**Video did not kill the radio star**

A quasi-experiment of featured songs in TV series and their music popularity

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**Abstract**

The changing way in which consumers discover music, especially with the use of technology, has an impact on music popularity. In this thesis, we study the influence of a song being featured in a TV series on its music popularity. Using a unique long-format dataset in which weekly song data serves as the unit of analysis, we estimate the treatment effect with a difference in differences analysis. The results suggest that featuring a song in a TV series can have a negative effect on its music popularity, although the model used in this study may not accurately represent the relationship. Further research is needed to fully understand the influence of a song being featured in a TV series on its music popularity, as well as the potential drivers of this effect.

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# Preface

Music has the power to evoke emotions and bring people together. It has the ability to influence our mood and shape our experiences. With the emergence of streaming platforms and on-demand television shows, the way in which people discover and consume music has changed significantly. In recent years, there has been a trend known as the "Netflix effect", where old and sometimes forgotten songs gain popularity after being featured in a popular TV series. This trend highlights the impact that a TV series can have on the popularity of a song.

In this thesis, we aim to investigate the relationship between a song being featured in a TV series and its music popularity. Through a quasi-experimental approach, we examine the main effect of a song being featured and its drivers for music popularity. Our findings contribute to the existing literature on music and film by exploring the effect of a song being featured in a TV series and its impact on music performance. We hope that this research will shed light on the changing landscape of music discovery and the role that TV series play in the popularity of songs.

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# Management summary

In this thesis, we studied the influence of a song being featured in a TV series on its music popularity. The rise of platforms like Shazam, Spotify, and Snapchat has made it easier for consumers to discover and explore new music from their favorite TV series. The changing ways in which consumers discover music, especially with the use of technology, have an impact on music popularity (e.g., streaming). Previous studies have primarily focused on the effect of music on film performance. However, they have not explored the reverse effect of a song being featured in a film and its impact on music popularity. This study aimed to fill that gap by examining the effect of a song being featured in a TV series on its music popularity and two potential moderators of that effect (featured song order and featured song duration). By being featured in a TV series, a song may receive more exposure and may be enhanced by the moving images and emotions of the TV series.

Our study used a quasi-experimental design and applied propensity score matching to equally match songs that have been featured in TV series with similar songs that have not been featured. The treatment effect was analyzed using a difference-in-differences analysis, and the study uses song-level and week-level fixed effects to control for omitted variable bias and self-selection due to differences in song popularity.

The results indicated that featuring a song in a TV series had a negative effect on its music popularity. The interaction effect accounting for the difference in difference was negative and statistically significant. This suggests that the treatment group had on average fewer playlist additions compared to the control group. Moreover, we investigated the short-, medium-, and long-term effects. The treatment group performs on average less well than the control group, respectively. These findings do not support our hypothesis that featuring a song in a TV series would increase its music popularity. However, it is worth noting that the results may have been influenced by overfitting in the model, which may have resulted in the regression coefficient representing random noise rather than the actual effect. Further research is necessary to fully understand this relationship, as the model used in this study may not accurately represent the relationship in the population.

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# Introduction

A song by Kate Bush, “Running Up That Hill”, was featured in the Netflix series called “Stranger Things” last year. The song started to climb the Billboard Hot 100 chart, with a great number of streams on TikTok and Spotify (57.2 million streams) in a matter of days (New York Times, 2022). Recently, a new phenomenon has emerged called “The Netflix effect”. This is when an old, sometimes even forgotten song, enters or re-enters the top rankings because it has been used in a popular TV series. The Kate Bush example is not the only one in which a song featured in a TV series increases in popularity. On platforms such as Shazam, Spotify, and Snapchat, the name of a soundtrack can be generated within seconds (Business Insider, 2020). These platforms can be used to explore a song and create a way to discover new music. Furthermore, as the content of on-demand platforms such as Netflix has grown, and its TV series have attracted ever-larger audiences, fans are tracking down the music of their favorite TV series via Shazam and Tunefind (The Guardian, 2019). “That is a true game-changer, as it lays down a precedent for other music to do the same if circumstances meet.” (The Guardian, 2022). The way consumers are discovering music is changing, mostly with the aid of technology (Datta et al., 2018). This change also affects music popularity, as music discovery is an important indicator of music popularity. If a song is discovered more, it will have more listeners and therefore more music popularity. Thus, it is important to study the drivers affecting music popularity and examine the relationship between a song being featured in a TV series and music popularity. To explore the drivers affecting music popularity, we investigate the moderating effect of featured song order and featured song duration.

