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International Music Preferences: An Analysis of the Determinants of Song Popularity on Spotify for the U.S., Norway, Taiwan, Ecuador, and Costa Rica

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Abstract

This paper examines data from Spotify's API for 2017-2018 to determine the effects of song attributes on the success of tracks on Spotify's Top 200 Chart across five different countries: the U.S., Norway, Taiwan, Ecuador, and Costa Rica. Two dependent variables are used to measure the success of a song – a track's peak position on the charts and the number of days it survives on a country's Top 200 Chart. Using ten separate regressions, one for each dependent variable in all five countries, it is concluded that the presence of a featured guest on a track increases a song's peak position and the number of days it survives on the charts in almost every country. Further, songs that are perceived as "happier" are more successful for both metrics in Norway and Taiwan while those that are louder and more aggressive have a shorter lifespan on the charts in three out of five of the countries studied. The paper concludes that further research should be conducted with a larger, more diverse dataset to see if these findings hold and if they are present in other countries as well.

I. Introduction

> *"Music is changing so quickly, and the landscape of the music industry itself is changing so quickly, that everything new, like Spotify, all feels to me a bit like a grand experiment*" - *Taylor Swift (excerpt from the Rolling Stone article from 2014, "Taylor Swift Shuns 'Grand Experiment' of Streaming Music" by Kory Grow)*

Digital technologies have rocked the music industry to its core. Two decades ago, in 1999, the global music industry was worth $25.2 billion, whereas in 2017 it was just below 75% of that value at $17.3 billion (IFPI Global Music Report 2018). As digital technologies proliferated on a global scale, the music industry experienced a sharp decline in sales of records, CD's, and other forms of physical purchases. Consumers turned to downloading as a more convenient and, often, cheaper means of obtaining music. Following a universal scare regarding the future of the music industry after the advent of Napster, a number of music streaming platforms surfaced in the late 2000's – most notably, Spotify. As of 2018, streaming platforms represent the largest revenue stream for the global music industry, making up 38% of total revenue (IFPI Global Music Report 2018). Thus, the economic relevance of music streaming platforms and their effects on the market has grown considerably.

Spotify dominates the music streaming market and serves as one of the main avenues through which over 200 million global users find new music. Users can follow artists, playlists, look at their country's top 200 daily hits, and hunt for music via a search function. Rather than having access to a few thousand records at a local music store, streaming platform users have access to millions of songs right at their fingertips. Considering that users can access nearly any song, the following question arises: what song attributes affect a track's popularity and how does that differ between countries? More specifically, which factors affect popularity on Spotify?

Previous studies in this field have examined variables influencing song popularity based on data obtained from the Billboard Hot 100 or other popular music charts, but none have looked specifically at streaming platforms. Further, no previous studies have compared determinants of song popularity between different countries. I fill this gap by applying previous studies' methodologies to Spotify-specific data that is segmented by country.

In this paper, I conduct an analysis of art popularity with economic tools – I examine the determinants of song popularity by measuring two outcomes: a song's peak position in Spotify's daily Top 200 Chart and the number of days it survives in the Top 200. The data used for this research was sourced from Spotify's API and is limited to the year of 2017 to isolate current trends in popular music. Similar to previous literature, I use an ordinary least squares (OLS) regression to examine how various audio and artist features affect the success of a song in five countries: the U.S., Norway, Taiwan, Ecuador, and Costa Rica. By identifying different attributes that affect a song's popularity, artists and record labels will be able to have a greater sense of consumer preferences and how they vary in different countries.

There are a number of song and artist attributes that affect song popularity in the same ways across the majority of the countries studied. First, the presence of a featured guest on a track is likely to increase a song's peak position on Spotify's charts as well as the number of days it survives on the charts. Second, songs that are perceived as "happier," which results from a higher valence, are likely to have a better peak position and stay on the charts longer. Third, tracks that are abrasive to listen to, meaning that they have high energy and are particularly loud, are significantly more likely to have a shorter survival period on the charts. Ceulemans and Detry (2013) found that the presence of guest artists improved the popularity of a track, though not with the same degree of significance. Further, none of the previous literature has found valence or energy to be significant in regression analysis.

I first discuss the literature that underpins this topic and examine what previous researchers have found with regard to song popularity. Next, I provide an overview of the data collected for this research. Following a summary of the data, I present my regression analysis for both dependent variables in each of the five countries to show which variables influence song popularity. Finally, I end with a discussion of the results and their implications for record labels as well as future research in the field.

II. LITERATURE REVIEW

Song popularity and its determinants have been studied extensively across differing academic fields. Sociologists have examined the social circumstances that influence a song's success as well as the optimal level of differentiation in popular music. Data scientists and economists, however, have diverged in the subjects of their research. Most data scientists have examined the impact of a song's features on their success in charts such as the Billboard Hot 100, whereas economists have focused on the impact of streaming platforms on the music industry. Much of the existing research in this field ignores one of the main platforms from which people source their music – Spotify.

A key determinant of a track's success is social influence. In an experimental study of an artificial music market, Salganik et al. (2006) found that consumer choice is largely a function of how many times a song has been downloaded by other users as well as their own music preferences. Participants of this study were randomly sorted into two groups that differed only in the amount of information available to the consumer. In the independent group, consumers only had access to the name of the band and song. Participants in the treatment group, however, had the same information in addition to the number of times a song had been previously downloaded, thereby serving as a proxy for popularity. Salganik et al. (2006) found not only that the number of downloads affects how highly people rate their enjoyment of a song but also that the degree to which a consumer can determine how other users view a song affects the magnitude of its impact on popularity. Songs with a higher number of downloads (or streams) breed more success because consumers assume that they are better than other songs, thereby contributing to a superstar effect in the music industry.

