience as well as attract the attention of companies such as Google, which acquired the company in 2006 for $1.65 billion (Kim 2012). Even though music videos and song recordings were already present on YouTube, big record companies did not make an issue of free use of their copyrighted songs on the website since “YouTube was such a small venture group that even if it was sued and had to pay, the young founders could not afford to pay much.” (Kim 2012, p.55), however this changed with Google’s purchase, which made them realize the economic potential of the platform. In order to continue the proliferation of copyrighted content, YouTube had to enter a revenue-sharing partnership with content providers as early as 2006, and with major labels in 2007 (Hiller 2016, p.18), which resulted in the creation of VEVO, an online music video distributor owned by the three major music labels and which provides copyrighted content on YouTube, allowing the content to stay on the channel without copyright disputes. In 2014 YouTube launched the streaming service YouTube Red, later renamed YouTube Premium, which offered consumers the possibility of accessing all the content on YouTube without advertisements, as well as with other features. Unlike the original website, YouTube Premium is subscription based and does not offer any free alternatives besides the free thirty-day trial. YouTube Premium is available in 50 countries, whereas YouTube is available in every country except for China, Iran, North Korea, Pakistan and Syria; with 95 local versions available worldwide.

The presence of a vast catalogue, with over combined with the low costs of reproduction and the wide spread of the website, has allowed YouTube to become a main choice for consumers to listen to music and share the videos among friends. This is also supported by the fact that around 23–30% of its videos bear the ‘‘Music” categorization (Liikkanen and Salovaara 2015) and that 95% of the most viewed videos are music (Purdon 2018). Among the three platforms presented in this study, YouTube is the largest; with over 1.9 billion active monthly users, and geographical reach (if we only take in consideration the website) and in 2017 YouTube accounted for 46% of on-demand music streaming time (IFPI 2018). Furthermore, since 2010, YouTube is consistently among the three most visited websites online, together with Google and Facebook (Hiller 2016).

Despite the increased consumption in music generated by the popularization of YouTube, there is still a mismatch between the amount of music consumed and the actual revenue generated, also defined as the Value Gap (Colangelo & Maggiolino 2018). For instance, in 2016 Spotify generated US$3.9billion from 212million users, whereas YouTube only generated US$553million from 900million users (IFPI 2017). This is because on websites like YouTube the license provides that the author retains all ownership for the content submitted, but as a condition of submission YouTube retains a license to reuse videos at their sole discretion and for any purposes (O’Brien & Fitzgerald 2006, p.7). Another argument put forward in favor of YouTube is the gained publicity and visibility that is gained thanks to a successful or viral video. Furthermore, an argument is to be made that even though the returns for the artists may not be proportional to the popularity of the content, it is still contributing to the music industry. Aguiar (2017) determine the effect of free and payed streaming services on the music purchasing and piracy activities of lighter streamers, and identifies a positive relationship between free streaming and alternative methods of consumption, whether legal or not. These findings demonstrate that in both cases the consumption of music ha increased. Similarly, Hiller (2016) investigates the impact of online content availability on album sales, and demonstrates a negative relationship between album sales and YouTube content presence. Despite this negative relationship, there is no doubt that YouTube has played a fundamental role in the increase of popularity and profitability of the music industry as a whole, whether through promotion, direct compensation, or by connecting people.

2.5. Spotify

Spotify is an online music streaming service that was launched in Sweden in 2008; unlike previous attempts made by other streaming services, the founders of Spotify were able to raise enough capital for operations, marketing, and prepayments at the time of its launch, meaning that they did not encounter legal disputes in order to distribute music on their platform. To do so, the founders established deals with major labels allowing Spotify to access a vast catalogue of content from all majors involved in exchange of approximately 18% of the ownership in Spotify (Kask and Öberg 2019, p.453). One of the defining characteristics of Spotify that contributed to its success was the Social Media features included within the service, which allowed users to share tracks and personalized playlist, a well as showing what one user's 'friends' were listening to at the time such features instantly attracted attention and created network benefits that in turn attracted more users. In order to amplify these effects, Spotify has also established a partnership with the social media platform Facebook, enabling an even larger reach for both producers and consumers (Thomes 2013). Other innovations brought in by Spotify within the music streaming industry include the introduction of a new hybrid business model, which offered both ad-supported free services as well as subscription-based services, and reduced subscription rates for students and for families, making it affordable even for those consumers who may not be able to pay for the full membership. These features, in combination with the possibility of sharing music among friends on social media, has allowed users with varying willingness to pay for music to adopt a legal digital mode for music consumption.

According to the services annual financial performance report, Spotify has over 30million songs in its catalogue, is currently available in 78 countries, and it counted 207 million monthly active users and 97 million paying subscribers in 2018; making it one of the most widespread and important music streaming services. However, the adoption of these new business models, combined with the high costs incurred by Spotify in accessing licensed content, has raised questions on whether Spotify raises music-industry revenue, Aguiar & Waldfogel (2015) find evidence that Spotify "displaces piracy, [and] the new revenue generated through streaming payments (…) is roughly offset by revenue reductions from the sale of permanent downloads." (Aguiar & Waldfogel 2015, pp.22-23) , similarly, Datta et al. (2017), find that even though the adoption of Spotify cannibalizes consumption on iTunes, it increases overall music consumption as well as the variety in types of music consumed.

2.6. Apple Music

Apple Music was born in 2014 thanks to the acquisition by Apple of Beats Electronics for 3 billion dollars (Arditi 2018). By doing so, Apple retained the rights for the online subscription streaming music service Beats Music, which was renamed to Apple Music in June 2015. According to Arditi (2018), Apple's acquisition of Beats Music was remarkable since Beats Music was in a weak financial position at the time of the acquisition, struggling to acquire subscribers; and according to co-founder Jimmy Iovine, Beats Music had 250,000 subscribers around the time of the merger while at the same time, whereas Spotify had around ten million subscribers worldwide (Arditi 2018, p.310). Despite so, Apple Music has managed to rise as one of the most important and beloved music streaming platforms, and in 2018 it counted around 56 million subscribers (Billboard 2018). Unlike Spotify, Apple Music only offers a subscription-based service, with reduced prices for families and students; furthermore, thanks to the partnership with the American mobile service provider AT&T, Apple Music has managed to attract a vast number of audience in a relatively short time, and in 2019 Apple Music had more paying customers in the USA than Spotify (Yoo 2019). Arditi (2018) attributes much of this success to the partnerships established by Apple with brands that were seen as 'cool' (in the case of Beats) or offering auxiliary services to their consumers, creating a close relationship with its costumers. Today, Apple Music is available in over 110 countries and has a catalogue of over 45million songs (Hall 2019) and since 2016 it has also started to offer the option to consumers to watch the music videos of the songs, approaching the model proposed by YouTube.

2.7. Language and Country of Origin

Gomez and Martens (2015), identify language as a significant factor for determining consumer preference as well as availability. The authors, by collecting data on the iTunes store of 27 EU countries come up with the following results:

> Songs of domestic origin represent only a very small share (1-4%) of the available supply of music, except in the UK where domestic songs account for 14% of the available supply. While the UK is a dominant supplier of music in the EU, it has relatively little (non- English) music from other EU CoO in its iTunes store. Close to 60% of that supply comes from other EU countries, of which about 40% non-English language supply. The dominant sources of song supply are the US with about 26%, followed by 12% from the UK. The remainder comes from the rest of the world, most

> of which will be English language music too. As a result, English language songs account for about two thirds of all music available. (Gomez and Martens 2015, p.10)

Similarly, Gomez-Herrera et al. (2014) analyze the trade patterns of songs and identify language as a significant factor for the success of a song's popularity among different countries, and those who share the same language are more likely to present similar charts for the top hits. Among others, the authors also recognize a substantial home bias, which varies strongly across countries; with an elasticity of trade with respect to distance of -0.37 and a Home Bias coefficient of 2.46, making domestic repertoire 10.7 times more attractive than foreign repertoire (p.7). Furthermore, language barriers may be a good proxy for cultural distance, since unlike other cultural products like film and books, music is usually not translated (Gomez-Herrera et al. 2014,p. 12).

Regarding the diversity of country's repertoires in terms of the song's country of origin, in particular the effect that YouTube has on the European market of music, George and Peukert (2014) find that free and open access to music videos on YouTube has contributed to the steady increase in US music on European top charts (George and Peukert 2014, p.14), however the magnitude of this effect is quite modest, suggesting that YouTube does not drive out the market for local artists. These findings suggest that the adoption of music streaming services may cause a decrease in diversification of different songs and artists present on the top charts. In this regard, the increase in consumption of US artists in Europe can be seen as a convergence towards a more homogeneous market, possibly indicating the presence of superstars. Following this reasoning, it would be worth to include in the comparison whether one music streaming services presents a more diversified Top rankings in comparison to others, indicating a greater diversification in supply. In addition, finding out whether there is a link between language or country of origin and the presence in the Top 100 of different music streaming services may provide useful suggestions on future strategies by the companies and whether they should focus on targeting specific under developed markets. Even though language and country of origin are a trait that may help distinguish one song or artist from another, there are other characteristics that may be more specific for the classification of a song. This is reflected by the fact that some languages are more closely tied to specific cultural settings and musical genres (Skowron et al. 2017); therefore, by combining language with other features may contribute to a more comprehensive and all round description on the factors influencing success on different online music streaming platforms.

2.8. Genre

Abrahamsen (2003) describes issues related to the classification of music in genres, such as the existence of two distinct paradigms (traditional or classical music and popular music) that makes it difficult to have a complete and coherent genre classification. This is because of the prevalence of the traditional paradigm in musicology and academia in general is another source of discrepancies in genre classification, especially when looking at popular music (Abrahamsen 2003, p,155). In addition, the author states that the notion of musical genre, as well as that of paradigm, has been too heavily shaped by western notions of music, which have left major gaps in the classification of non-western music. The author therefore urges for a more comprehensive and precise classification of genre, in particular with popular music. This is justified by the function of music genre in indicating customers towards new products without needing to know further information about the artist or the album in which the song was published. However, musical genre is not only beneficial for consumers, but also for producers and distributers, since knowing the specific sets of rules and criteria which delimit a specific genre may help them target specific segment of the audience, as well as finding a 'community' in which their music can be better acknowledged and appreciated.

Furthermore, as presented by Skowron et al. (2017), genre preference may also be affected by cultural and socio-economic indicators; determining that different indicators are more influential for various genres, therefore providing further explanations on why certain genres are more popular in different parts of the world. In terms of this research this may be useful given the different geographical reach of the different music streaming platforms. Even though it is not specified what genre is more popular in which culture, one could expect to find a higher degree of diversity in genre for the Top 100 songs as the geographical reach of the streaming service increases. For example, Long Term Orientation (the orientation of a country to stick to its roots and traditions or to adapt to the globalizing world) is the most informative feature for the largest number of genres: rock, alternative, new age, rap, R&B, electronic and jazz; whereas Power Distance (the extent to which power is distributed unequally by less powerful members of institutions) is the most important feature for classical, blues and reggae genres (Skowron et al. 2017, p.4).

2.9. Featuring

Another way that producers and artists manage to reach new fan communities and to venture into new genres is through the introduction of 'featuring' credits with other artists. Featuring is defined as a type of creative collaboration that "involves one artist integrating another artist's contribution, either instrumentally or vocally, into their work and publicizing it with a 'featuring' credit" (Ordanini et al. 2018, p.486), this collaboration features a 'host' artist and one or more 'guest' artists. Furthermore, musical featuring can happen both within and across genres, making it an important marketing and co-branding tool for artists. Ordanini et al. (2018) observe that songs featuring other artists have a greater chance on making it into the *Billboard Top 10* charts, and that artists with greater cultural distance between genres are more likely to have songs reach the top of the charts. The reason for such success is attributed to two main factors: the fact that a featuring is a distinct type of creative collaboration, and the fact that featuring artists typically stay true to their respective genres rather than blending two or more genres together. However, the benefit of distance between genres is only relevant when the genres have less 'strict' category boundaries, meaning that this positive effect is not universal among all songs. Despite so, the fact that generally speaking, featuring songs contribute to the introduction of songs in top charts, indicates that this criteria should still included for the scopes of this research.

However, having more artists and more musical genres feature together are not enough to determine the degree of diversity present within different musical streaming platforms, especially when considering Abrahamsen's (2003) findings indicating serious pitfalls in genre classification. Indicators of genre and featuring are therefore important factors determining the success or failure of a song, especially when looking at their effect in very specific and well-defined markets. In order to provide further explanations regarding the success or failure of a song, more specific aspects concerning the artist as well as the songs will be presented and their relevance within the academic field.