The relationship between TV series and music is worth studying as the music industry exhibits continuous annual growth, mainly thanks to streaming platforms such as Spotify (Friedlander, 2016). Music sales generated 26 billion dollars in revenue in 2021 (IFPI, 2022). Despite this success, artists who produce independently from commercial record labels face greater difficulty in gaining online streams and making revenue (Chiftalaryan, 2019). A report from the Intellectual Property Office showed that the top 1% of artists account for 80% of all online streams (The Guardian, 2021). If our research supports that making an appearance in a TV series increases music popularity, then a music label can use this in its strategic marketing implications to increase music popularity, music streams, and revenue (Spilker, 2017).

This research relates to two main literature streams. First, we discuss previous research that elaborates on music that has been featured in a film or film soundtrack. Second, there is a stream of music marketing that discusses film music as a promotional tool. Beaster-Jones (2009) studied the relationship between Indian film songs and popular music in India and found a positive relationship. The songs featured in a film serve as a representative of that film. The music sales indicated that both the music and the film were a success. According to Beaster-Jones, songs featured in the film are also used as a promotional tool, which demonstrates their importance and generates profits and online streams for the artist/music label (Beaster-Jones, 2009). Second, Simon Frith (2002) examines music marketing and the relationship between television and music. The author discusses the impact of television on music culture and how television can change perceptions about music (Frith, 2002). Frith’s research is not directly in line with ours since the study focuses on music culture instead of music popularity. However, it suggests that film can strengthen perceptions about music and in this matter influence the outcome variable, music popularity.

Current studies mainly focus on the effect music has on films. Research about film music emotion (Juslin & Sloboda, 2011), psychology (Nagari, 2015), and arousal (Ellis & Simons, 2005) indicates that music has a positive influence on film performance. These researchers did not analyze the effect a film can have on music performance. A song being featured in a film may influence its music performance. Our research investigates if the music popularity of a song increases when it is featured in a TV series. We expect this because the song may be given greater exposure and the listener's experience may be enhanced by the scene. Our study extends existing research by investigating the effect of a song being featured in a TV series and its drivers for music popularity.

Our research objective is to identify a causal relationship between a song being featured in a TV series and music popularity, measured by the number of playlist additions (the number of playlists a song is added to per week). A challenge is that causality is very hard to satisfy without a randomized control trial. This research follows a quasi-experimental approach, aiming to identify exogenous shocks that can approximate random assignment (Goldfarb et al., 2022). We do this by combining an existing dataset from Chartmetric, a platform that provides data for music industry professionals, with our new dataset from Tunefind, an index of songs appearing in television shows. By merging the datasets, we combine the treatment (when a song is featured in a TV series) with a song’s music popularity. Furthermore, the merger creates two groups. One group appears in the Tunefind dataset and is therefore treated. The other, leftover, group is not treated in the observation window and is therefore the control group. We compare songs that are featured/are not featured and assess the average treatment effect with a difference in differences analysis.