Salganik et al. (2006) suggest that the quality of a song impacts its success because absent of signals of a song's popularity - such as number of downloads – certain tracks appeal to a broader group of listeners' preferences. Though Salganik et al. (2006) do not estimate a song's "quality" specifically, as it is nebulous and highly subjective, it is possible to measure certain objective attributes of a track. Research that examines the relationship between song "quality" on popularity (Ceulemans and Detry 2013; Herremans et al. 2014) often leverages data from the Echo Nest Corporation, which has developed a program that measures a song's duration, key, time signature, acousticness, instrumentalness, speechiness, valence, and more. The Echo Nest has since been acquired by Spotify. While these metrics do not provide an objective scale from which one can gage a song's intrinsic quality, they allow for the comparison of features between different tracks.

Ceulemans and Detry (2013) collected data on 514 songs from Echo Nest and the Billboard Hot 100 to determine the effects of song features and attributes about the artist on a track's peak position as well as the number of days they survive on the charts. In addition to these variables, the authors manually added the type of production in the song – electronic, acoustic, or mixed – and included artist gender, artist nationality, and whether the artist is associated with a major label. Ceulemans and Detry (2013) found that songs with predominantly electric production features and those with female singers both increase the likelihood of the song reaching a higher peak position on the charts. Further, songs that are electronically produced and those that are in major keys tend to survive on the charts for longer periods of time. Askin and Mauskapf (2017) also examine the variables affecting a song's survival on the Billboard Hot 100 and find that being associated with a major label increased the likelihood of lasting on the charts longer, whereas having previous hits decreased the likelihood of a song's stickiness on the charts.

Herremans et al. (2014) use very similar data but narrow their focus to dance songs and attempt to build a model that can predict whether a song is a top 10 dance hit. They use similar metrics to Ceulemans and Detry (2013) but add more song features such as the loudness, danceability, and energy of a song. Their paper aims to determine which model best predicts a song's success, which they find to be a logistic regression, rather than determine what attributes of a song affect its success.

Consumer choice, however, is not merely a function of song characteristics and social influence in real world music markets. Listeners are more frequently exposed to songs funded by major music labels than independent ones, they possess knowledge of artists' reputation, an awareness of popular trends, and countless other pieces of information that inform their decision of what to listen to. Askin and Mauskapf (2017) attempt to account for artist reputation and previous success in studying how consumers differentiate between popularized songs that have high degrees of substitutability. They hypothesize that songs that are similar to those that have been successful in the past but have enough differentiation to be unique will be most popular. A key difference between Askin and Mauskapf's (2017) approach in comparison to Herremans et al. (2014) and Ceulemans and Detry (2013) is that they focus on the latent associations consumers draw between songs they have enjoyed in the past to songs that they interact with for the first time. To do so, the authors include independent variables such as song typicality – a metric the authors constructed to show a song's similarity to others in its genre that had been previously released – and dummy variables for the number of songs that an artist had previously released that were on the charts. For example, one of the variables was "2 to 3 previously charting songs," which would take the value of one if the artist fell within the range but be zero if the artist had fewer or greater charting songs. The results show that being associated with a major music label, creating a track that was a crossover between different genres, and having over ten previous charting songs positively affected a song's popularity. Conversely, songs that are similar to their peers – in metrics such as key, tempo, acousticness, energy, valence, and genre – are less likely to reach the top of the charts.

Song popularity is almost always measured in reference to Billboard's charts because its rankings account for album sales, downloads, radio airplay, social media interactions with songs, and streaming numbers on different platforms (*Billboard*). While Billboard's rankings are comprehensive, their utilization precludes analysis from occurring at the individual platform level. The primary motivation for examining data at the streaming platform level as opposed to in aggregate through the Billboard charts is due to Spotify's recent dominance as a music provider. Spotify has grown in popularity to become one of the leading channels through which consumers access music. While Spotify grants premium users the ability to listen to millions of tracks, most listen to a small list of songs. Many listeners stick to popular playlists that are curated by Spotify, such as "Rap Caviar," which has over 8 million subscribers. The layout of the application itself as well as the ways in which users interact with the platform may alter the music that they listen to. Analysis at the platform level could indirectly touch on this topic and juxtapose preferences identified in the Billboard data and those of Spotify users. Additionally, Spotify added a feature that allows users to buy concert tickets to their favorite artists in the application itself. Thus, better understanding the music tastes of listeners on the platform could not only inform which types of songs gain greater popularity but also which sell more concert tickets.

Spotify has quickly become the largest music streaming platform in the world, supporting 96 million paid subscribers and 207 million users total as of January 1st, 2019. On the other side of the platform, SpotifyforArtists.com has over 300,000 musicians who post their music to the platform and over 10,000 podcasters. They now operate in 78 different countries with a library of over 40 million songs and thousands of podcasts. While they have historically struggled to monetize their massive user base, in the fourth quarter of 2018 Spotify – for the first time ever – achieved a positive Operating Income, Net Income, and Free Cash Flows, bringing in €1,495 million in revenue the last quarter alone. Spotify operates such that the majority of their total revenue comes from premium subscriptions. Last quarter they earned over 88% of their income from premium subscriptions and the remainder from advertisements. Of the 207 million people who use the platform, 36% are in Europe, 30% in North America, 22% in Latin America, and 12% elsewhere in the world, with Latin America growing faster than any other region (Spotify Q4 Press Release).