2.10. Gender

Hamlen (1991), includes gender as a variable in order to represent singer's attributes when assessing the magnitude of the Superstar Effect in popular music. Their study, which concentrates on the elasticity of demand for songs of superstars in terms of voice quality for the period between 1955 and 1981 concludes that the gender of the artist is the second most powerful factor of success for artists after *career longevity.*

The authors clarify this by explaining that "[T]here is a general recognition in the professional literature that the common press has tended to underestimate the high success rate of female singers" (Hamlen 1991, p.731).

The gender variable is also included by Im et al. (2018), in their survival analysis of songs on digital streaming platforms for Korean musicians over a period of three years; and it is justified by the fact that different segments of consumers tend to idolize artists and singers, and this is affected both by the gender of the artist as well as their nature. Wells (2001) investigates the degree to which gender, nationality, and race are reflected in the pop music charts using the Billboard top 50 annual album charts from 1985 to 1999, and finds out that on average, men have double or more the women's score (Wells 2001, p. 226) furthermore, the author shows that women are still concentrated at the upper levels of the charts, and while this may indicate the presence of legitimate female superstars, it also shows that female success is not very deep (Wells 2001, p.229).

Despite so, the inclusion of this characteristic may be useful for the understanding of the different dynamics that take place within each platform, as well as provide further characteristics of the artists present within the top charts. This variable, even though possibly useful for describing which artists are present within the Top 100 charts, does not provide any information regarding the individual track or even the characteristics of the platforms in which the songs may be found. To do so, other variables must be included.

2.11. Nature

In order to determine factors influencing the success of a song or musical collaboration, Ordanini et al (2018) attempt to include gender and nature in their model but find no significance. However, their study focused on the effect of these two characteristics as parameters for distance between two featuring artists, concluding that a host comprised of mixed genders already provides substantial diversity, tempering any desire to further increase the distance between the host and guest artist (Ordanini et al. 2018, p.496). Therefore, even though these two parameters may not help much with determining the distance between two artists, they are clear indicators of diversity. This is important in the scope of this study as it may be useful for providing a general overview on the type of songs present within the Top 100 charts of Spotify, Apple Music and YouTube.

For instance, Im et al. (2018) explain how music consumers in Asian countries such as South Korea there is “[A] unique culture that idolizes groups of male and female artists. Fans are likely to download or stream their idol’s song to make an emotional connection and attachment.” (Im et al 2018, p.1678). The effect of idolatry is said by the authors to be positive when associated to CD sales as well as an increased consumer loyalty, therefore it could be interesting to determine whether these findings are reflected within the Top 100 charts of various streaming platforms and their role in the perception of the Superstar effect; especially considering the global reach of such services.

2.12. Track Length

Parameters tied to the specific song characteristics such as song length (Karidis 2017) were included in order to provide a more accurate description of the types of songs present within the different Top 100 charts. Even though there are no studies relating the presence of a song or artist on the Top Charts to the length of the songs published, this variable is useful when comparing repeating songs on different platforms. This is justified by the different nature of songs YouTube compared to Spotify and Apple Music; on YouTube users upload the video of the song rather than the song itself, therefore songs may differ from each other significantly, which may in turn affect their presence in the top charts. Despite so, YouTube music videos can still be considered as an audio-first format, as pointed out by Liikkanen & Salovaara (2015) by showing how users engage with still music videos in almost the same way as they do with other videos, demonstrating that music remains the main focus for users regardless of the presence of motion pictures as an accompanying medium (Liikkanen & Salovaara 2015, p.122). This is also stated by Liikkanen (2014), describing the emergence of YouTube as a music source as unexpected, especially considering the lower audio quality of music files on YouTube, and the incoherence of musical meta information. Even though YouTube may not have been originally conceived for consumption of music, their business model reflects some of those of streaming websites, even before their venture into music streaming.

2.13. Platform

Wlömert and Papies (2016) classify music streaming according to their revenue model and streaming mode: advertisement-based free model or subscription-based `able 3.1. *Description of Variables Used in Analysis*

streaming model (Wlömert and Papies 2016, p.316). Even though the study does not reveal the effect of different business models on the success of individual songs, they demonstrate that the adoption of paid streaming services has a significant and substantial positive net effect on revenue, while the effect of free streaming services is negative but insignificant (Wlömert and Papies 2016, p.324).

Kim et al. (2017) add to the definition of different business models of streaming services by including the hybrid model, which provides two different services: a free service including advertisements and a service without advertisements, based on a monthly subscription fee (Kim et al. 2017, p.264). Their study focuses on the relative importance different attributes of music streaming platforms for consumers in the US and South Korean market; and their findings suggest that the differences in preferences for on-demand streaming can be attributed to the differences between typical product attributes of the two streaming industries, with the US market being, for example, more tolerant of advertisements than Korean respondents since they have been using ad-based free streaming services for a longer time. The authors predict that given the preferences presented by US consumers, with streaming mode and advertisements being the two most important ones, the main business plan for music streaming services will most likely become the primary platforms for online music streaming. Interestingly, the authors also find out that the provision of exclusive content and offline usage were the two least important features to both strands of the consumers, suggesting that consumers give more importance to the defining characteristics of the streaming service rather than the products contained within.

Besides the payment and revenue models, the free and subscription-based models differ also in quality, with ad-supported free streaming platforms being lower than their subscription-based counterparts (Thomes 2013, p.82), and it is for this reason that the hybrid business model has risen as one of the most prominent models for streaming platforms, giving the opportunity to consumers who are willing to pay for a higher quality service and those who are not without having to choose a competing service.

Variable	Abbreviated Name	Description	Operationalization	Variable Type	Source
Artist Name	*Artist*	Name of the artist present on list	In the case that more than one artist was credited, the first artist to appear on the list was used.	Nominal	Computed Author, Kworb.
Song Name	*Song*	Name of song present on list	In the case of YouTube videos, this was done manually as most tracks included "OFFICIAL VIDEO" or similar features	Nominal	Computed Author, Kworb.
Number of Streams	*Streams/Plays*	Number of streams for song	For YouTube:"If there's at least one music video, lyric video or official audio on their official channel(s), then I add all of that channel's videos. Afterwards I check if the artist has music videos on label-owned or other official channels. I add those as well, usually by searching for all of the videos on that channel that have the artist's name in the title"(Kworb.net)	Ratio	Kworb.
Year of publication	*Year*	Year that the song was digitally published	The year of release was set to the digital worldwide release of the track, which also corresponded to the upload year of the song.	Interval	MusicBrainz.c
Length of Song	*Length*	Length of song (minutes)	For Apple Music and Spotify, the digital worldwide release version was used to determine the track length. For YouTube, the length of the video was used.	Interval	MusicBrainz.c
Country of Origin	*COO*	Artist's country of origin	Looking at the artist's nationality on the artist page. In case that more than one nationality was listed, the first listed was included	Nominal	MusicBrainz.c
Song Language	*Language*	Language in which the analyzed version song was performed	Looking at the language in which language the digital worldwide release version of the song was released on the song's page on MusicBrainz.com	Nominal	MusicBrainz.c
Song Genre	*Genre*	Genre of the song present on list	Looking at the song page on MusicBrainz.com. All genres were then fitted into general terms according to musicgenrelist.com. In the case that more than one genre was listed, the first one was included	Nominal	MusicBrainz.co musicgenrelist.c
Platform of Choice	*Platform*	Platform in which song is found	Looking at ,Kworb.net. Data extracted using online data scraping program.	Nominal	Kworb.
Artist Gender	*Gender*	Gender of the credited artist	Looking at the *bio* section on the artist's official website.	Nominal	Computed Author, Art official websi
Song Featuring	*Feat.*	Whether the song is a featuring, and whether featuring artist is present on list	Looking at the digital worldwide release version of the song page on Musicbrainz.	Nominal	MusicBrainz.c
Artist Nature	*Nature*	Whether the artist is solo or part of a group/band	Looking at the artist page on Musicbrainz, if the artist was listed as solo, it was included.	Nominal	MusicBrainz.c

3. Data Collection

The data concerning artist name, song name and total amount of views was extracted from Kworb.net by using an online data-scraping tool. Kworb.net is a publicly accessible online database that collects data on the music industry, including databases of the most played songs of several online streaming platforms. According the website's creator, the songs are collected directly from the sources following different methodologies, and the data is automatically updated twice a day. Data regarding the total amount of streams is readily available from Spotify, and the author utilizes this data to compose the list. However, since YouTube is not primarily a music streaming service, the author has generated the following methodology in order to account for plays:

> "If there's at least one music video, lyric video or official audio on their official channel(s), then I add all of that channel's videos. Afterwards I check if the artist has music videos on label-owned or other official channels. I add those as well, usually by searching for all of the videos on that channel that have the artist's name in the title. This way almost every new video is picked up automatically when the list is updated, which happens about twice a day."(Kworb.net, FAQ)

Furthermore, the author explains that considering unofficial channels and other user generated content would be too complicated, therefore he excluded them from the classification**;** and since the YouTube section of kworb.net focuses on music videos, live performances are also excluded from the selection.

In order to determine the rank of popularity on Apple Music, the author applies a point-based methodology, which is constructed as following: countries are divided into four tiers, in relation to its market size, then each tier is assigned a set of points, (1500 for 1st place in tier 1, 1000 tier 2, 500 tier 3, 150 tier 4). These rankings take in consideration almost all the available iTunes markets, with the exception of a few inactive ones, and the data is periodically checked to verify if new countries have updated their ranks. Further justifications are provided by the creator:

> The point of the chart is to measure the worldwide popularity of songs and albums. If I were to use the actual market shares, then the US and the UK combined would dwarf all other countries. To me that is not very interesting. If you want sales figures, use sources such as IFPI or Mediatraffic. The points used for this chart have absolutely nothing to do with sales.(Kworb.net, FAQ)

Since this methodology does not take in consideration the total amount of streams but rather the overall popularity of a song, the descriptive statistics regarding the total amount of views will not be provided for Apple Music. However, this methodology can still be useful to indicate popularity, and since the following sections will be based on the overall rankings rather than the amount of views, it is still possible to utilize them. Furthermore it is worth pointing out that also total streams or play may not be a universal indicator for popularity, since a user may passively play a song if present on playlists or suggested by music recommendation systems, which is still registered whether the opinion was positive or negative. Nevertheless, this should not be an issue considering that by looking at the top charts it is assumed that even if there were a certain amount of involuntary streams, these should be negligible.

By using Kworb.net, it was possible to extract a total of 9559 songs, 2500 for YouTube, 2657 for Apple Music, and 4402 for Spotify. The following step involved a manual separation of the name of the song from the name of the artist, and in order to match the song with the relevant artist and track information, an identification was made based on the artist's name and the worldwide digital release version of the song on Musicbrainz.com. Musicbrainz has been used in previous studies (Schedl et al. 2012, Aguiar & Waldfogel 2014, Gomez-Herrera 2014, George & Peukert 2014, Datta 2018) as a source for son and artist information and, according Aguiar and Waldfogel (2014), "The MusicBrainz database is sufficiently authoritative that the BBC relies on it to support the artist and music information on their music website." (Aguiar and Waldfogel 2014 p.6).

In the case of YouTube videos, most of which included "OFFICIAL VIDEO" or similar features, a manual matching with the title of the track was made. By doing so, it was made possible to obtain a coherent name, artist, release date, song time and genre for the different platforms; the only exception was track length, which on YouTube is on average longer than on other platforms, even for the same song. In order to obtain the details of the songs present on YouTube, a manual search in accordance to the title present on the list was made in order to determine the track length. Since the release date corresponds to the year of release rather than the exact date, the dates were the same across all platforms. This allowed for a correction of the discrepancies across platforms, especially between YouTube and the other streaming services. With this method it was made possible to match all the YouTube videos with their respective song titles. Give the manual inclusion of the other song features, as well as to have a more manageable sample, the Top 100 songs for each platform was selected. In order to verify the validity of the total amount of views, s a manual search with the corresponding video was made, in the case of YouTube, as well as a manual search on Spotify for a random sample selection of songs. This was not possible for Apple Music but it was assumed that the entries were valid given the reliability of the other platforms.