This research merges a dataset of more than 8 million songs on Spotify with a dataset from Tunefind of 264,826 songs that made an appearance in a TV series. Using web scraping, we collected all the songs that had been featured in a TV series. The resulting dataset includes all metadata for each song (artist, genre, acoustics, etc.), with a deviation between songs that were or were not featured in a TV series and all metadata for each TV series (episodes, release date, etc.). Furthermore, the dataset includes the order in which the featured songs are played and the duration of a featured song. The order and duration account for the moderation of the main effect and inspect the drivers of music popularity. Each song has a timeline of playlist additions between 2016 and 2020, which is derived to approximate the change in music popularity. After cleaning, filtering, merging, and matching the datasets, the final dataset has 2,420 songs, consisting of 1,210 treated and 1,210 untreated songs. Due to memory restraints, we were not able to analyze the entire sample. The available computers did not have enough RAM to process (merge, match, analyze) all observations. Nevertheless, our sample highly exceeds the central limit theorem for symmetrical distribution (Kwak & Kim, 2017). In addition, propensity score matching is used to strengthen causal claims and reduce selection bias (Goldfarb et al., 2022).

We have obtained insights into how being featured in a TV series affects a song’s music popularity. Taken together, our results demonstrate a significant negative interaction on the overall main effect. This suggests that the treatment group has a lower music popularity after the treatment, compared to the control group. Our finding contradicts the hypothesis that featuring a song in a TV series will increase its music popularity. It may be that our expected relationship does not exist in our sample, since each song is featured in a different setting. However, since our results may have been influenced by overfitting in the model caused by the fixed effects, we do not believe our sample is representative of the population. Further research is necessary to fully understand the relationship.

In the following sections, this research reviews the existing literature on music popularity and the relationship between film and music. Subsequently, we look at the data and the methodology of this research. This study then presents the analysis and findings, and, finally, we draw conclusions and make recommendations based on the previous sections.

# Literature review

This chapter gives an overview of research related to the point of interest of this thesis. Two major streams of the literature suggest the relationship between film and music. The first stream takes a deep dive into the relationship between a song that is featured in a film and its music popularity. The second stream takes a closer look at music marketing and focuses on the promotional effect on a song when it is featured in a film. Appendix A provides an overview of the literature streams used in this research. We make a distinction between main and secondary literature, where secondary literature consists of interpretations that refer to the main source literature.

In the literature, a film soundtrack is suggested as “an intentional sound which accompanies moving images in narrative film” (Deutsch, 2007). A soundtrack can be literal (a voice or footsteps) or emotive. In this study, we focus on emotive sound, which is music that is used to add emotion to a film scene. Furthermore, this research makes a distinction between a film score and a film soundtrack. Film scores are created by only one composer and are specially developed for a particular film or TV series, while film soundtracks are a composition of featured songs by different bands, artists, or musicians (Cohen, 1993). This research focuses on film soundtracks, as this gives the best representation of the relationship between featured songs and their popularity. In contrast to film soundtracks, film scores are normally not released before the film. It would therefore be unrealistic to estimate the effect of the treatment in such cases, as there is no ‘before’ situation.

## The relationship between a song featured in a film and music popularity

The influence of film on music has been studied from multiple angles, Appendix A provides a general overview. One main literature sourceis Beaster-Jones (2009). The author found that songs that serve as a soundtrack in Indian films have a high impact on culture, including music culture, and music popularity in India. Furthermore, the author states that being featured in a film is a promotional tool and is one of the primary modes of exposure to new music. Based on these results, the author concludes that Indian Bollywood movies positively influence music popularity in India. Another study on digital music contributes to our knowledge about this relationship. Lee & Kim (2022) found that television and film exposure positively affects the performance of digital music, providing further evidence for the relationship between film and music performance. Both studies describe the effect of film soundtracks on music popularity in Asian culture.