Existing research on Spotify has largely focused on their impact on the music industry amidst growing concern from industry participants over royalty payments from streaming platforms (Marshall 2015). The narrative that streaming services have not been not treating artists fairly became widely discussed in the media when news articles were published claiming that Pharrell Williams had been paid less than $3,000 for his song "Happy," which had been played on Pandora over 43 million times (Kosoff 2014). Spotify structures its royalty payments through contracts directly with labels rather than artists. Thus, the amount of money an artist makes from the number of streams on Spotify is a function of their contract with their music label (Marshall 2015). Additionally, Spotify has consistently paid out roughly 70% of their revenue to music rights holders which matches the historically conventional allocation of revenue that existed even before iTunes (Marshall 2015).

In numerous press releases addressing the controversy of royalty payments, Spotify has explained that artists should shift their understanding from unit-based payment to consumption-based payments because the ways in which consumers pay for music has fundamentally changed. Under the current subscription-based model, scale is the key to payment. Not only will a larger customer base increase advertisement-based and premium account-based revenue streams, but it will also allow for the platform to evolve into a marketplace. Spotify founder and CEO Daniel Ek explains that "artists could up-sell to their shows on our platform," which is where most of an artist's money comes from (Safian 2019). In most major countries Spotify has started selling concert tickets on artists' home pages directly from the application. While Spotify has demonstrated its ability to disrupt the music industry on both the demand and supply side, the question remains on whether the presence of streaming platforms affects music sales.

Music streaming parallels traditional radio airplay in the sense that listeners select playlists or songs but do not own the song (Aguiar and Waldfogel 2015). Rather, they interact with the platform that the song exists on – similarly to how one chooses a radio station. Aguiar and Waldfogel (2015) researched this dynamic to determine whether streaming platforms, specifically Spotify, stimulate music sales, as airplay often does, or depress sales. While some radio stations play a broad range of music, exposing the listener to countless new tracks, most popular stations have been pressured to play songs on the Billboard Hot 100. Streaming services, however, create an even narrower selection of music by allowing users to choose which songs they want to hear while also giving them the option to listen to radio stations built around different genres or artists. Spotify takes this one step further by curating a daily and weekly playlist that feeds the user songs that are similar to ones that they have repeatedly played. The amount of choice available to the user on Spotify far exceeds that of traditional radio airplay, which is a key distinction between the two forms of consumption.

In studying how streaming affects music sales, Aguiar and Waldfogel (2015) examine the number of streams for the top 50 songs each week on Spotify from April 2013 to March 2015 in a number of different countries. This data was then compared to music sales in 21 different countries that included digital track, digital album, and physical album sales as well as data on the weekly volumes of music piracy in number of downloads from Musicmetric to determine the overall displacement in sales. The authors first consider individual song-level analysis by regressing song streams on music sales, which suggests that 14 streams sell an additional digital download of a song on iTunes. This conclusion is uncertain, however, because song streams and sales both peak during a song’s popularity. Aguiar and Waldfogel (2015) also aggregate sales, piracy, and streams by country for artists and songs to measure the effect of increases of streaming on piracy and digital music sales. Ultimately, they find that approximately 137 Spotify streams are likely to reduce digital track sales by one unit. Despite this, the authors show that this loss is likely offset by the amount of revenue artists receive from streaming platforms. While music labels receive an average of \$0.82 per song sold on iTunes, the average payment to the label for each stream is \$0.007, the quantity of which often greatly surpasses song sales. Aguiar and Waldfogel’s (2015) research builds a greater understanding of Spotify’s impact on the music industry, though its 21-country study ignores the largest growing segment of the market: Latin America.

My research contains several new contributions to the existing literature on the topic. First, I examine the determinants of song popularity specifically for Spotify in contrast to the Billboard Hot 100. This distinction is important because Spotify, and other streaming services like Pandora, has fundamentally altered the way in which consumers choose their music. Users of streaming platforms have the ability to select individual tracks out of a sea of millions of mp3s. The means by which people interact with music have changed, which could potentially alter their preferences as well. A comparison between what affects song popularity on the Billboard Hot 100 versus Spotify should illuminate differences in preferences for Spotify’s users. Second, my regression analysis extends beyond the U.S another four countries: Ecuador, Costa Rica, Taiwan, and Norway. No other research has examined what variables affect song popularity in different countries. This analysis is particularly valuable because it identifies song attributes that sell better in certain markets as opposed to others, which is an important financial consideration for artists who now make most of their income from domestic and international tours. Further, the juxtaposition of different countries allows for the identification of variations in musical taste and similarities that transcend cultural differences. Third, the most recent data used to study song popularity stopped in March of 2016 (Askin and Mauskapf 2017), whereas the data for my research goes through January of 2018. Trends in popularized music change frequently, thus necessitating a constant reevaluation of preferences.

III. DATA

The purpose of this paper is to address two questions. First, what affects the peak position of a song on the Spotify charts for different countries? Second, what affects the number of days a song survives within the top 200 songs on Spotify for different countries? Current literature examines song popularity from the Billboard Hot 100, but none specifically examine Spotify or disaggregate popularity by region. This paper contains data from Spotify's API that includes song and artist features. Given that trends in popular music change quickly, I chose to examine a fixed, one-year time period from the beginning of 2017 through the first week of 2018. The data contains information on the daily top 200 songs for 373 days in five different countries – the United States, Norway, Taiwan, Costa Rica, and Ecuador.

I use these countries in my analysis for a number of reasons. First, I was constrained to working with these countries because they were the best options in terms of data availability for their region. Given the model necessary for this analysis and the relevant independent variables, the five countries selected provided the most reliable data. In the dataset that was accessible to me for this research, many countries had less than six months of data, whereas the five selected had just over a year's worth of data. Further, many other countries had fewer songs in their samples than the ones selected. For the sake of using the most complete data available and increasing the validity of my model, I was limited to the five countries in this study.