The same methodology used by Gomez-Herrera et al. (2014) in their research on cross-border interaction was used to determine the nationality of the artist, which involved consulting the artist's page on Musicbrainz.com, and the country of origin listed on the page was included in the list; once the country of origin of the artist was established, it was assumed that all songs of the artist belonged to the country of origin of the artist. This was made to obtain a more consistent set of data, since the country of publication of some songs might not be the same for one artist. In total, 23 different nationalities were identified, the largest population belonging to the USA with 144 artists, following with the UK with 47 and Canada with 32. In order to determine the language of the song, a similar operationalization was applied, and 6 languages were identified in the population, although of these sets include a mix of English with either Spanish or Korean. Song genre was also determined from the song page on MusicBrainz and in the case of mixed genres, such as with featurings, Ordanini et al.'s (2018) methodology was followed, in which "Whenever more than one artist (host or guest) were present, genre was determined by whichever artist was credited first" (Ordanini et al. 2018, p.490). However, to avoid a list with too many entries, the musical genres were split into five separate categories, which encompassed a wide range of genres: *Pop, Rap/Hip Hop, Latin, Dance/Electronic*, and *Other*; these categories were retrieved from Musicgenrelist.com, a website which has been already been used in previous studies such as Herrera and Pugliese (2017). In order to determine the artist for a song, only the host artist was considered, which is also the same methodology as Ordanini et al. (2018). The variables constructed for the purposes of the research were made to determine whether the song presented a featuring or not, and whether the guest artist was also on the Top 100 of any of the three music streaming services. Finally, in order to determine the nature and gender of the artists, a consultation on the artists' official website was made and by looking at the bio section of the artist. This was also accompanied by a visual inspection of pictures of the artists.

3.1. Methods

The several variables gathered were then assigned a numerical code and put into SPSS in order to run tests to present the descriptive statistics and frequencies of the variables. This method and sample size was hosen because of the large amount of manual entry, since this could yield too many errors when done in a larger scale and may interfere with the results with other methods, such as a regression analysis between the variables listed. Furthermore, these results are already large enough to yield generalizable results regarding concentration, making it an acceptable sample size for the scopes of this research.

The second section of the analysis will present a list of the total amount of songs per platform for each artist found within the sample. By doing so, it will be possible to visualize better the level of concentration of popular artists; however, this list will be expanded in the following section by calculating the ranking scores of each song so that another dimension of popularity can be added to the study. In order to calculate the aggregate rankings for each song, a score from 1 to 100 was assigned to each song based on its ranking on the music streaming service; with a score of 100 assigned to the first spot, 99 points for the second, and so forth. By using this method it is possible to obtain another measure of popularity that does not take in consideration the amount of views, which is very different from one platform to another.

The final section will determine the distribution of popularity among the Top100 and 2500 songs of each platform, as well as for the artists found in the Top100 charts by plotting the cumulative percentage of streams or, in the case of Apple Music, rankings of the most popular songs, creating a Lorenz Curve. The areas between the Lorenz Curve and the line of Equality Line will generate the Gini Coefficient. The closer the Gini Coefficient is to 1, the larger the inequality, whereas a smaller Gini Coefficient indicates a more even distribution. As it is explained by Krugman and Wells (2015), a Gini Coefficient of 0.25 or smaller is considered acceptable (Krugman & Wells 2015, p.518), so if this were to reflect in our findings, it would mean that the Superstar Effect is weak on music streaming services. The Gini Coefficient is usually used in studies to determine the distribution of wealth among populations, but it can be applied to other paradigms in order to represent an unequal distribution. Since both the total amount of views for YouTube and Spotify, as well as the rankings generated by Kworb.net for Apple music can be somewhat considered an index of popularity, they will be used in the scope of the analysis. Although this might generate differences in the results, especially with Apple Music, which could affect the comparison across platform it is still a reliable representation to visualize the distribution within the platform.

4. Results

4.1.Total Population

The table indicating the descriptive statistics for the total sample population is available on Appendix A. The average amount of views is around 860 million streams, (Min=539 million, Max=6.02 billion, SD=771 million. The year of publication for the three platforms ranged between 2005 and of 2019 (M=2017, SD=2.04); although only three songs out of three hundred were published before 2010.The song length varied between 1:59 minutes and 7:03 (M=3:04, SD=00:37), although also here there are maximum and minimum outliers.

Other song characteristic include the language, whose biggest groups were English with 86% of the songs, then Spanish with 11% and lastly a mix of Spanish and English, with 2%; the remaining 1% comprised of Korean, Patois and Korean/English. The share of song genres was composed by 31% Pop songs, 23.3% Rap/R&B, 23%Dance/Electronic, 14% Latin, and 8.7% other genres. Finally, 53.7% of the songs were not featurings, 24.7% of the songs involved the featuring with another artist present on the Top100 charts, whereas the remaining 21.7% involved featurings with artists not present on the Top100 charts.

As for the artists, there were 23 individual nationalities involved, with 48% songs from artists coming from the USA, 15.7% from the UK, and 10.7% from Canada. The distribution between Solo artists and groups or bands is 84% to 16%. Finally, 76% of the artists were male, 20% female, and 3.7 mixed/other.

4.2. Samples

The tables with the descriptive statistics for the samples of YouTube, Spotify and Apple Music are available on Appendix B, C and D. The Average amount of plays for songs on YouTube was around 1.82 billion (Max=6.02 billion, Min=1.02 billion, SD=749 million), and 755 million for Spotify (Max=2.05 billion, Min=539 million, SD=243 million).

The publication year for songs on YouTube ranged between 2005 and 2019 (M=2014, SD= 2.55), between 2014 and 2018 for Spotify (M=2016, SD=1.15) and between 2015 and 2019 for Apple Music (M=2017, SD= 0.62). YouTube had also the highest average song length (M=4.06 minutes, Min=2.44 minutes, Max=7:03 minutes, SD=00:42 minutes), the second highest Spotify M=3.37 minutes, Min=1.59 minutes, Max=5:12 minutes, SD=00:31 minutes), and last Apple Music (M=3.30 minutes, Min=2.13 minutes, Max=5:12 minutes, SD=00:29).

In terms of language, YouTube had the highest variety, with five different languages identified; the largest populations were English (70), and Spanish (26), and the rest are divided among Korean(1); Korean/English (1); and Spanish/English (2). The second most diverse music streaming service in terms of language is Spotify, with four languages, although here the share of English songs is even higher (93), with the remaining 7 songs sang in Spanish (4), Spanish/English (2) and Patois (1). Apple Music was the less diverse in terms of total languages spoken (3), as well as their distribution among the songs; for instance, 95 songs out of 100 were in English, 3 in Spanish and 2 in Spanish/English.

Another category that varied significantly among the different platforms is genre, the share among YouTube's Top100 is comprised of 30 Latin songs, 29 Pop songs, 16 Hip Hop/R&B songs, 15 Dance/Electronic, and 10 belonging to Other genres. This is quite different from Spotify, whose Top 100 charts comprised of 28 Pop songs, 28 Dance/Electronic, 27 Hip Hop/R&B, 7 Latin and 10 Other in other genres. This is quite similar to the distribution of genres found on the Top100 of Apple Music: 36 Pop songs, 27 Hip Hop/R&B, 26 Dance/Electronic, 5 Latin, and 6 'Other' genres.

As for the featurings, the rate is quite similar across all platforms for the distribution for songs that are not featurings (58 for YouTube, 50 Spotify and 53 Apple Music), the songs that are featurings with artists present on list (23 YouTube, 28 Spotify, 23 Apple Music), and the songs that are featurings with artists not present on list (19 YouTube, 22 Spotify, 24 Apple Music).

In terms of artists, YouTube had the Highest range of countries of origin, with 20 different involved. The largest populations for YouTube were USA, with 40 songs, UK with 15, Colombia with 11, and Canada with 9; the 16 remaining countries were all responsible for less than 2 songs each. The second highest number of individual nationalities is Spotify with 16 countries, and even though the largest population remains USA with 52 songs, the second largest is Canada with 15 songs, then UK with 12, whereas the remaining 13 countries accounted for less than 3 songs each. The least diverse is Apple Music with 14 nationalities, and here the largest populations are again USA with 52 songs, then UK with 20, and Canada with 8, whereas the other 11 countries accounted for less than 3 songs each.

Quite interestingly the rate of solo artists and groups is almost the same for each platform, with 82 solo and 18 groups for YouTube, 84 and 16 for Spotify, and 86 and 14 for Apple Music. Finally the distribution of genders is more equally spread out for YouTube with 27 females, 68 males and 5 mixed/other, second Apple music with 20 females, 76 males and 4 mixed/other, and last Spotify with 13 females, 85 males and 2 mixed/other.

4.3. Differences and Similarities of Top100 Songs on YouTube, Spotify and Apple Music

4.3.1. Views

The total average amount of views has a very wide range and this is given by the difference in sizes of the platforms, as well as the different years of foundation of each platform. The maximum outliers here are provided by YouTube, whereas the minimum by Spotify. Quite unexpectedly, the results show that the platform with the largest total amount views is also the one that was funded the earliest, as well as the largest in terms of catalogue and active users. These results show that YouTube is the platform that obtains the highest amount of views, which in turn indicates a wider reach, and this could be useful for artists to determine which could be the most effective platform to promote their works. Although it is worth to point out that given the larger catalogue, which is not limited to music videos but includes all kinds of content, this may be only true for artists with an already solid fan base. Furthermore, a higher amount of views does not necessarily mean an increased profit for artists, as shown by the discrepancies between active users and monetary returns pointed out with the Value Gap.

4.3.2. Year of Publication

The results regarding the average year of publication go in line with Aguiar (2017)'s findings saying that on average newer songs are found on music streaming services. This also makes sense considering that songs published prior to the use of music streaming services as the main mode of consuming and distributing music would have already been sold through alternative channels such as downloads or record sales rather than online streams. Furthermore, it seems that the average year of publication is very closely related to the year in which the platform was launched. This could be an interesting insight for new artists trying to emerge and reach out a wider audience. It is also worth pointing out that a large amount of recent songs on such platforms could possibly indicate that music streaming services are increasingly becoming a primary medium for consumers to listen to music than a tool for discovery, as observed Datta et al. (2018) since if the opposite were to be true, there would have possibly been a higher variety in the release dates of the songs. However, further studies focused on consumer research would be necessary to determine this.

4.3.3. Song Length

The maximum outliers are explained by YouTube videos, which had the highest average song length, as well as the widest range and standard deviation. These results are not unexpected as most of the songs found on YouTube include the music video for the song, extending the average length of a song. Even though this may not be true for all songs, the difference of around thirty seconds is quite large when compared to the other music streaming services. Despite so, the average song length does not say much regarding the concentration of the artists present on the list, although it may provide insights regarding other factors such as costumer or artist preference. Moreover, a wider difference between track length and the length of the music video could provide further understandings regarding the artists; usually a longer video compared to the song length may in some cases indicate a larger investment since it requires the hiring of professionals by the artist or its record label, it could be interesting to find out whether the average song length and the concentration of artists are somehow related.

4.3.4. Language

This category yielded some of the most unexpected results. Although it was expected to find a high concentration of English songs, it is still quite surprising that there aren't more languages, like French, Chinese, Portuguese. This can be seen by the fact that even though 74.4% of the total songs were produced by artists in Anglophone countries, 86% of the songs are performed in English. Furthermore, as Gomez-Herrera (2014) points out, songs by native English speakers are more successful; however the list presents also artists from other nationalities which sing in English, indicating that perhaps even though within national borders it may be more likeable to sing in the local language, this is quite different when looking at global hits. Looking at the individual platforms, YouTube has the largest amount of Spanish songs, and is also the only platform to not have an English song as the number one on the list Furthermore, YouTube is also the only music streaming service to have a song in an

Asian language (Korean), and the fact that Spotify and Apple Music have the same amount of Spanish/English songs as YouTube, but lower Spanish songs indicates that there is a lower diversity in artists and perhaps a different consumer base, although all 3 services are available in Spanish-speaking countries.

4.3.5. Genre

Although the total distribution of genres is quite even, this is not the same for the individual platforms. These results are among the most interesting as they could be important in order to determine the characteristics of the users of each service, as well as the dominant markets in which they are consumed. For instance, as pointed out Skowron et al. (2017), certain song genres are more associated with different cultures. This is also confirmed by the fact that YouTube has a higher amount of Latin songs and of songs in Spanish, although the two are not mutually exclusive. Therefore by pointing out the preferences for each platform may provide a significant insight for emerging artists. Furthermore, skewness for more 'local' genres such as *Latin* or *Other* music may also indicate a vaster geographical reach for the platform as well as a larger user base, which is the case of YouTube. Pop music was the most popular genre across all three platforms, and this indicates a high concentration of Superstars, as the boundary strength for pop music, is particularly weak compared to other genres and pop is considered music intended for charts, asnd "a way of doing business, or a target demographic, rather than a genre (Lena and Peterson 2008, p.489). The fact Hip Hop/R&B and Dance/Electronic were the second most popular genres are also quite significant, as it shows the trends of music consumption on music streaming services. This is true when thinking at how large the *Other* category could potentially be, including genres like Rock, Reggae, Soul, and others. It would therefore be interesting to see whether these trends also reflect on offline sales, which would potentially either confirm the relationship between music streaming services and the concentration and diversity of artists and songs.