In addition, there is also evidence of this relationship in the western world. A study by Simon Nugent (2018) explores how Celtic music is used to represent medieval music in historical and fantasy films in Hollywood, the center of the music industry in The United States. The author found that Hollywood enhanced the popularity of modern Celtic music. Based on these results, it can be stated that Hollywood affects consumers through film and positively influences the music popularity of Celtic music. Therefore, a song that is being featured in a film or TV series may gain popularity, regardless of the continent's culture. In addition, a survey study found that 20% of respondents discovered a new song by watching a film in which the song or artist was featured as part of the soundtrack (Tepper & Hargittai, 2009). Since music discovery is an important indicator of music popularity, this means that film exposure leads to new music discovery and in turn increases music popularity.

Furthermore, a secondary literature stream (see Appendix A) is concerned with the changes in perception when looking at the relationship between a song that gets featured in a film and its music popularity. Simon Frith (2002) discusses the idea that television can change perceptions about music. The author states that television can strengthen perceptions about music and influence music popularity. Negus & Street (2002) add that television directly affects the music experience and enhances music performance. The relationship between film and music is therefore based not only on the appearance of the song, but also on the moving images around it. According to these results, music has a greater chance of becoming popular when it is guided by moving images, such as television. That would also explain the success of MTV and YouTube (Cayari, 2011).

These studies all examine the relationship between film and music, or aspects of this relationship. However, they do not include the digital age of film streaming on platforms such as Netflix. Streaming services have accelerated and changed the way we watch TV series by making it easier to watch on demand. Since streaming is enjoying increased popularity, more content is being watched and discovered than ever (Matrix, 2014). Therefore, the effect of a song being featured in a TV series on its music popularity may be greater than before. It is important to conduct a new study to analyze this relationship within our digital age.

Furthermore, the use of technology has made it easier to discover music and influences the relationship between film and music. Since 2012, the technology of Shazam has been able to locate the title of a song using a listening function (Business Insider, 2020). Alongside this technology, it is easier for consumers to discover and listen to new music, and this can influence music popularity. Since some literature dates from before this digital age, it does not take more recent developments into account. Even though the mechanics remain the same, it is important to consider the effect that technology can have on music popularity in a new study. Thus, technology has an impact on music popularity, and it is important to acknowledge this when demonstrating the relationship between a song being featured in a TV series and its music popularity

Another gap in the literature is that it has not been investigated what the results are when a song is featured in a TV series, as opposed to a movie. The difference between movies and TV series is that for movies, the effect is spread out over a longer period, while TV series are mostly not watched many years after their release date. Therefore, the short-term effects can be captured more easily with TV series.

This current research fills these gaps by focusing on TV series with recently featured songs (between 2016-2020). Therefore, the recency of our data captures the impact of technology on music popularity. We investigate the relationship between film and music by linking songs featured in a TV series with their music popularity. By creating a new dataset to follow the music popularity over time when the treatment effect is activated, we can determine whether the popularity of a song increases when it has been featured in a TV series. Therefore, our study addresses both the digital age of streaming and TV series to ensure the research is well-demarcated.

## Music Marketing

As stated by Beaster-Jones (2009), featuring music in a film is a form of music marketing. By making an appearance in a film, music is given extra exposure. From a marketing perspective, featuring a song in a film is a form of product placement. We define product placement as the purposeful incorporation of a song into a film (Russel & Belch, 2005). A study by D'Astous & Chartier (2000) investigated the effectiveness of product placement and brand recall in movies. They found that product placement influences memory recall and product evaluations. This relationship is strengthened when a main actor is present, and the product is well integrated into the film scene. Other studies confirm these findings and add that extensive on-screen time and verbal references are important moderators (Wilson & Till, 2011; Wiles & Danielova, 2009). In addition, Charry (2014) found that popular actors within a popular TV series improve the effectiveness of product placement. Since featuring a song is a form of product placement, it is expected that the evaluation of a song will be better stored in memory when the main actor is present in a well-integrated scene and when the song is played for a longer duration of time.