Second, these countries cover Spotify's largest geographical regions. The United States is included in this research because it is the powerhouse of the music industry. It nearly accounts for the entirety of the North American market, which is the global leader in terms of revenue. Further, 75% of revenue in North America is now generated from digital sources, thereby necessitating an examination of preferences on the leading digital platform (IFPI Global Music Report). Norway stands in for Europe, the second biggest region in the music industry, and Taiwan for Asia. I chose two countries for Latin America because it is fastest growing region in the music industry in terms of revenue growth, streaming adoption, and for Spotify specifically. In 2017, streaming revenue in Latin America grew by 48.9% and 17.7% for the music industry as a whole (IFPI Global Music Report).

Third, barring the U.S., the selected countries are not the dominant players in their market. Further, they are culturally divergent from the main players in their region. Similarities in significant variables between diverse regions may also suggest some universal trends that defy cultural barriers. Additionally, it may be worth testing this methodological approach on smaller countries before analyzing larger music markets (i.e. Brazil, Germany, Mexico, etc.).

Though there were hundreds of unique songs across the five countries, I analyzed a random sample of 370 tracks with roughly the same number of songs showing up in each country's charts. Each track has a series of attributes, ranging from tempo to danceability, that are measured through a music intelligence database originally created by the Echo Nest Corporation. Audio features for any song can now be obtained through Spotify's API because they acquired the Echo Nest in 2014. A full list of audio features can be found below in *Table 1*.

Table 1. Spotify audio features.

Attribute	**Scale**	**Explanation**
Acousticness	0 - 1	Measures the likelihood a track is acoustic, where 1 represents high confidence that a track is acoustic.
Danceability	0 - 1	Describes how suitable a track is for dancing. Danceability incorporated tempo, rhythm stability, beat strength, and overall regularity.
Duration (ms)	n/a	Quantifies the length of the track in milliseconds.
Energy	0 - 1	Represents a perceptual measure of intensity and activity in the song. Energetic tracks are fast, loud, and noisy (i.e. rock music).
Instrumentalness	0 - 1	Predicts the likelihood that a track has no vocals.
Key	0 - 11	A dummy variable representing the estimated overall key of the track in pitch class notation, where integer values represent different notes. For example, 0 = C, 4= E, 7 = G, 11 = B.
Liveness	0 - 1	Accounts for the presence of an audience in the recording. Studio recordings with minimal background noises score low.
Loudness	-60 - 0 (dB)	The loudness of a track measured on a negative decibel (dB) scale averaged across the entire track. 0dB is a upper-bound on loudness whereas -60dB is the quietest a track can be.
Mode	0 or 1	Indicates whether a song is Major (1) or minor (0).
Speechiness*	0 - 1	Detects the presence of spoken words in the track. The more exclusively speech-like the recording, the closer to 1 the attribute value.
Tempo	Beats per minute (BPM)	Estimated tempo of a track in BPM.
Valence	0 - 1	The musical positiveness conveyed by the track. Songs with high valence sound happy, while low valence songs sound negative.

Note: Audio features and descriptions were obtained from Spotify for Developers. All features are included here except for Time Signature because almost all tracks were in 4/4 time.
*The difference between speechiness and instrumentalness is that speechiness only increases when there are exclusively spoken words (e.g. from a poem, talk show, or audio book). Instrumentalness measures the probability of no voice on a track at all.

Though Spotify provides a generous amount of data on each track, it lacks information on certain song attributes and the artists themselves. After collecting data from Spotify, I spent 10 hours manually entering in the following features for each track: gender of the singer(s), whether the track was a remix, whether the track featured a guest, if the song was released on one of the four major music labels (Sony, Universal, Warner Music, EMI), the genre, and the language. The combination of song attributes and external features allows for a more complete understanding of what affects song popularity by region.

There are two dependent variables with which I am concerned: *peak position* and *survival*. The *peak position* of a song is the highest rank it achieves on the charts, 1 being the maximum and 200 the minimum, over the given time period. This metric measures a track's popularity by accounting for how relevant it was at a given point in time. *Survival* represents the number of days that a song stays in the top 200, the maximum of which is 371 days for this data. This measure of success is a necessary addition to a song's peak position because it describes the intensity and length of a song's popularity, thereby serving as a proxy for the duration of a track's relevance in popular culture.

Table 2 outlines the summary statistics for all songs in this research. It is important to note the discrepancy in the sample size between the song attributes and the dependent variables. There are 370 unique tracks in this research, which is why the sample size for features related to songs is at 370. However, each country contains a different number of songs in its regression, causing the sample size for the summation of the different countries' datasets to be 699.

Table 2. *Summary Statistics*

Variable	n	Mean	Std. Dev.	Min	Max
Peak Position	699	75.010	60.341	1	200
Survival	699	127.558	126.743	1	371
Acousticness	370	0.170	0.209	0.00004	0.97
Danceability	370	0.662	0.132	0.224	0.959
Duration (ms)	370	228354	53155.21	52006	745643
Energy	370	0.691	0.170	0.057	0.992
Instrumentalness	370	0.033	0.138	0	0.892
Liveness	370	0.177	0.134	0.022	0.775
Loudness	370	-5.998	2.482	-18.127	-1.708
Mode	370	0.614	0.488	0	1
Speechiness	370	0.095	0.093	0.023	0.622
Tempo	370	118.851	27.464	69.77	202.013
Valence	370	0.534	0.225	0.044	0.967
Key0	370	0.097	0.297	0	1
Key1	370	0.162	0.369	0	1
Key2	370	0.076	0.265	0	1
Key3	370	0.022	0.146	0	1
Key4	370	0.060	0.237	0	1
Key5	370	0.084	0.277	0	1
Key6	370	0.081	0.273	0	1
Key7	370	0.103	0.304	0	1
Key8	370	0.076	0.265	0	1
Key9	370	0.087	0.281	0	1
Key10	370	0.057	0.232	0	1
Key11	370	0.097	0.297	0	1
Male	370	0.673	0.470	0	1
Duo	370	0.119	0.324	0	1