4.3.6. Featurings

Interestingly enough, the distribution of featurings and non-featurings is almost exactly the same across all three platforms. The results indicate that featurings may be a significant factor influencing the presence on the songs on the top charts, and therefore concentration, just as discussed by Ordanini et al. 2018. However, these results may seem unexpected considering Ordanini et al.'s (2018) findings, which show that song featurings are able to increase the popularity of a song or an artist. Therefore one may expect to find a higher degree of featurings, in particular among Superstar artists, across the top hits on music streaming services rather than an almost equal share. Nevertheless, coherent results across platforms may indicate that there is a high concentration of song featurings, meaning that song featurings could be an important quality indicator for users when listening to music.

4.2.7. Nature

The same argument made with Featurings could be made with the artist's nature. The almost identical share of solo artists and groups across all platforms seem to indicate that there is a relationship between the artist's nature and the presence on the Top100. It seems in fact, that on average, solo artists have higher chances to reach the top charts; however this is not the scope of this research, and much like in the case of featurings, a high concentration of solo artists could indicate a preference for consumers for one specific artist nature over another which, as discussed by Kim et al. (2017) could vary significantly across different cultures. Another possible factor causing this high concentration of solo artists could perhaps be the increased reliance on social media as a promotional tool, which allows individuals to emerge as online personalities and to be more self-reliant.

4.2.8. Gender

The results regarding gender indicate that there is an uneven distribution of male artists over female artists across all music streaming platforms, although with varying degrees. These results seem to go in line with Hamlen's (1991) findings indicating that on average, men have higher scores than women on top charts. It is interesting to notice how these findings are similar even though Hamlen's (1991) study focuses on offline consumption rather than online streaming services. Such similarities between offline and online platforms may provide useful insights on consumer preferences and the availability of artists and whether they have changed throughout the years. It seems like this uneven distribution is tilted towards male artists, which are on average more present on the top charts, and even though Apple Music is the only music streaming service to have a woman as number one on the rankings, it is also the platform with the lowest amount of views.

Table 4.1: ***Frequency Table of Artists' Appearance on YouTube, Spotify and Apple Music (n=121)***

Rank	Artist	YouTube	Spotify	Apple Music	Total	Percentage (%)	Cumulative Percentage(%)
1	Ed Sheeran	3	4	5	12	4	4
2	Drake	1	6	3	10	3.33	7.33
3	Post Malone	0	5	5	10	3.33	10.67
5	Calvin Harris	3	2	3	8	2.67	13.33
6	Justin Bieber	4	3	1	8	2.67	16
7	The Chainsmokers	3	3	2	8	2.67	18.67
8	Ariana Grande	1	2	4	7	2.33	21
9	Marshmello	1	3	3	7	2.33	23.33
10	Bruno Mars	3	1	2	6	2	25.33
11	Clean Bandit	1	2	3	6	2	27.33
12	Luis Fonsi	2	2	2	6	2	29.33
13	Maroon 5	2	2	2	6	2	31.33
14	Shawn Mendes	1	3	2	6	2	33.33
15	The Weeknd	2	3	1	6	2	35.33
16	Charlie Puth	1	2	2	5	1.67	37
17	Dua Lipa	1	2	2	5	1.67	38.67
18	Imagine Dragons	0	2	3	5	1.67	40.33
19	Nicky Jam	4	0	1	5	1.67	42
20	XXXTENTACION	0	3	2	5	1.67	43.67
21	Adele	3	1	0	4	1.33	45
22	Camila Cabello	1	1	2	4	1.33	46.33
23	J Balvin	2	1	1	4	1.33	47.67
24	Major Lazer	1	3	0	4	1.33	49
25	Taylor Swift	3	0	1	4	1.33	50.33
26	Zedd	0	2	2	4	1.33	51.67
27	Aviici	1	0	2	3	1	52.67
28	Cardi B	0	1	2	3	1	53.67
29	David Guetta	1	0	2	3	1	54.67
30	DJ Khaled	0	1	2	3	1	55.67
31	DJ Snake	0	2	1	3	1	56.67
32	Eminem	2	0	1	3	1	57.67
33	Fifth Harmony	2	1	0	3	1	58.67
34	Kendrick Lamar	0	1	2	3	1	59.67
35	Selena Gomez	0	1	2	3	1	60.67
36	Sia	2	1	0	3	1	61.67
37	Travis Scott	0	2	1	3	1	62.67
38	Twenty One Pilots	1	2	0	3	1	63.67
39	5 Seconds of Summer	0	1	1	2	0.67	64.33
40	Alan Walker	1	1	0	2	0.67	65
41	Becky G	2	0	0	2	0.67	65.67
42	Benny Blanco	0	1	1	2	0.67	66.33
43	Daddy Yankee	2	0	0	2	0.67	67
44	Danny Ocean	1	1	0	2	0.67	67.67

45	Ellie Goulding	2	0	0	2	0.67	68.33
46	French Montana	0	1	1	2	0.67	69
47	G-Eazy	0	1	1	2	0.67	69.67
48	Jason Derulo	1	1	0	2	0.67	70.33
49	Jonas Blue	0	0	2	2	0.67	71
50	Juice WRLD	0	1	1	2	0.67	71.67
51	Katy Perry	2	0	0	2	0.67	72.33
52	Khalid	0	1	1	2	0.67	73
53	Kygo	0	1	1	2	0.67	73.67
54	Maluma	2	0	0	2	0.67	74.33
55	Mark Ronson	1	1	0	2	0.67	75
56	Martin Garrix	1	1	0	2	0.67	75.67
57	PSY	2	0	0	2	0.67	76.33
58	Rihanna	1	1	0	2	0.67	77
59	Rita Ora	0	0	2	2	0.67	77.67
60	Sam Smith	0	1	1	2	0.67	78.33
61	Shakira	2	0	0	2	0.67	79
62	Tyga	0	1	1	2	0.67	79.67
63	ZAYN	0	1	1	2	0.67	80.33
4	Anne-Marie	0	0	1	1	0.33	80.67
64	Ava Max	0	0	1	1	0.33	81
65	Axwell Λ Ingrosso	0	0	1	1	0.33	81.33
66	Bad Bunny	0	0	1	1	0.33	81.67
67	Bazzi	0	0	1	1	0.33	82
68	Bebe Rexha	0	1	0	1	0.33	82.33
69	BlocBoy JB	0	1	0	1	0.33	82.67
70	Carlos Vives	1	0	0	1	0.33	83
71	Casper	1	0	0	1	0.33	83.33
72	Chino y Nacho	1	0	0	1	0.33	83.67
73	Christina Perri	1	0	0	1	0.33	84
74	CNCO	1	0	0	1	0.33	84.33
75	Crazy Frog	1	0	0	1	0.33	84.67
76	Dean Lewis	0	0	1	1	0.33	85
77	Dennis Lloyd	0	0	1	1	0.33	85.33
78	Desiigner	0	1	0	1	0.33	85.67
79	Disney UK	1	0	0	1	0.33	86
80	DNCE	0	1	0	1	0.33	86.33
81	Dynoro	0	0	1	1	0.33	86.67
82	Enrique Iglesias	1	0	0	1	0.33	87
83	Future	0	1		1	0.33	87.33
84	George Ezra	0	0	0	1	0.33	87.67
85	Gummibär	1	0	0	1	0.33	88
86	Halsey	0	0	1	1	0.33	88.33
87	James Arthur	0	1	0	1	0.33	88.67
88	Jennifer Lopez	1	0	0	1	0.33	89
89	Jessie J	1	0		1	0.33	89.33

90	Joey Montana	1	0	0	1	0.33	89.67
91	John Legend	1	0	0	1	0.33	90
92	Justin Timberlake	0	1		1	0.33	90.33
93	Keala Settle & The Greatest Showman Ensemble	0	0	1	1	0.33	90.67
94	Lady Gaga	0	0	1	1	0.33	91
95	Lauv	0	1	0	1	0.33	91.33
96	Liam Payne	0	0	1	1	0.33	91.67
97	Lil Uzi Vert	0	1	0	1	0.33	92
98	LMFAO	1	0	0	1	0.33	92.33
99	Logic	0	1	0	1	0.33	92.67
100	Loud Luxury	0	0	1	1	0.33	93
101	Lukas Graham	0	1	0	1	0.33	93.33
102	Macklemore & Ryan Lewis	1	0	0	1	0.33	93.67
103	Magic!	1	0	0	1	0.33	94
104	Manuel Turizo	1	0	0	1	0.33	94.33
105	Meghan Trainor	1	0	0	1	0.33	94.67
106	Mike Posner	0	1	0	1	0.33	95
107	Natti Natasha	1	0	0	1	0.33	95.33
108	NF	0	0	1	1	0.33	95.67
109	Nio Garcia	0	1	0	1	0.33	96
110	OneRepublic	1	0	0	1	0.33	96.33
111	Ozuna	1	0	0	1	0.33	96.67
112	P!nk	0	0	1	1	0.33	97
113	Passenger	1	0	0	1	0.33	97.33
114	Piso 21	1	0	0	1	0.33	97.67
115	Pulcino Pio	1	0	0	1	0.33	98
116	Ricky Martin	1	0	0	1	0.33	98.33
117	Romeo Santos	1	0	0	1	0.33	98.67
118	Rudimental	0	0	1	1	0.33	99
119	Silentò	1	0	0	1	0.33	99.33
120	Wiz Khalifa	1	0	0	1	0.33	99.67
121	Zara Larsson	0	1	0	1	0.33	100

4.4. Concentration of Artists per Appearance on Youtube, Spotify and Apple Music

Table 2.0 presents the amount of songs per each artist present on the Top100 charts of YouTube, Spotify and Apple Music. Most overlaps are found between Apple Music and Spotify (39), then YouTube and Spotify (20), then YouTube and Apple Music (2), ten songs appear on all three platforms. These results seem to comply with the previous section, which identified many similarities between Apple Music and Spotify in terms of song genre and language. In total, 120 artists were identified, with

62 artists that have at least one song on two or more music streaming services. This is a quite large number and it indicates a high degree of concentration across the music streaming services; however, this was to be expected considering that we are dealing with the 100 most popular songs, and therefore it is not surprising to find many similarities across all music streaming services.

The fact that there are more overlaps between the two platforms that are closer in terms of the date that they were funded, the catalogue size, the size of their markets and business model, could indicate that these two services attract a similar type of audience. Further justifications for the business model to be an important decisional factor for consumers is also seen by the fact that the degree of songs overlapping appears to coincide with the 'distance' of each business model. For instance, Spotify, which offers both ad-supported free and subscription based services, has the most commonalities with both YouTube, a primarily free service (although it is possible to pay for a subscription) and with Apple Music, an exclusively subscription-based service; whereas YouTube and Apple Music have only two songs in common. It would therefore be worth to analyze what are the factors that make a potential costumer choose one over the other, and how influential the business model is for the decision making process. Although Kim et al. (2018) have already discussed this matter, concluding that the business model does have an influence on the decision making process, but this is highly dependent on the current local market and customs; the fact that their study was conducted on already well-developed markets for music streaming services (USA and Korea) rather than emerging ones indicates that further developments can be made regarding what exactly about each service attracts users universally.

Going back to the results, what is quite surprising is to see that the top 10 artists have more than one quarter (27.67%) of the total songs present on the lists, whereas the Top 25 artists have 50.33% of the total views, the top half (n=60) of the artists have 79.33% of the total videos. This shows that even though one artist may be able to achieve high levels of popularity thanks to music streaming services, the distribution is still somewhat disproportionate and skewed towards the most popular musicians. Although the skewness of the total amount of videos towards the top artists is a clear indication of a concentration of Superstars, already being part of the top 100 charts may be a good indicator of the overall popularity of the song, it does not take in consideration how popular each individual song is. To do so, it is necessary to determine the relative popularity of each song present on the list, so that it may be possible to obtain an aggregate ranking of the most popular songs across all 3 music streaming services.