Next to music marketing, there is also a secondary literature stream (see Appendix A). Music marketing is based on technology. Dewan and Ramaprasad (2014) studied the relationship between social media and music sales. They found that blogs, a form of social media, are not related to album sales and are negatively related to song sales. This contradicts the research of Abel et al. (2010), which suggests that blogs can positively influence music popularity. A clarification for this contrast is that any potential positive effect of blogs on song sales appears to be swamped by the negative effect of free sampling on sales (Dewan & Ramaprasad, 2014). Making an appearance in a blog and making an appearance in a TV series are similar in a way, as both create exposure to consumers and are placed within a media form. As mentioned above, appearing in a blog can have a positive effect on music popularity. Therefore, we also expect this relationship to exist for an appearance in a TV series. Just as being featured in a blog, a song being featured in a TV series should create extra marketing exposure, more listeners, and greater music popularity.

Studies regarding music marketing lack literature about the relationship between music marketing in TV series and music popularity. The above-mentioned studies elaborate on the effect music marketing can have on the popularity of a song or a product, but they do not investigate the effects of music marketing in TV series. Some studies, such as Beaster-Jones (2009), mention the value of music in films as a promotional tool. However, only a few studies have added this relationship into their research framework.

This study fills the gap in the current literature by focusing on music marketing in TV series and aiming to provide that the relationship between music marketing in TV series and music popularity exists. We have already seen some examples of the existence of this relationship (Beaster-Jones, 2009; Nugent, 2018; Lee & Kim, 2022). Furthermore, we extend the existing literature by looking at the relationship and computing the strength of the effect. Music marketing is an important aspect of the relationship between film and music, and it represents one of the ways in which music and film are connected. Thus, through music marketing, we investigate the relationship between a song being featured in a film and its music popularity.

# Conceptual framework

Our research investigates the relationship between a song being featured in a TV series and music popularity. In addition, this research is interested in the influence of song order and song duration on this relationship. We expect that these variables can influence the strength of our main effect because there is convincing evidence from the psychological literature. To investigate our model (Figure 1), a quasi-experimental approach is used to determine the presence of a causal relationship. The definitions of the variables and the expected relationships, as depicted in the conceptual model, will be discussed in the next section.

Chart, diagram, box and whisker chart

Description automatically generated**Figure 1**: Conceptual model

## Influence of song featuring on music popularity

This research is interested in the relationship between a song that is featured in a TV series and its music popularity, because we believe this effect occurs on a larger scale and because previous literature indicates this (Beaster-Jones, 2009; Lee & Kim 2022). Our study agrees with this literature due to multiple indicators. First, a song being featured in a film serves as a promotional tool (Beaster-Jones, 2009). Therefore, it gains more exposure and can reach a wider audience. With a broader audience, a song has a greater chance of increasing its music popularity, since more consumers are targeted. Secondly, technological innovation (e.g., Shazam) has created an environment where songs are easily discovered (Datta et al., 2018). Therefore, technology decreases the cost to the consumer (e.g., time) of discovering a song. By making it easier to discover featured songs, this technology also increases the likelihood of their music popularity increasing. A survey study about music discovery by Tepper & Hargittai (2009) agrees with this justification. They found that 20% of students discovered music through film using digital media. Third, film music has an emotional impact on culture (Navarro, 2019; Frith, 2002). Music can impact emotions, and this can lead to changes in perception and behavior. Music is used to provide reasoning behind what people see, to tie a moment to a familiar song. As an example, pop songs are being used to activate emotional memories and to dramatize intense scenes. The emotional connection created between a scene, a song, and a consumer may result in the song being liked more. In turn, this change in perception may result in behavior change. Because of the emotional connection, consumers will memorize songs better and start listening to them (Boltz, 2004). Therefore, this behavior change positively affects music popularity. A song being featured in a TV series impacts music popularity because it can change perceptions. When these perceptions are positive, they may positively influence music popularity. Regarding these results and justifications, it is expected that featuring a song in a TV series increases that song’s music popularity.

H1: A song's popularity increases when it gets featured in a TV series.