Remix	370	0.024	0.154	0	1
Guest	370	0.357	0.480	0	1
Spanish	370	0.130	0.336	0	1
Finnish	370	0.003	0.052	0	1
French	370	0.014	0.116	0	1
German	370	0.019	0.136	0	1
Italian	370	0.008	0.090	0	1
Korean	370	0.014	0.116	0	1
Mandarin	370	0.005	0.073	0	1
Label	370	0.751	0.433	0	1
Alternative	370	0.035	0.184	0	1
Country	370	0.068	0.251	0	1
Dance	370	0.165	0.372	0	1
Rock	370	0.038	0.191	0	1
Hip-Hop	370	0.049	0.215	0	1
Reggéaton	370	0.051	0.221	0	1
Rap	370	0.159	0.367	0	1
Latin Pop	370	0.078	0.269	0	1
R&B/Soul	370	0.041	0.197	0	1

Note: The first two variables, Peak Position and Survival, are the dependent variables for the regressions. An omitted music genre is "pop," which is associated with 106 of the 370 songs. "K-Pop" was an included genre that was omitted due to collinearity with the "Korean" language variable.

The average peak position of the songs researched across the five countries was 75 with a 128 day-long survival period. Despite both averages being high, the standard deviation is high as well, reflecting a high degree of variability across the data.

Though 45 inputs is a large number of independent variables to consider, there are a few worth highlighting. The average danceability of a track in this research is just over 66%, showing that popular songs for 2017 centered around the right side of the distribution. This result is unsurprising considering the rising trend in electronic dance music that has been popularized by producers such as Calvin Harris, Diplo, and DJ Snake. Music that has typically been localized to club settings now plays regularly on the radio, making danceability a relevant metric.

Valence and mode are also noteworthy because both reflect, to varying degrees, the relative level of happiness of a song. Songs that are in a Major key tend to be happier than those in minor, and a higher valence indicates a more positive sounding track. Thus, both measures will test whether popular songs are overwhelmingly happy.

Roughly 67% of songs in this study contain a male singer, 21% a female singer, and 12% a combination of the two. In this research, gender is assigned to the voice of the singer audible on the track, which is not necessarily the same as the artist who releases the song. For example, the song “Scared to Be Lonely” by Martin Garrix, a male producer from the Netherlands, is classified as “female” because the singer on the track, Dua Lipa, is a woman. The significance of the gender of the lead singer may be a notable issue to examine across different countries and cultures. Similarly, whether or not a guest artist is featured on the track may also affect both the peak position and the number of days a song survives. It seems likely that a featured guest would increase both measures of success for a track because it is likely that an additional artist on a song attracts a separate fan base. For example, “Despacito - Remix” by Puerto Rican singer Luis Fonsi featuring guest artist Justin Bieber became a wild success because it appealed to listeners in English and Spanish-speaking communities.

The last variable of particular importance is a song’s association with a major music label. The four major music labels are Universal music Group, Sony Music Entertainment, Warner Music Group, and EMI Group, which collectively control around 90% of the music market. Music labels create contracts with their artists that stipulate agreements pertaining to the licensing, distribution, marketing, and payment of an artist’s records. Major music labels can pay for more exposure of their artists' music, thus, in theory, influencing the popularity their songs (Ceulemans and Detry, 2013; Herremans et al., 2014; Askin and Mauskapf 2017). On Spotify, however, independent artists can upload their music at no cost, though they may not be able to garner the same level of visibility on the platform as an artist associated with Universal or Sony.

IV. RESULTS

Regression results for a song's peak position are outlined in *Table 3*, whereas results for the number of days a song survives in the top 200 are presented in *Table 4.* In conducting my data analysis, I incurred the problem of a large number of explanatory variables. I combatted this in a two-step procedure to strengthen the validity of my model. First, I conducted a stepwise regression in which I cut variables one-by-one if they showed high correlation with other variables and were insignificant in the regression. For example, "Loudness" was highly correlated with "Energy," which is why it was cut from each country's regression. Further, genres, languages, and keys were removed when the number of observations was low and the variable was insignificant. Norway's data only had two songs that were classified as "Country" and almost no songs of a language different from English. Since all of these variables were highly insignificant, they were eliminated to strengthen the fit of the model for more pertinent variables. Second, I regressed each country's independent variables on the dependent variables: peak position and number of days surviving on the charts.

Each country's regression on a song's peak position and the number of days a song survives in Spotify's top 200 were run with and without outliers, thus creating four separate regressions for each of the five countries. In this research, outliers were defined as songs with standard errors whose absolute value was greater than two. The models were run without outliers to tighten up the regression and get more accurate results. There were a number of songs – including "Despacito – Remix," "Shape of You," and "Faded (Alan Walker Remix)" – that scored exceptionally high on peak position and survival but deviated significantly in their attributes. *Table 3* and *Table 4* only show results from regressions run with the outliers included because the differences between the regression results were negligible and the songs that were outliers were highly relevant. Not only did many of them occupy a top position on the charts and survive for months, but many were influential in terms of breaking popular music conventions. “Redbone,” written and performed by Childish Gambino, for example, is “a full-blown funk slow jam” that is intricately constructed to “parse love, lust, reconciliation, generations of black soul, and wokeness” that topped multiple countries’ charts (Pearce 2016). Songs that defy popular music conventions rarely garner a mass following, but those that do tend to create new trends. Thus, outliers are included in this analysis because of their effect on music trends and because they did not change anything fundamental to the results.