Table 4.2. ***Combined Ranking Scores for Artists in Sample (n=121)***

Rank	Artist	Combined Ranking Scores	Percentage (%)	Cumulative Percentage (%)
1	Ed Sheeran	929	6.17	6.17
2	Post Malone	647	4.3	10.46
3	The Chainsmokers	576	3.82	14.29
4	Justin Bieber	566	3.76	18.04
5	Drake	559	3.71	21.75
6	Calvin Harris	468	3.11	24.86
7	Luis Fonsi	462	3.07	27.93
8	Maroon 5	415	2.75	30.68
9	Dua Lipa	378	2.51	33.19
10	Imagine Dragons	365	2.42	35.61
11	Marshmello	346	2.3	37.91
12	Ariana Grande	301	2	39.91
13	Charlie Puth	299	1.98	41.89
14	Taylor Swift	271	1	43.69
15	Camila Cabello	270	1.79	45.49
16	Bruno Mars	268	1.78	47.27
17	Major Lazer	268	1.78	49.04
18	Shawn Mendes	266	1.77	50.81
19	XXXTENTACION	265	1.76	52.57
20	J Balvin	263	1.75	54.31
21	Clean Bandit	247	1.64	55.95
22	The Weeknd	208	1.38	57.34
23	Adele	203	1.35	58.68
24	DJ Khaled	194	1.29	59.97
25	Fifth Harmony	184	1.22	61.19
26	Katy Perry	181	1.2	62.39
27	Zedd	170	1.13	63.52
28	Sia	168	1.12	64.64
29	DJ Snake	164	1.09	65.73
30	French Montana	164	1.09	66.81
31	Shakira	160	1.06	67.88
32	Twenty One Pilots	157	1.04	68.92
33	Kendrick Lamar	149	0.99	69.91
34	Selena Gomez	142	0.94	70.85
35	Alan Walker	137	0.91	71.76
36	ZAYN	133	0.88	72.64
37	Mark Ronson	118	0.78	73.43
38	Nicky Jam	115	0.76	74.19

39	Eminem	108	0.72	74.91
40	Cardi B	107	0.71	75.62
41	Avicii	103	0.68	76.3
42	Juice WRLD	99	0.66	76.96
43	PSY	99	0.66	77.62
44	Ellie Goulding	98	0.65	78.27
45	Wiz Khalifa	98	0.65	78.92
46	David Guetta	96	0.64	79.55
47	Enrique Iglesias	91	0.6	80.16
48	James Arthur	91	0.6	80.76
49	Jonas Blue	90	0.6	81.36
50	OneRepublic	89	0.59	81.95
51	Lil Uzi Vert	88	0.58	82.53
52	Travis Scott	86	0.57	83.11
53	Passenger	84	0.56	83.66
54	Meghan Trainor	82	0.54	84.21
55	Sam Smith	82	0.54	84.75
56	Mike Posner	77	0.51	85.26
57	Benny Blanco	74	0.49	85.75
58	Maluma	72	0.48	86.23
59	Becky G	71	0.47	86.7
60	Khalid	68	0.45	87.15
61	Natti Natasha	65	0.43	87.59
62	Rudimental	64	0.42	88.01
63	Rihanna	63	0.42	88.43
64	Casper	62	0.41	88.84
65	Disney UK	61	0.4	89.25
66	Danny Ocean	58	0.39	89.63
67	Dynoro	58	0.39	90.02
68	Justin Timberlake	58	0.39	90.4
69	Gummibar	57	0.38	90.78
70	LMFAO	56	0.37	91.15
71	Silentò	55	0.37	91.52
72	Kygo	54	0.36	91.87
73	Lady Gaga	54	0.36	92.23
74	MAGIC!	54	0.36	92.59
75	Halsey	53	0.35	92.94
76	Crazy Frog	51	0.34	93.28
77	Lukas Graham	51	0.34	93.62
78	Dennis Lloyd	47	0.31	93.93
79	Daddy Yankee	46	0.31	94.24
80	Ricky Martin	45	0.3	94.54
81	CNCO	41	0.27	94.81
82	Anne-Marie	39	0.26	95.07
83	5 Seconds of Summer	38	0.25	95.32
84	Romeo Santos	38	0.25	95.57
85	Bebe Rexha	37	0.25	95.82
86	John Legend	37	0.25	96.06
87	Logic	36	0.24	96.3

88	P!nk	36	0.24	96.54
89	Chino y Nacho	34	0.23	96.77
90	Lauv	34	0.23	96.99
91	Keala Settle & The Greatest Showman Ensemble	33	0.22	97.21
92	Piso 21	33	0.22	97.43
93	Desiigner	31	0.21	97.64
94	G-Eazy	29	0.19	97.83
95	Jason Derulo	26	0.17	98
96	Martin Garrix	25	0.17	98.17
97	Jessie J	24	0.16	98.33
98	Loud Luxury	22	0.15	98.47
99	Axwell & Ingrosso	21	0.14	98.61
100	George Ezra	19	0.13	98.74
101	Macklemore & Ryan Lewis	18	0.12	98.86
102	Bazzi	16	0.11	98.96
103	Carlos Vives	16	0.11	99.07
104	Dean Lewis	14	0.09	99.16
105	Future	13	0.09	99.25
106	Liam Payne	13	0.09	99.34
107	Rita Ora	13	0.09	99.42
108	Christina Perri	11	0.07	99.5
109	Ava Max	10	0.07	99.56
110	Manuel Turizo	9	0.06	99.62
111	Bad Bunny	8	0.05	99.67
112	Nio Garcia	8	0.05	99.73
113	Pulcino Pio	8	0.05	99.78
114	Tyga	6	0.04	99.82
115	NF	5	0.03	99.85
116	Ozuna	5	0.03	99.89
117	Zara Larsson	5	0.03	99.92
118	Joey Montana	4	0.03	99.95
119	Blocboy JB	3	0.02	99.97
120	Jennifer Lopez	3	0.02	99.99
121	DNCE	2	0.01	100

4.5. Concentration of Artists per Combined Ranking Scores

A table indicating all the scores of the individual songs can be found in Appendix D. The points for each platform were calculated by assigning a score based on the chart position charts of each music streaming platform. Even though the streaming services are not equally sized in terms of subscriptions as well as catalogue size, these rankings give an overlook of the absolute popularity of these artists on online music streaming services. Since the rankings were calculated in terms of the amount of total streams, or in the case of Apple Music with the total index points, this method allows to obtain a more comparable overlook of the popularity and concentration of consumption of artists in each different online music streaming service. By applying this method it was made possible to have a new list of the most popular artists across YouTube, Spotify and Apple Music, and at the top 10 level there are four artists which were not present in the top 10 rankings of the previous list; however, there are still many similarities, for instance, when looking at the top 25 artists, there is just one different artist from 4.1. This method also allows to assess multiple dimensions to the dynamics of popularity which were not possible to observe with the previous method, this is observable at the lower levels, in which there is a much higher turn around and the distances more clearly listed. However, it is important to stress that even the lower ranked artists can still be considered to be part of an elite of artists which achieve popularity on a global scale, and that even these artists may display a high level of concentration if compared to a larger population.

Nevertheless, there are also noticeable differences between the two lists when looking at the degree of concentration: here, the top 10 artists have 35.61% of the total assigned points, the top 25 61.19 and the top half (n=60) 87.15. These findings indicate that the amount of total views of Superstar artists is quite high, and there is an uneven distribution even among the top charts. The fact that some artists generate such a high amount of in comparison to others can be attributed to many factors that characterize music streaming services, such as the reliance on music recommendation systems or the inclusion of popular songs into playlists. Other possible explanations could be that there is a high difference in quality between the top artists compared to the ones on the bottom of the list, or that there are other common features that increase the chances of making it into the top charts. However, given the nature of the study, which attempts to assess the concentration of consumption in music streaming services, as well as the difficulty in quantifying concepts such as quality, these matters should be evaluated in further studies.

4.6. Gini Coefficients for Songs and Artists in Sample

Appendix C1 presents the Lorenz Curves for YouTube, Spotify and Apple Music. The Gini Coefficient for YouTube and Spotify is quite similar (0.15 and 0.17 respectively), whereas the coefficient for Apple Music is slightly higher (0.27). These are pretty fair distributions, as indicated by Krugman & Wells (2015), who say that an Gini Coefficient under 0.25 is acceptable. However it is worth to point out that the different results yielded by Apple Music may be a consequence of the fact that the popularity of the songs were not calculated in base of the total amount of plays, as it happened with the other streaming services. Nevertheless, the graphs show a visualization of the distribution of popularity across the streaming services. Despite so, the fact that the Gini Coefficient for the Top 100 songs is not very significant, as it is already assumed that the top 100 songs have a high concentration of streams, and in order to generalize, a larger sample is required.

Appendix C2 presents the Lorenz Curves for the Top2500 songs for each platform. The selection of this sample size is determined by the availability on Kworb.net, and although there are 2607 and 4402 songs for Spotify and Apple Music respectively, there are only 2500 YouTube songs. This required a restriction of the sample size, nevertheless, it can still considered large enough to extract generalizations. Here, we see more detailed results and the differences between the platforms more easily demarcated. For instance, Spotify had the largest inequality, with a Gini Coefficient of 0.67, Apple Music was second with 0.59 and YouTube third with 0.38. These results are very interesting, and the considerable difference between the two Gini Coefficients of Spotify appear to indicate that in this platform the superstar effect is stronger. However, it is also worth to point out that given the significantly larger size of YouTube's catalogue, the Top2500 constitute a different percentage of the total available songs. This is why it is expected to find a more equal distribution of views on YouTube. Despite so, all values are larger than 0.25, indicating that even in this relatively small sample there is still an uneven distribution of popularity among the most popular songs.

As previously pointed out, possible explanations for high levels of concentration of consumption of songs can be explained by features such as music recommendation systems, or the presence of playlists. However, there may be alternative explanations; for example, the possibility of connecting one's Spotify account with their Facebook profile means that there is a higher level of interaction between users, and therefore more exchange and less diversity in the music consumed. Other possible explanations connected to Spotify's business model are their agreements with record labels, which may cause their signed artists to have a preferential lane in terms of visibility and promotion. On the other hand, YouTube is more centered on original creators and the provision of videos besides only the music, meaning that even songs considered of 'lesser' quality may be able to stand out thanks to a well made video which manages to become viral. However, also Apple Music provides the videos of the songs, and although this is a relatively new feature, one would have expected more similarities in terms of the distribution of popularity between the two services.

Looking at the artists on Appendix C3, we also find a high Gini Coefficient of 0.52, confirming the findings of the previous sections. Even though the Gini Coefficient does not express at exactly what point the inequality of distribution is happening, this graph helps to visualize the extent of the Superstar Effect among the artists present on the most popular lists of YouTube, Spotify and Apple Music. Further confirmations of these findings are reflected in the 2015-2019 IFP Global Music Reports, that show that on the yearly charts of the most popular musicians, more than one third of the musicians were present more than once. As discussed by Kask and Öberg (2019), music streaming services increase the converging of musical tastes, and although this does not exclude local artists to emerge, there are less chances for them to do so. A verification of this theory is reflected in these findings, as if the opposite were to be true, we would observe at least a few local artists from countries with large populations.

5.1. Conclusion

This research intended to answer the following questions: what are the differences and similarities between the Top 100 most popular songs on YouTube, Spotify and Apple Music; and how evenly distributed is the consumption of the most popular artists and songs on these music streaming services. To do so, the first section of the paper introduced some previous research around similar matters, following with a definition of the different variables involved in the research; subsequently, some descriptive statistics and frequencies regarding characteristics such as total amount of view, publication year, song length, country of origin, language, genre featuring, artist nature and gender. The final sections of the paper presented an index of popularity in order to visualize the extent of concentration of consumption for the most popular songs and artists, as well as a Gini Coefficient in order to determine the inequality of distribution of attention and popularity.

The most distinctive differences can be seen especially with YouTube in terms of language, country of origin and genre, which indicated a more diversified environment and possibly a larger user base compared to Spotify and Apple Music. It is however the similarities across the platforms that are quite interesting: such as the almost equal distribution of featuring and non featuring songs, as well as an equivalent level of solo artists across all the three music streaming services. Possible explanations could be the increased reliance of artists to promote their works on social media, giving them a chance to emerge for their personalities or by connecting different user bases. Such similarities indicate that these might be influencing factors that increase the possibility of an artist to reach the top charts and increase their popularity, or that they could act as quality indicators that steer consumers into listening to their music.