## Moderating effect of song order

This research investigates the moderating effect of the song order and determines whether the difference in song order has an impact on music popularity. The research available on this effect is mainly psychological and not centered on music popularity. Our discussion is therefore broadly investigative. We aspire to examine if the order of a song influences its music popularity since it can have an impact on customers' perceptions (Treloyn, 2007). We suggest that there is a difference in music popularity related to the order, with intro and outro songs often being more important, as they create recognizability for the TV series (Withey, 2001). Furthermore, an intro or outro song may gain more exposure because it occurs more often than a song from a scene. A song from a scene occurs only in that scene, sometimes with repetition, while an intro or outro song is played in every episode. When we look at the order of songs, we find psychological evidence. A theory called ‘the serial position effect’ explains that humans have greater awareness and memory qualities at the beginning and end of a list (Feigenbaum & Simon, 1962). This would indicate that songs featured at the beginning and end of an episode have a greater effect on the relationship between song featuring and music popularity because they are memorized better. Other studies also address the importance of song order (Treloyn, 2007; Vall et al., 2019; Badue, 2017). Sally Treloyn (2007) agrees with the psychological evidence by stating that the difference between a fixed and unfixed song order lies in the shifting memory of songs. We therefore expect the intro and outro songs to gain in popularity because the first and the last song attract more attention and are memorized better. Moreover, intro and outro songs attract more attention and have therefore a greater probability of being discovered through Shazam. Alternatively, consumers may not be ready to shazam songs at the beginning of an episode. However, since intro songs occur more often consumers have more chances to shazam them and can always pause and rewind a song in on-demand TV series. According to these results, the relationship between a song that is featured, and its music popularity is stronger for songs at the beginning and end of a TV series.

Furthermore, the moderating effect of song order is also influenced by emotion. Research has shown that emotions play an important role in shaping cognitive processes, such as attention, perception, and memory (Blanchette & Richards 2003; Nabi 2003; Niedenthal & Setterlund 1994; Richards et al. 2002). This would mean that a scene, and the music accompanying it, would be better recognized, and memorized if the scene was high in emotion. If executed correctly, a scene can be higher in emotion at the end, because of the storyline and the cliffhanger effect (Fredrickson & Branigan, 2005). That is why the song order matters, as the end of an episode is higher in emotion and may trigger greater awareness and be memorized better. Based on these results and justifications, this study suggests that for TV series, the relationship between songs that are featured in a TV series and music popularity is stronger for songs played at the beginning or end than for songs played in the middle.

H2: The relationship between a song featured in a TV series and music popularity is stronger for songs that are played at the beginning or ending than for songs that are played in the middle of a TV series.

## Moderating effect of song duration

This research investigates the moderating effect of the song duration and determines whether this variable strengthens the relationship between a song that is featured in a TV series and its music popularity. Again, the research available on this effect is mainly psychological and not centered on music popularity. Our discussion is therefore broadly investigative. Intuitively, it is expected that a longer song will have a greater influence on this relationship. Since the assumption is that when the featured song duration is longer, a song gets more exposure and more chance to get noticed by the consumer. This also accounts for Shazam; this platform is only able to provide an output for a song that lasts a minimum of 6 seconds. Therefore, a featured song has a greater chance of gaining music popularity when its duration is longer because Shazam will be able to recognize the song. Thus, song duration strengthens the relationship between a song that gets featured in a TV series and its music popularity because it has a greater chance of being noticed and because technology can register the song and give an output.

The literature states that emotion positively influences attention, perception, and memory (Blanchette & Richards 2003; Nabi 2003; Niedenthal & Setterlund 1994; Richards et al. 2002). This is relevant because music adds emotion to a scene and when the music in a scene is longer, there is a greater opportunity for emotion to increase. Therefore, heightened emotion will result in a higher level of attention and memory, which will positively influence music discovery and music popularity. A study by Bachorik et al. (2009) investigated the length of time required for participants to initiate emotional responses to music and found it was an average of 8.31 seconds. Because eight seconds is relatively long for a featured song, this would indicate that a song receives more attention and emotion if it is played for a longer duration of time. Thus, when the song duration is longer, it will strengthen the relationship between a song that is featured in a TV series and its music popularity, because it is higher in emotion and is more likely to attract attention. Therefore, greater attention will increase the chance of music discovery and strengthen the relationship with music popularity.