Table 3. *Regression results for a song’s peak position on Spotify’s Top 200 Chart with standard errors in parentheses.*

Variable	U.S. Coefficients	Norway Coefficients	Taiwan Coefficients	Ecuador Coefficients	Costa Rica Coefficients
Acousticness	-20.503 (27.236)	6.977 (24.696)	-7.690 (29.728)	-5.133 (25.534)	14.637 (29.044)
Danceability	-60.243* (39.184)	-37.708 (41.984)	-12.905 (43.496)	6.152 (43.884)	-53.660 (47.219)
Duration (ms)	.0001 (.0001)	.00001 (.0001)	-.00003 (.0001)	.0002 (.0001)	.00005 (.0001)
Energy	53.825 (37.138)	23.990 (35.861)	74.219* (40.493)	11.569 (39.316)	-58.326* (39.923)
Instrumentalness	-42.365 (53.431)	33.980 (34.904)	-8.446 (45.275)	-87.641* (49.402)	-74.207 (52.068)
Liveness		-9.386 (45.625)	76.429 (42.993)	-1.093 (35.230)	-5.143 (41.681)
Mode		-15.196 (9.452)		-6.650 (9.211)	-8.274 (10.260)
Speechiness				-40.539 (59.677)	
Tempo	-.029 (.190)	-.250 (.205)	-.405* (.230)	.130 (.146)	.040 (.169)
Valence		-42.107* (26.280)	-49.333** (28.216)		
Key2	-21.296 (20.147)	25.541* (16.763)	12.777 (20.217)	40.723 (16.731)	6.168 (21.289)

Key7		20.547 (15.106)	17.981 (16.606)	20.545*** (16.203)	10.051 (18.615)
Key9		34.373** (17.155)	12.867 (18.659)	23.751* (15.042)	21.056 (16.792)
Key10		38.506* (22.540)	40.79378 (25.12775)	27.770 (21.076)	18.383 (24.781)
Male	12.079 (14.416)	2.066 (11.345)	5.680 (11.381)	-15.726 (12.392)	-1.007 (13.953)
Duo	1.712 (19.834)	31.052** (16.050)	4.879 (16.911)	-3.697 (16.843)	9.235 (19.426)
Remix	4.329 (29.102)	-25.511 (24.946)	-59.250* (32.098)	-24.603 (23.503)	-12.699 (28.404)
Guest	-10.065 (10.898)	-38.058*** (9.781)	--34.494*** (11.832)	-19.242** (10.309)	-21.387** (10.958)
Label	-14.789 (14.069)	-11.904 (12.223)	-24.099* (13.098)	-15.380 (10.186)	-11.272 (12.021)
Alternative	44.485 (32.797)		-41.096 (28.829)		
Country	33.535* (17.590)				
Rock	-11.096 (24.542)		-47.234 (31.409)	48.929** (22.787)	24.637 (26.508)
Hip-Hop	20.316 (20.620)	14.709 (23.472)	-1.212 (31.835)	-12.011 (43.649)	8.950 (39.451)
Reggéaton	26.812 (30.076)			-57.151 (13.551)	-47.626*** (15.798)
Rap	11.085 (14.108)	-34.492* (19.218)	-16.163 (22.570)	47.298** (19.852)	-34.229 (23.063)
Latin Pop				-66.856*** (11.475)	39.451*** (13.006)
R&B/Soul	-4.223 (23.070)	37.181* (22.983)	37.837* (26.015)	-41.126 (31.425)	-11.859 (32.061)
Intercept	74.928 (59.858)	152.885 (54.168)	139.237 (59.195)	45.656 (59.301)	161.768 (63.587)
R^2 [Adjusted R^2]	0.144 [0.039]	0.294 [0.166]	0.242 [0.123]	0.575 [0.455]	0.363 [0.211]
F-Stat	1.37	2.30	2.03	4.80	2.38

Sample Size	175	138	156	110	120

Note: The analysis was conducted with and without outliers, however the results were practically and had similar robustness. Data without outliers is available from the author upon request. Additionally, variables that were not included in the regression due to collinearity and/or low observations (i.e. the languages and many of the keys) have been removed from the table.
Numbers in parentheses are the standard errors for the given variable.
*, **, *** indicate that the coefficients are significant at the 10%, 5%, and 1% probability levels respectively.

Overall, there is no clear formula for pop music hit – different genres and attributes pull more weight in different countries. There are, however, a number of patterns across the five countries in this research. The most universally significant song attribute is the presence of a featured guest on the track. As mentioned previously, a possible explanation is that artists may feature guests on their tracks to appeal to new fan bases. Therefore, songs with guests may gain greater popularity simply because they appeal to a larger subsection of the population. Alternatively, songs with featured guests may perform better on Spotify's charts because they create a greater perception of popularity regardless of the song's actual quality. Salganik et al. (2006) show that social influence greatly affects the performance and perception of a song. Though their research solely examines the effect of showing consumers the number of times a song has been downloaded by other listeners, it is conceivable that knowledge of the main and featured artists' popularity may influence a consumer's perception of a track's quality.

"Valence" is negative and significantly different from zero for Norway and Taiwan, meaning songs that sound happier are more likely to reach a higher position in the charts for both of these countries. The narrative that popular music is overly cheerful and feel-good is supported by this finding (for Norway and Taiwan, at least). Valence was unfortunately not included in the regressions for Ecuador and Costa Rica because it was highly correlated with "Energy."

"Instrumentalness" is negative and significant for Ecuador at the five percent level, suggesting that music with less vocals – such as instrumental beat music, classical, electronic music, and so on – does better on the Spotify charts in Ecuador.

While there are a number of different key signatures that are significant for different countries, "Key2" – the key of D – is positive and significant at the ten percent level Norway. Thus, songs in the key of D perform worse in Norway than songs in any other key. "Key9," or the key of A, is also positive and significant for both Norway and Ecuador. This information likely does not matter too much to the artist, who can write the song in whichever they please, but more to the producers who may want to alter the key after the song has been recorded.