The second section of the paper identified a high concentration of consumption for the most popular artists, both in terms of the amount of songs (around 25% for the top 10 artists out of 121), and absolute ranking positions (around 35% for the top 10 artists). As for the types of songs present in the different services, there are several overlaps, which seem to coincide with the business models of the music streaming services and their availability in terms of market size and catalogue size; although further studies should concentrate on establishing this relationship, if any. This inequality in terms of attention and popularity is also expressed with the Gini Coefficient of the artists of 0.52, which is higher than the threshold of 0.25; and even though this inequality is not clear when looking at the Top100 songs of YouTube, Spotify and Apple Music, it becomes more evident when expanding the sample of analysis from 100 to 2500. The differences between the two Gini Indexes, in particular those between the Spotify Top100 and Top2500, with an increase from 0.17 to 0.62, seems to indicate that there is a clear concentration of consumption, which could be caused by many factors such as recommendation systems, playlists, or the business models of the intended platform.

5.2. Limitations and Further Research

Despite the fact that the results address the questions put forth in the introduction, this study has different limitations. Firstly, it was not possible to obtain data regarding the development of these top charts across several years, which could have been useful to track better the common characteristics of these songs and artists and possibly find a relationship. Secondly, it was not possible to obtain the data regarding the total amount of streams regarding Apple Music, and even though the index created by Kworb.net, which assigns points to rankings depending on the sizes of the market can be seen as a quite reliable indicator of overall popularity within the platform, the results would have probably differed, especially in the second section of the paper, from the ones that were obtained. Nevertheless, the index created by Kworb.net seems to indicate a considerable inequality of popularity among the Top2500, and the coherence with the other results could possibly indicate the goodness of such methodology. Finally, it would have been beneficial to obtain localized charts for each service, so that a new index of popularity could be created which relies on common features of the different streaming services instead of total amount of views, which is not necessarily an indicator of quality or excellence. Future studies should take these limitations in consideration and build up from them.

Nevertheless, the study is relevant for establishing the characteristics of the top hits and presenting a visualization of the concentration of consumption within music streaming services. Secondly, we are at the forefront of new big shift in music industry thanks to the rapid growth of the Asian market (+11.7% since last year), and the South American market (+16.8%), with South Korea, China and Brazil presenting the most noticeable growth (IFPI 2019). This means that there may be a significant shift in the following years regarding the dominant worldwide hits and superstars. Another possible significant shift in the industry is the introduction of Spotify in India in February 2019, which could suddenly change all the dynamics of the top selling hits within the platform. By more clearly defining characteristics of the current western-centric music streaming markets this research may become a starting point to delineate the future changes in the concentration of superstars as well as possibly track the changes in preferences for new emerging markets and personalities, and whether these eventual changes are reflected throughout all 3 platforms or whether these changes will only affect on specific streaming service over another.

Future studies should focus on whether there will be a shift in consumption, and which will be the major actors to emerge as the most influencing and which ones will shape the market for music streaming services in the coming years.

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Appendix A1.

Key descriptive statistics for Amount of Streams (n=300)

Variable	Σ	σ	Min	Max	μ
Streams/Plays)	$2.58x10^{11}$	771375335	$5.39x10^{8}$	$6.02x10^{9}$	$1.29x10^{9}$

Appendix A2.

Key descriptive statistics for Year of Publication and Song Length (n=300)

Variable	Σ	σ	Min	Max	μ
Year	-	2.04	2005	2019	2016
Length	-	00:37	01:59	07:03	03:44

Appendix A3.

Key descriptive statistics for Amount of Streams, Year of Publication and Song Length on YouTube (n=100)

Variable	Σ	σ	Min	Max	μ
Streams/Plays	$1.83x10^{11}$	$7.49x10^{8}$	$1.21x10^{9}$	$6.02x10^{9}$	$1.82x10^{9}$
Year	-	2.55	2005	2019	2014
Length	-	00:42	02:13	05:12	04:06

Appendix A4.

Key descriptive statistics for Amount of Streams, Year of Publication and Song Length on Spotify (n=100)

Variable	Σ	σ	Min	Max	μ
Streams/Plays	$7.55x10^{10}$	$2.43x10^{8}$	$5.39x10^{8}$	$2.05x10^{9}$	$7.55x10^{8}$
Year	-	1.15	2014	2018	2016
Length	-	00:31	01:59	05:12	03:37

Appendix A5.

Key descriptive statistics for Year of Publication and Song Length on Apple Music (n=100)

Variable	Σ	σ	Min	Max	μ
Year	-	0.64	2015	2019	2017
Length	-	00:29	02:13	05:12	03:30

Appendix A6.

Total Frequencies for Country of Origin, Language, Genre, Featuring, Nature and Gender of Total Population (n=300)

Category	Variable	Frequency	Percent (%)
Country of Origin	Australia	6	2
	Barbados	2	0.7
	Canada	32	10.7
	Colombia	14	4.7
	Cuba	4	1.3
	Denmark	1	0.3
	Dominican Republic	1	0.3
	France	6	2
	Germany	1	0.3
	Israel	1	0.3
	Italy	1	0.3
	Jamaica	4	1.3
	Lithuania	1	0.3
	Netherlands	2	0.7
	Norway	4	1.3
	Panama	1	0.3
	Puerto Rico	12	4
	Russia	4	1.3
	South Korea	2	0.7
	Spain	1	0.3
	Sweden	6	2
	UK	47	15.7
	USA	144	48
	Venezuela	3	1
	Total	300	100
Language	English	258	86
	Korean	1	0.3
	Korean/English	1	0.3
	Patois	1	0.3
	Spanish	33	11
	Spanish/English	6	2
	Total	300	100
Genre	Dance/Electronic	69	23
	Hip Hop/R&B	70	23.3
	Latin	42	14
	Other	26	8.7

	Pop	93	31.0
	Total	300	100
Featuring	No	161	53.7
	Yes, List	74	24.7
	Yes, No List	65	21.7
	Total	300	100
Nature	Solo	252	84
	Group	48	16
	Total	300	100
Gender	Female	60	20
	Male	229	76
	Mixed/Other	11	3.7
	Total	300	100

Appendix A7.

Total Frequencies for Country of Origin, Language, Genre, Featuring, Nature and Gender of YouTube (n=100)

Category	Variable	Frequency
Country of Origin	Australia	2
	Barbados	1
	Canada	9
	Colombia	11
	Cuba	1
	Dominican Republic	1
	France	1
	Germany	1
	Italy	1
	Jamaica	1
	Netherlands	1
	Norway	1
	Panama	1
	Puerto Rico	1
	South Korea	2
	Spain	1
	Sweden	2
	UK	15
	USA	40
	Venezuela	2
	Total	100
Language	English	70
	Korean	1
	Korean/English	1
	Spanish	26

	Spanish/English	2
	Total	100
Genre	Dance/Electronic	15
	Hip Hop/R&B	16
	Latin	30
	Other	10
	Pop	29
	Total	100
Featuring	No	58
	Yes, List	23
	Yes, No List	19
	Total	100
Nature	Solo	82
	Group	18
	Total	100
Gender	Female	27
	Male	68
	Mixed/Other	5
	Total	100

Appendix A8.

Total Frequencies for Country of Origin, Language, Genre, Featuring, Nature and Gender of Spotify (n=100)

Category	Variable	Frequency
Country of Origin	Australia	2
	Barbados	1
	Canada	15
	Colombia	1
	Cuba	1
	Denmark	1
	France	2
	Jamaica	3
	Netherlands	1
	Norway	2
	Puerto Rico	3
	Russia	2
	Sweden	1
	UK	12
	USA	52
	Venezuela	1
	Total	100
Language	English	93
	Patois	1

	Spanish	4
	Spanish/English	2
	Total	100
Genre	Dance/Electronic	28
	Hip Hop/R&B	27
	Latin	7
	Other	10
	Pop	28
	Total	100
Featuring	No	50
	Yes, List	28
	Yes, No List	22
	Total	100
Nature	Solo	84
	Group	16
	Total	100
Gender	Female	13
	Male	85
	Mixed/Other	2
	Total	100

Appendix A9.

Total Frequencies for Country of Origin, Language, Genre, Featuring, Nature and Gender of Apple Music (n=100)

Frequency	Variable	Frequency
Country of Origin	Australia	2
	Canada	8
	Colombia	2
	Cuba	2
	France	3
	Israel	1
	Lithuania	1
	Norway	1
	Puerto Rico	3
	Russia	2
	South Korea	3
	Sweden	3
	UK	20
	USA	52
	Total	100
Language	English	95
	Spanish	3
	Spanish/English	2

	Total	100
Genre	Dance/Electronic	26
	Hip Hop/R&B	27
	Latin	5
	Other	6
	Pop	36
	Total	100
Featuring	No	53
	Yes, List	23
	Yes, No List	24
	Total	100
Nature	Solo	86
	Group	14
	Total	100
Gender	Female	20
	Male	76
	Mixed/Other	4
	Total	100

Appendix B1.

Total Calculated Score for Individual Songs (n=221)

Rank	Artist	Song	YouTube Score	Spotify Score	Apple Music Score	Total Score	Percentage (%)	Cumulative Percentage (%)
1	Ed Sheeran	Shape of You	99	100	100	299	1.96	1.96
2	Luis Fonsi	Despacito	100	71	95	266	1.75	3.71
3	Ed Sheeran	Perfect	68	90	98	256	1.68	5.39
4	Dua Lipa	New Rules	63	92	97	252	1.66	7.05
5	The Chainsmokers	Closer	79	98	67	244	1.6	8.65
6	Camila Cabello	Havana	47	94	99	240	1.58	10.23
7	The Chainsmokers	Something Just	53	84	94	231	1.52	11.75
8	J Balvin	Mi Gente	81	59	73	213	1.4	13.15
9	Maroon 5	Girls Like You	70	56	85	211	1.39	14.53
10	Post Malone	Rockstar	-	97	96	193	1.27	15.8
11	Drake	God's Plan	-	96	91	187	1.23	17.03
12	Ed Sheeran	Thinking Out Loud	90	95	-	185	1.22	18.25
13	Imagine Dragons	Thunder	-	86	92	178	1.17	19.42
14	Justin Bieber	Sorry	95	82	-	177	1.16	20.58
15	Imagine Dragons	Believer	-	80	87	167	1.1	21.68
16	Major Lazer	Lean On	87	79	-	166	1.09	22.77
17	French Montana	Unforgettable	-	76	88	164	1.08	23.85
18	Calvin Hrris	One Kiss	-	64	93	157	1.03	24.88
19	Cardi B	I Like It	-	66	90	156	1.03	25.9
20	Bruno Mars	That's What I Like	36	65	50	151	0.99	26.89
21	XXXTENTACION	SAD!	-	75	69	144	0.95	27.84
22	Post Malone	Better Now	-	72	70	142	0.93	28.77
23	Charlie Puth	Attention	-	52	89	141	0.93	29.7
24	Drake	In My Feelings	-	69	72	141	0.93	30.63
25	Calvin Harris	This is What You	78	60	-	138	0.91	31.53
26	Justin Bieber	What Do You	71	67	-	138	0.91	32.44
27	Alan Walker	Faded	80	57	-	137	0.9	33.34
28	Ava Max	Psycho	-	68	65	133	0.87	34.21
29	Khalid	Young Dumb &	-	81	48	129	0.85	35.06
30	Clean Bandit	Rockabye	74	48	7	129	0.85	35.91
31	Adele	Hello	86	43	-	129	0.85	36.76
32	Dua Lipa	IDGAF	-	49	77	126	0.83	37.58
33	Fifth Harmony	Work From Home	73	53	-	126	0.83	38.41
34	The Weeknd	Starboy	42	83	-	125	0.82	39.23
35	Justin Bieber	Love Yourself	39	85	-	124	0.81	40.05
36	Marshmello	Silence	-	46	76	122	0.8	40.85
37	Twenty One Pilots	Stressed Out	59	63	-	122	0.8	41.65
38	Bruno Mars	Uptown Funk	97	21	-	118	0.78	42.43