There is also a counterargument. An empirical study investigated the time course of emotional responses to music. They provide consistent findings that less than 1 second of music is enough to create emotional responses in listeners (Bigand et al., 2005). Since this timeframe is rather short for a featured song, this would indicate that song duration does not influence the relationship between song featuring and music popularity. However, we believe that the duration in seconds is an important component to strengthen the relationship between a featured song and its music popularity. Technology and innovation are growing, enhancing the importance of platforms such as Shazam. Shazam needs an average of 6 seconds to use its music recognition algorithm to provide a song output (Shazam, 2021). Therefore, a longer song duration can strengthen the music popularity of a featured song. Shazam can only give a correct output if the featured song is long enough. Since we believe that the number of seconds it takes consumers and/or Shazam to recognize a song is more important than the emotional component. We are willing to overrule the counterargument and suggest that the relationship between songs that are featured in a TV series and music popularity is strengthened by the song duration in seconds.

H3: The relationship between a song that is featured in a TV series and music popularity is strengthened by the song duration (in seconds).

# Data

This chapter describes the steps taken to gather and use the data. Our collected data was used to estimate the model. The first section explains how the data was collected. Secondly, we document data cleaning and preparation. Next, we present an overview of the final data set, alongside its variable operationalization in Appendix B. In addition, this chapter will introduce the treatment effect: a song that is featured in a TV series at a given time.

## Data collection

A paper by Boegershausen et al. (2022) reports steps to take and challenges to overcome when collecting data online. We have used this paper to guide our process and overcome these challenges (technical feasibility, validity, ethical/legal risks, etc.). We have collected songs that are featured in a TV series via Tunefind and merged these with an existing Chartmetric database. The process is described in the sections below.

### *4.1.1 Tunefind*

The first dataset is collected through web scraping “Tunefind.com”. This social platform is an index of songs appearing in movies, television shows, and games. The platform is based on peer-to-peer contribution, which means that the content is uploaded by consumers and used by consumers (just like social media). Since the platform is user-generated, songs that belong to an episode are not validated. Furthermore, it is possible that some episodes do not contain any information because it was not uploaded by the users of the website. Therefore, the platform does not represent a complete population but instead gives a sample. The above-mentioned missing values do not decrease the accuracy of representing the characteristics of the larger population, as the missing values are as random as possible. Tunefind is a growing platform and has been used for multiple research projects (Wells, 2014; Abdouli, 2021). The researchers on these projects supply Python codes and SQL databases. However, this is not completely applicable to our research design because we include two extra moderators and collect different seeds. We collect recent TV series data while other researchers use outdated movie data. Therefore, we decided to write our Python code to gain control of the research validity and outcome.

Using Python and BeautifulSoup, raw data is directly stored in a JSON file. The dataset contains exactly 8,152 TV series with a total of 106,672 episodes. Each row in the dataset represents a song that is featured in a TV series. This raw dataset has 267,682 rows, which means that this dataset contains information about 267,682 songs. Due to technical feasibility (power outage), we have only managed to gather 89% (number of episodes in file / total number of episodes) of the website content on TV series. Since the collection process has a duration of 3 weeks, we chose not to recollect the sample. By shuffling the data extraction, we have made sure that at any given time, the output represents a sample of the population.

The web scraper had to be restarted multiple times and as it has stored all observations in the same JSON file, this caused the JSON file to contain several duplicates. After the removal of the duplicates, the dataset contains 204,414 observations/songs.