Though not universally significant, it is worth noting the strong significance of reggaetón and Latin pop in Ecuador and Costa Rica, most likely because of the pervasive popularity of these music genres in Latin America.

There are a number of variables that are unexpectedly insignificant for most countries. The most notable of these is the "Label" variable. In previous literature (Ceulemans and Detry 2013; Askin and Mauskapf 2017), a song's connection with a major record label was found to be significant. The results of this research show that association with a record label is negative and significant at the five percent level for Taiwan, but insignificant for the other countries. Over 75% of the songs in this study were released on a major music label (or its subsidiary), which may be why the variable is insignificant in the regression analysis. The "Label" variable's insignificance is likely an issue that stems from the selection of data used in the study. It is possible that a broader, more diverse dataset that included songs that did not make it to the Top 200 Charts on Spotify within any of the countries would likely alter the significance of being associated with a major label.

"Danceability" is also mostly insignificant, except for the U.S. where it is negative and significant at the five percent level. This result is somewhat unexpected considering the metric was found to be significant in Askin and Mauskapf's (2017) research. Further dance music, especially electronic dance music, has been quickly growing in popularity globally, which would make one think that danceability would be positive and significant. There are three potential reasons for this difference. First, music taste in the U.S. could be fundamentally different from other music markets due to differences in intrinsic preferences or culture. For this reason, music with high danceability could simply be assigned greater value by U.S. consumers than those in other countries researched. Second, the preferences of the Spotify listener could be different than the preferences that are aggregated through Billboard's data. This difference in taste could be a form of selection bias, in which people who use Spotify's services did not enjoy songs with high danceability before joining the platform. However, it seems more likely that the user's interaction with the platform may diversify or reshape their tastes. Spotify users, on average, use the platform for just under two and a half hours each day (Spotify Technology S.A). With the ability to freely choose which songs to listen to, it is likely that consumers will diversify the type of tracks they listen to every day. Given the different contexts in which users may use Spotify's services – at work, during a workout, on a commute, while studying, and so on – songs that fast tempo and have high danceability may only fit users' preferences for small segments of their daily lives. A third reason for danceability's insignificance is the selection of data used in this research. Examining data outside of Spotify's Top 200 Charts may reveal that danceability is significant overall.

Finally, both the "Male" and "Duo" variables were found to be insignificant, barring "Duo" for Norway, which was positive and significant at the five percent level. Of the 370 songs used in this research, 249 had a male singer, 75 had a female singer, and 43 were a combination. A larger sample of songs may change the significance of one of the gender variables, though in this data the gender of the artist does not affect the demand for a given track.

Table 4. *Regression results for the number of days a song survives on Spotify's Top 200 Chart with standard errors in parentheses.*

Variable	U.S. Coefficients	Norway Coefficients	Taiwan Coefficients	Ecuador Coefficients	Costa Rica Coefficients
Acousticness	13.368 (47.699)	-51.985 (49.535)	-68.055 (46.955)	-26.014 (59.229)	-61.740 (66.487)
Danceability	116.253* (68.642)	-20.469 (83.560)	19.696 (68.703)	-112.214 (104.627)	-97.247 (112.643)
Duration (ms)	-.00007 (.0002)	-.0001 (.0002)	-.00008 (.0002)	-.0004 (.0003)	-.00002 (.0003)
Energy	-184.080*** (64.931)	-136.445* (71.598)	-158.338** (64.148)	45.0285 (90.432)	102.738 (89.748)
Instrumentalness	-78.314 (93.463)	-96.455 (68.142)	-26.944 (71.643)	-84.874 (108.252)	-39.443 (112.915)
Liveness		-1.805 (90.211)	-26.063 (67.897)	.275 (84.416)	6.628 (96.715)
Mode		19.086 (18.835)		-20.795 (20.778)	-8.984 (22.798)
Tempo	.277 (.332)	.0282 (.400)	.227 (.350)	-.377 (.350)	-.219 (.393)
Valence		89.822* (52.304)	104.927** (44.476)		
Male	5.540 (25.025)	-7.633 (22.238)	-9.868 (17.860)	32.469 (29.331)	-3.816 (31.434)
Duo	.286 (34.682)	-52.643 (31.388)	-42.278 (26.704)	17.928 (40.167)	-12.642 (45.451)
Remix	19.082 (50.789)	35.422 (49.051)	104.800** (49.605)	48.660 (53.620)	54.791 (62.708)
Guest	10.900 (19.099)	48.760*** (19.520)	50.311*** (18.218)	32.150* (23.433)	27.555 (24.918)
Label	-6.863 (24.373)	-11.502 (24.489)	5.494 (20.584)	6.603 (24.132)	11.144 (28.004)
Alternative	-87.402 (57.337)		3.856 (42.526)		
Country	27.123 (30.649)				

Rock	-41.379 (41.334)		-27.886 (45.008)	-82.637 (55.082)	-107.582 (58.008)
Hip-Hop	-23.692 (36.044)	-29.892 (45.040)	-21.872 (50.264)	-49.020 (105.120)	-116.644 (91.147)
Reggéaton	31.847 (52.582)			156.821*** (31.983)	143.784*** (36.239)
Rap	10.330 (24.834)	94.954*** (38.372)	57.260* (35.645)	-58.526 (47.670)	74.877 (53.464)
Latin Pop				142.427*** (26.865)	114.370*** (30.177)
R&B/Soul	83.144** (40.365)	-26.811 (45.738)	-1.241 (40.972)	176.999** (73.991)	124.614* (73.290)
Intercept	119.774 (104.528)	182.409 (104.355)	103.626 (93.204)	291.842 (140.185)	172.613 (148.560)
R^2 [Adjusted R^2]	0.155 [0.057]	0.162 [0.044]	0.194 [0.088]	(0.545) [0.449]	0.365 [0.245]
F-Stat	1.459	1.37	1.84	5.68	3.03
Sample Size	175	138	156	110	120

Note: The analysis was conducted with and without outliers, however the results were practically and had similar robustness. Data without outliers is available from the author upon request. Additionally, variables that were not included in the regression due to collinearity and/or low observations (i.e. the languages and many of the keys) have been removed from the table.
Numbers in parentheses are the standard errors for the given variable.
*, **, *** indicate that the coefficients are significant at the 10%, 5%, and 1% probability levels respectively.