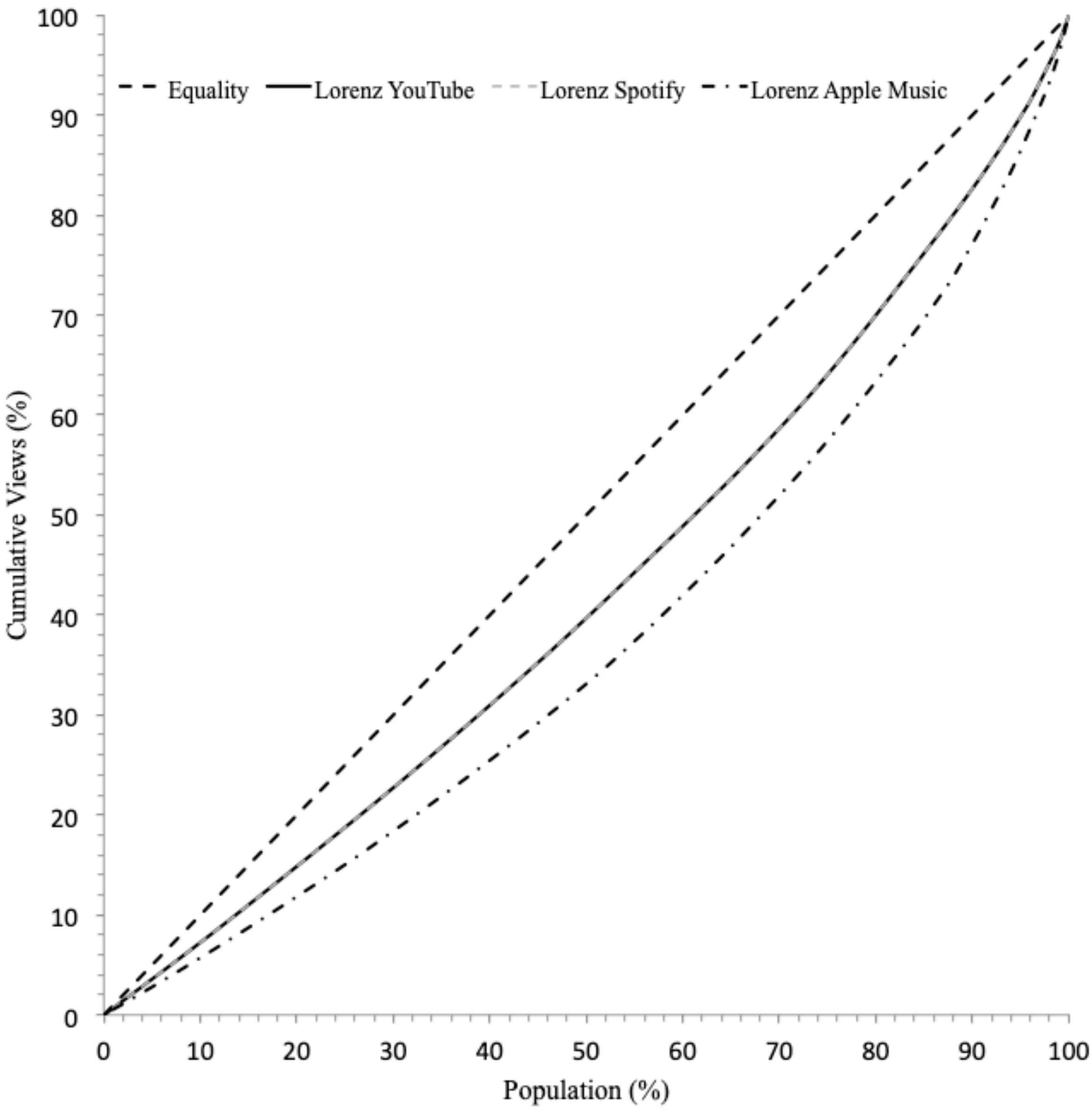
39	Kendrick Lamar	HUMBLE.	-	89	28	117	0.77	43.2
40	Marshmello	Friends	-	45	71	116	0.76	43.96
41	Shawn Mendes	Treat You Better	60	55	-	115	0.76	44.71
42	DJ Khaled	I'm the One	-	61	51	112	0.74	45.45
43	Maroon 5	What Lovers Do	-	44	66	110	0.72	46.17
44	Charlie Puth	We Don't Talk	76	33	-	109	0.72	46.89
45	Ariana Grande	No Tears Left to	-	25	83	108	0.71	47.6
46	Marshmello	Happier	-	26	80	106	0.7	48.29
47	Zedd	The Middle	-	32	72	104	0.68	48.98
48	Luis Fonsi	Échame La Culpa	66	-	37	103	0.68	49.66
49	The Chainsmokers	Don't Let Me Down	20	81	-	101	0.66	50.32
50	Juice WRLD	Lucid Dreams	-	54	45	99	0.65	50.97
51	Selena Gomez	Wolves	-	18	81	99	0.65	51.62
52	Drake	One Dance	-	99	-	99	0.65	52.27
53	Wiz Khalifa	See You Again	98	-	-	98	0.64	52.91
54	Ariana Grande	Thank U, Next	-	22	74	96	0.63	53.54
55	Sia	Cheap Thrills	26	70	-	96	0.63	54.18
56	PSY	Gangnam Style	96	-	-	96	0.63	54.81
57	Maroon 5	Sugar	94	-	-	94	0.62	55.42
58	Luis Fonsi	Despacito (Remix)	93	-	-	93	0.61	56.04
59	Katy Perry	Roar	93	-	-	93	0.61	56.65
60	Taylor Swift	Shake it Off	92	-	-	92	0.6	57.25
61	Enrique Iglesias	Bailando	91	-	-	91	0.6	57.85
62	James Arthur	Say You Won't Let	-	91	-	91	0.6	58.45
63	DJ Snake	Taki Taki	-	30	60	90	0.59	59.04
64	OneRepublic	Counting Stars	89	-	-	89	0.58	59.62
65	Katy Perry	Dark Horse	88	-	-	88	0.58	60.2
66	Lil Uzi Vert	XO Tour Llif3	-	88	-	88	0.58	60.78
67	Ed Sheeran	Photograph	-	87	-	87	0.57	61.35
68	ZAYN	Dusk Til Dawn	-	-	86	86	0.57	61.92
69	Taylor Swift	Blank Space	85	-	-	85	0.56	62.47
70	Calvin Harris	Feels	-	-	84	84	0.55	63.03
71	Passenger	Let Her Go	84	-	-	84	0.55	63.58
72	Shakira	Chantaje	83	-	-	83	0.55	64.12
73	Shawn Mendes	There's Nothing	-	27	55	82	0.54	64.66
74	Sam Smith	Too Good at	-	19	63	82	0.54	65.2
75	Meghan Trainor	All About That	82	-	-	82	0.54	65.74
76	DJ Khaled	Wild Thoughts	-	-	82	82	0.54	66.28
77	Taylor Swift	Look What You	-	-	79	79	0.52	66.8
78	Post Malone	Congratulations	-	78	-	78	0.51	67.31
79	Mike Posner	I Took a Pill in	-	77	-	77	0.51	67.82
80	Shakira	Waka Waka (This	77	-	-	77	0.51	68.32
81	Travis Scott	SICKO MODE	-	17	59	76	0.5	68.82
82	Justin Bieber	Baby	75	-	-	75	0.49	69.31
83	Clean Bandit	Solo	-	-	75	75	0.49	69.81

84	Benny Blanco	Eastside	-	6	68	74	0.49	70.29
85	DJ Snake	Let Me Love You	-	74	-	74	0.49	70.78
86	Major Lazer	Cold Water	-	73	-	73	0.48	71.26
87	Nicky Jam	X (EQUIS)	49	-	23	72	0.47	71.73
88	Sia	Chandelier	72	-	-	72	0.47	72.21
89	Casper	Te Boté (Remix)	62	7	-	69	0.45	72.66
90	Ellie Goulding	Love Me Like You	69	-	-	69	0.45	73.11
91	Drake	Hotline Bling	43	24	-	67	0.44	73.55
92	Avicii	Wake me Up	67	-	-	67	0.44	73.99
93	Natti Natasha	Criminal	65	-	-	65	0.43	74.42
94	Drake	Nice for What	-	23	41	64	0.42	74.84
95	Eminem	Love the Way You	64	-	-	64	0.42	75.26
96	XXXTENTACION	Jocelyn Flores	-	62	-	62	0.41	75.67
97	Calvin Harris	Promises	-	-	62	62	0.41	76.08
98	Post Malone	I Fall Apart	-	50	11	61	0.4	76.48
99	Ed Sheeran	Galway Girl	-	-	61	61	0.4	76.88
100	Disney Uk	Let it Go	61	-	-	61	0.4	77.28
101	Post Malone	Sunflower	-	-	61	61	0.4	77.68
102	Zedd	Stay	-	16	44	60	0.39	78.07
103	XXXTENTACION	Moonlight	-	28	31	59	0.39	78.46
104	Danny Ocean	Me Rehuso	19	39	-	58	0.38	78.84
105	Justin Timberlake	Can't Stop the	-	58	-	58	0.38	79.22
106	Dynoro	In My Mind	-	-	58	58	0.38	79.6
107	The Weeknd	Worth It	58	-	-	58	0.38	79.99
108	Calvin Harris	2U	-	-	57	57	0.37	80.36
109	Gummibar	The Gummy Bear	57	-	-	57	0.37	80.73
110	LMFAO	Party Rock Anthem	56	-	-	56	0.37	81.1
111	Jonas Blue	Rise	-	-	56	56	0.37	81.47
112	Silento	Watch Me	55	-	-	55	0.36	81.83
113	Kygo	It Ain't Me	-	42	12	54	0.35	82.19
114	MAGIC!	Rude	54	-	-	54	0.35	82.54
115	Lady Gaga	Shallow	-	-	54	54	0.35	82.9
116	Rudimental	These Days	-	-	54	54	0.35	83.25
117	Halsey	Without Me	-	-	53	53	0.35	83.6
118	Justin Bieber	Friends (Justin	-	-	52	52	0.34	83.94
119	Bruno Mars	The Lazy Song	52	-	-	52	0.34	84.28
120	Lukas Graham	7 Years	-	51	-	51	0.34	84.62
121	Crazy Frog	Axel F	51	-	-	51	0.34	84.95
122	J Balvin	Ay Vamos	50	-	-	50	0.33	85.28
123	Charlie Puth	How Long	-	-	49	49	0.32	85.6
124	Ariana Grande	Side to Side	48	-	-	48	0.32	85.92
125	ZAYN	I Don't Want to	-	47	-	47	0.31	86.23
126	Camila Cabello	Never be the Same	-	-	47	47	0.31	86.54
127	Dennis Lloyd	Nevermind	-	-	47	47	0.31	86.85
128	Ariana Grande	God is a Woman	-	-	46	46	0.3	87.15

129	Adele	Rolling in the Deep	46	-	-	46	0.3	87.45
130	Ricky Martin	Vente Pa 'Ca	45	-	-	45	0.3	87.75
131	Clean Bandit	Symphony	-	8	35	43	0.28	88.03
132	Selena Gomez	Back to You	-	-	43	43	0.28	88.31
133	Bruno Mars	Finesse	-	-	42	42	0.28	88.59
134	CNCO	Reggaetón Lento	41	-	-	41	0.27	88.86
135	Rihana	Work	-	41	-	41	0.27	89.13
136	Maluma	Felices Los 4	40	-	-	40	0.26	89.39
137	Shawn Mendes	Stitches	-	40	-	40	0.26	89.65
138	Anne-Marie	2002	-	-	39	39	0.26	89.91
139	5 Seconds of	Youngblood	-	12	26	38	0.25	90.16
140	The Weeknd	Can't Feel my Face	-	38	-	38	0.25	90.41
141	Romeo Santos	Propuesta Indecente	38	-	-	38	0.25	90.66
142	Eminem	River	-	-	38	38	0.25	90.91
143	John Legend	All of Me	37	-	-	37	0.24	91.15
144	G-Eazy	Me, Myself, and I	-	37	-	37	0.24	91.39
145	Logic	1-800-273-8255	-	36	-	36	0.24	91.63
146	P!nk	What About Us	-	-	36	36	0.24	91.87
147	Nicky Jam	Hasta el Amanecer	35	-	-	35	0.23	92.1
148	Twenty One Pilots	Heathens	-	35	-	35	0.23	92.33
149	Chino y Nacho	Andas en mi	34	-	-	34	0.22	92.55
150	Lauv	I Like Me Better	-	34	-	34	0.22	92.77
151	Jonas Blue	Mama	-	-	34	34	0.22	93
152	Piso 21	Déja la Que Vuelva	33	-	-	33	0.22	93.21
153	Keala Settle & The	This is Me	-	-	33	33	0.22	93.43
154	Kendrick Lamar	All the Stars	-	-	32	32	0.21	93.64
155	Maluma	Corazòn	32	-	-	32	0.21	93.85
156	Jennifer Lopez	On the Floor	31	-	-	31	0.2	94.05
157	Desiigner	Panda	-	31	-	31	0.2	94.26
158	Axwell & Ingrosso	More than You	-	-	30	30	0.2	94.45
159	The Weeknd	The Hills	30	-	-	30	0.2	94.65
160	Ellie Goulding	Burn	29	-	-	29	0.19	94.84
161	Shawn Mendes	In my Blood	-	-	29	29	0.19	95.03
162	Major Lazer	Light it Up	-	29	-	29	0.19	95.22
163	Adele	Someone Like you	28	-	-	28	0.18	95.41
164	David Guetta	Flames	-	-	27	27	0.18	95.58
165	Becky G	Sin Pijama	27	-	-	27	0.18	95.76
166	Jason Derulo	Swalla	17	9	-	26	0.17	95.93
167	Cardi B	Bodak Yellow	-	-	25	25	0.16	96.1
168	Daddy Yankee	Shaky Shaky	25	-	-	25	0.16	96.26
169	Jessie J	Bang Bang	24	-	-	24	0.16	96.42
170	Ed Sheeran	Castle on the Hill	-	-	24	24	0.16	96.58
171	Bruno Mars	Just the Way You	23	-	-	23	0.15	96.73
172	Loud Luxury	Body	-	-	22	22	0.14	96.87
173	Rihanna	Diamonds	22	-	-	22	0.14	97.02