Both peak position and the number of days a track survives on Spotify's Top 200 Chart measure popularity, but they reflect different types of success. In running the regressions separately for each dependent variable, there are a number of different variables that affect the two metrics. "Guest" is still significant, however, although it is limited to Norway, Taiwan, and Ecuador. It is possible that the initial perception of a song may benefit from having featured guests, though over time the inherent quality of the song itself may matter more.

"R&B/Soul" was also positive and significant for the U.S., Ecuador, and Costa Rica, showing that songs of this genre do better in these three nations. This finding makes more sense in the context of another widely significant variable: "Energy." "Energy" is negative and significant for the U.S., Norway, and Taiwan, suggesting that sounds that are louder, faster, and noisier do worse in these countries. While this variable is not significant for Ecuador and Costa Rica, this result implies that louder, more aggressive music does not hold up well over time. R&B as a genre tends to be slow in tempo and softer in sound than many other genres, such as rock, rap, or dance music. In this sense, R&B may be easier to listen to, thus helping it stay on the charts longer.

"Valence" was positive and significant for Norway and Taiwan at the ten and five percent levels respectively, suggesting that tracks that sound "happier" last on the charts longer than those that are "sadder." Songs that were remixed also showed up as positively significant for Taiwan five percent level. This finding supports the growing trend in electronic dance music and the growing interest in remixed tracks on streaming platforms.

Again, the "Label," "Danceability," and "Male" variables were mostly insignificant across the five countries researched, likely for the same reasons mentioned previously. To recap, songs that have a featured guest and sound happier are more likely to reach a higher peak position and survive longer on Spotify's Top 200 Chart in most of the five countries examined in this research. Additionally, songs with low energy, especially R&B tracks for certain countries, tend to last on the charts longer. However, these findings differ between countries, as preferences fluctuate by region. While there is no definite formula to constructing a hit song in any one of these countries, there do appear to variables that almost universally positively or negatively affect success.

V. Conclusion

The goal of this paper is to better understand what affects a song's peak position and the number of days it survives on Spotify's Top 200 Chart in five countries: the U.S., Norway, Taiwan, Ecuador, and Costa Rica. The data used in this research comes from Spotify's API and includes audio features of the track as well as dummy variables for artist and song attributes. The results and analysis from this research have implications for record labels and future research in the area.

Record labels with the goal of creating the next popular music hit should be aware of several takeaways that vary by region. First, it may be beneficial to feature popular guest artists on a track that is believed to be a potential hit. As seen in both *Table 3* and *Table 4*, the presence of a featured guest on a track makes it more likely to reach a higher peak position and survive on the charts longer in most countries examined. A potential explanation for the significance of a guest on a track is that it may attract a different artist's fan base, which is something music labels should keep in mind when selecting featured vocalists. Alternatively, the presence of a guest could serve as a signal to consumers that the song is popular because it attracted multiple artists to collaborate on the same track. Second, labels should encourage artists to produce songs that sound "happier" and have a higher valence rating because higher valence increased the likelihood that a song would reach a greater peak position and survive on the charts longer in different regions. Third, veer away from songs that are exceptionally loud and fast tempo. Songs with high energy performed significantly worse at staying on the charts in the U.S., Norway, and Taiwan. Ultimately, artists should produce music that reflects their desires and artistic intent; however, these findings may help record labels alter certain features of tracks during the production process to increase the number of listeners in specific countries.

Despite these findings, popular music charts are nearly impossible to predict, largely because trends change quickly and quality cannot be accounted for. Consider one of the most popular songs on Spotify in 2018 – "Finesse (Remix)" by Bruno Mars featuring Cardi B. The track is a pop song with high danceability (0.704), high energy (0.858), and high valence (0.926). This song tracks the findings from this research with high valence and danceability, but high energy would suggest that the track would not last on the charts as long as it did. This is, of course, only one example, but should illustrate how challenging it is to identify characteristics of song attributes that create universal success.

Future research in this field should examine a larger sample size over a longer time horizon to examine whether there are universal attributes (e.g. the presence of a featured guest) that hold up over time. This study is also incomplete in the variables used, as it misses information on songs' lyrical content and information on their release date, for example. Additionally, researchers should continue to explore the differences in features that increase the likelihood of song success in different countries to further elucidate the varying preferences of separate populations. As Spotify continues to expand geographically and develop its hegemonic presence as a music streaming platform, researchers should examine whether music preferences from different regions of the world begin to converge.

Additionally, research on Spotify's platform itself and the ways in which listeners interact with the platform is needed. It would be worth examining the impact of Spotify's curated playlists on a song's success. Is a rap track significantly more likely to be a hit if it is put on the "Rap Caviar" playlist? What are the other ways in which users find new music, and do those channels inherently change their preferences over time? The layout of Spotify's platform itself likely shapes consumer behavior and engenders habits in the ways people use the application, such as where they source new music. An analysis of how consumers interact with the streaming service would help to develop an understanding of the ways in which Spotify can alter users' preferences.

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