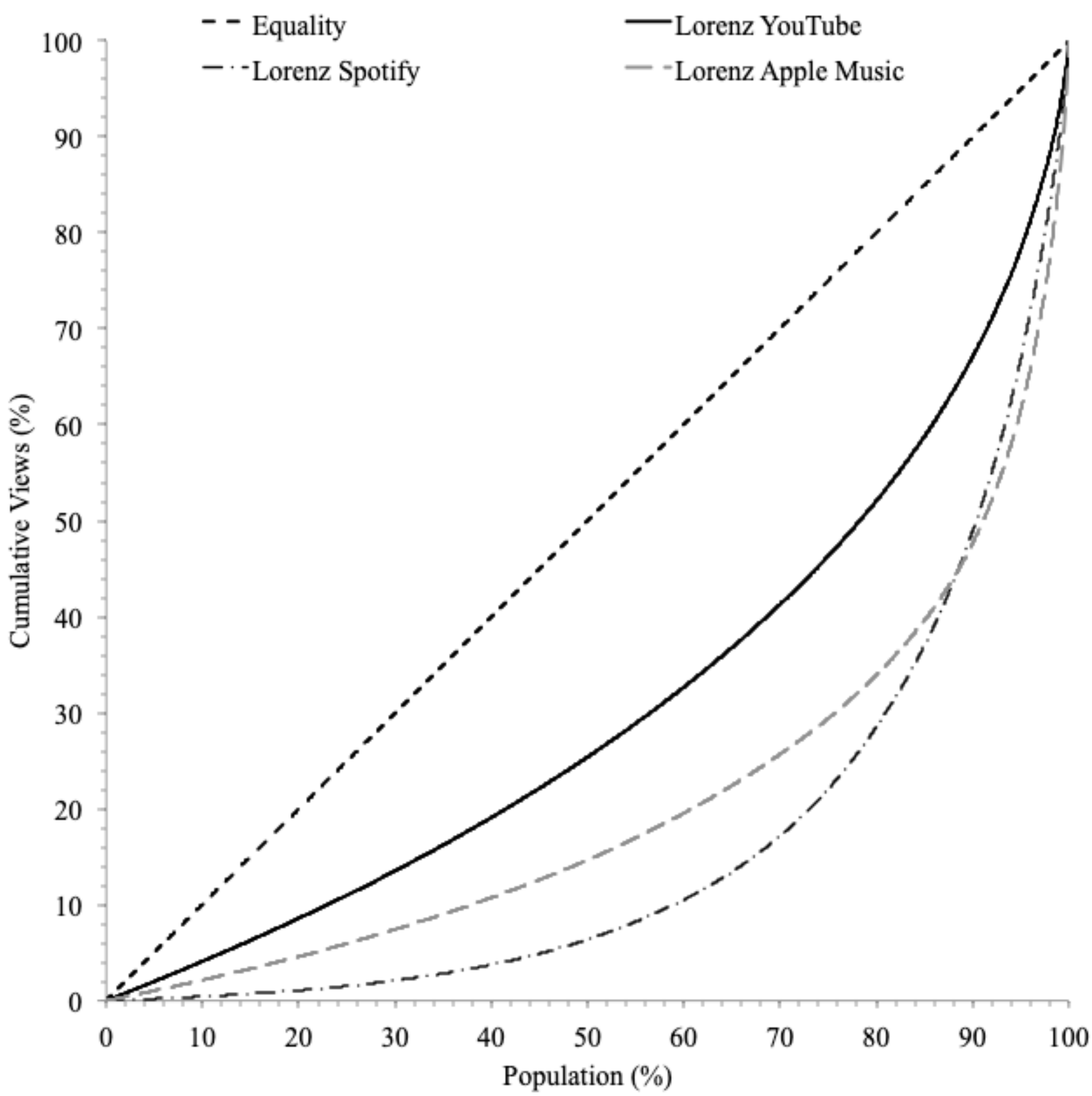
174	Daddy Yankee	Dura	21	-	-	21	0.14	97.15
175	bazzi	Mine	-	-	21	21	0.14	97.29
176	Imagine Dragons	Whatever it Takes	-	-	20	20	0.13	97.42
177	George Ezra	Shotgun	-	-	19	19	0.12	97.55
178	G-Eazy	Him & I	-	-	18	18	0.12	97.67
179	Macklemore &	Thrift Shop	18	-	-	18	0.12	97.79
180	Ed Sheeran	Perfect Duet	-	-	17	17	0.11	97.9
181	Carlos Vives	La Bicicleta	16	-	-	16	0.11	98
182	Bad Bunny	MIA	-	-	16	16	0.11	98.11
183	Taylor Swift	Back to You	15	-	-	15	0.1	98.21
184	Martin Garrix	In the Name of	-	15	-	15	0.1	98.3
185	Avicii	Lonely Together	-	-	15	15	0.1	98.4
186	Dean Lewis	Be Alright	-	-	14	14	0.09	98.5
187	Calvin Harris	How Deep is Your	14	-	-	14	0.09	98.59
188	The Weeknd	I Feel it Coming	-	14	-	14	0.09	98.68
189	Future	Mask Off	-	13	-	13	0.09	98.76
190	Liam Payne	Strip that Down	-	-	13	13	0.09	98.85
191	Calvin Harris	Summer	13	-	-	13	0.09	98.94
192	David Guetta	Hey Mama	12	-	-	12	0.08	99.01
193	Christina Perri	A Thousand Years	11	-	-	11	0.07	99.09
194	Becky G	Mayores	-	11	-	11	0.07	99.16
195	Martin Garrix	Animals	10	-	-	10	0.07	99.22
196	Travis Scott	Goosebumps	-	10	-	10	0.07	99.29
197	Ava Max	Sweet But Psycho	-	-	10	10	0.07	99.36
198	Rita Ora	Anywhere	-	-	9	9	0.06	99.42
199	Manuel Turizo	Una Lady Como Tù	9	-	-	9	0.06	99.47
200	Pulcino Pio	El Pollito Pio	8	-	-	8	0.05	99.53
201	Bebe Rexha	Meant To Be	-	-	8	8	0.05	99.58
202	Nicky Jam	El Perdòn	7	-	-	7	0.05	99.63
203	Tyga	Taste	-	4	2	6	0.04	99.66
204	Eminem	Not Afraid	6	-	-	6	0.04	99.7
205	Avicii	Without You	-	-	6	6	0.04	99.74
206	Ozuna	El Farsante (Remix)	5	-	-	5	0.03	99.78
207	NF	Let You Down	-	-	5	5	0.03	99.81
208	Zara Larsson	Lush Life	-	5	-	5	0.03	99.84
209	Rita Ora	Let You Love Me	-	-	4	4	0.03	99.87
210	Joey Montana	Picky	4	-	-	4	0.03	99.89
211	Ariana Grande	Breathin	-	-	3	3	0.02	99.91
212	PSY	Gentleman	3	-	-	3	0.02	99.93
213	Blocboy JB	Look Alive	-	3	-	3	0.02	99.95
214	Marshmello	Alone	2	-	-	2	0.01	99.97
215	DNCE	Cake by the Ocean	-	2	-	2	0.01	99.98
216	The Weeknd	Call Out my Name	-	-	1	1	0.01	99.99
217	Nicky Jam	El Amante	1	-	-	1	0.01	99.99
218	Drake	Too Good	-	1	-	1	0.01	100

Appendix C1.



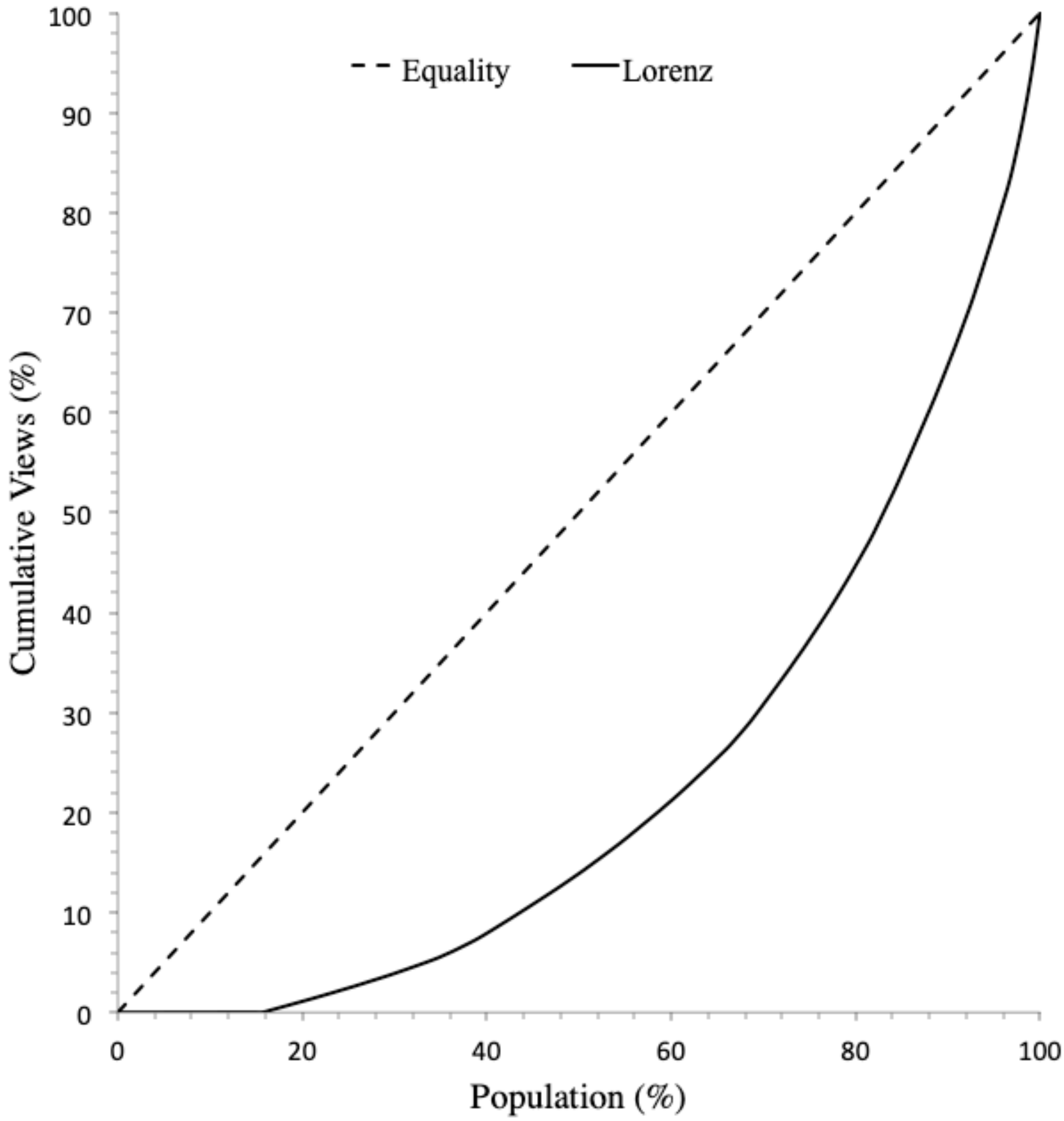
Lorenz Curves of Distribution of Popularity for Top100 songs **YouTube, Spotify and Apple Music (n=300)**

Appendix C2.



Lorenz Curves of Distribution of Popularity for Top2500 YouTube, Spotify and Apple Music (n=7500)

Appendix C3



Lorenz Curves of Distribution of Popularity for Artists on Top100 charts YouTube, Spotify and Apple Music (n=121)