Furthermore, important columns are ‘scene description’, which holds the duration of seconds for a featured song, and ‘order’, which represents the numeric order in which songs are featured. Both columns are used as variables to moderate the relationship between a song that is featured in a TV series and its music popularity. Furthermore, the dataset contains metadata that provides episode and season information and the release date of each episode. A timestamp (date and time) is added to each row to increase the internal and external validity of this research. This can be used for diagnostic purposes and to link our extracted web data to other datasets (Boegershausen et al., 2022). Finally, regarding the frequency of the data collection, the data was collected only once. Since the data undergoes no numeric change over time and because the data collection requires approximately three weeks per session. The descriptive statistics of the Tunefind dataset are presented in Appendix C. The first table describes the number of times a particular soundtrack appears in the dataset. The second table represents the same analysis at a song level. Some songs appear more in TV series for several reasons: they are intro/outro songs, or they are well-known and recognizable songs that simply fit well into several scenes.

We also plotted the growth in the number of songs per episode registered on Tunefind. This gives insight into the data we use and strengthens the relevance of Tunefind, our results are shown in Figure 2. Examining the number of songs per episode, the plot demonstrates a clear growth over time and results in high spikes after 2010. There are two possible explanations for this growth. Firstly, it would strengthen the relevance of Tunefind because this would indicate that the platform is growing. As more songs are registered on Tunefind, the website gains more importance in the online environment. Secondly, the growth in the number of songs per episode could mean that TV series are starting to use more music. This would indicate that music discovery, music popularity, and their relationship with TV series are gaining in importance, as more songs are given the opportunity to gain extra marketing exposure.

Chart, histogram

Description automatically generated

**Figure 2**: Growth in the number of songs on Tunefind per episode over time.

### *4.1.2 Chartmetric*

The second dataset is an existing dataset of Chartmetric, a platform that provides data for music industry professionals (Pachali & Datta, 2022). It contains more than 8 million songs with additional information. The content of this dataset is based on playlist additions, which is the number of playlists a song has been added to. Each row represents a song that has been tracked on a weekly basis to visualize the number of playlist additions. The main purpose of this dataset is to proxy music popularity with the number of playlist additions and to create a treatment and control group. The number of playlist addition is not the perfect proxy for music popularity, The number of listeners or the number of online streams per song would be a better measurement for music popularity. Unfortunately, the existing Chartmetric dataset lacked time series data on this measurement and therefore we use the number of playlist additions. In addition, the dataset contains metadata for each song. Each song is represented by a genre, song duration, release date, and music label.

Table 4 summarizes the descriptive statistics that represent the Chartmetric dataset. As shown in the table, this dataset contains more than 8 million observations. There are two metrics for interpreting music popularity: the number of playlists and Spotify popularity, both generated in 2016. Spotify popularity is an index between 0 and 100 for a particular song generated by Spotify. The Chartmetric dataset has time series data on the number of playlists, which is why we chose this as our outcome variable. Interestingly, the standard deviation of the number of playlists is rather high (29.94), which means that there is considerable variation between songs. This strong variation between observations shows that the data is widely spread. This is less reliable but helps to visualize unusual events. A standard deviation not centered around the mean (high SD) could result in a visible (but less reliable) effect of the treatment.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Number of playlists | Spotify popularity | N = 8,218,124 |
| Mean | 5.212 | 11.526 |  |
| SD | 29.940 | 12.906 |  |
| Min | 1 | 0 |  |
| Max | 4,222 | 100 |  |
| Observation date | 04-01-2016 | 04-01-2016 |  |

**Table 4**: Statistics of the number of playlists and Spotify popularity per song.

Furthermore, each song has received multiple attribute levels that represent different audio settings. All audio attributes are computed by Spotify and describe variety in songs. Each audio attribute is measured on a scale from 0 to 1. The closer the value is to 1, the higher the song loads on this attribute. These values are important since the attributes will be used to match control and treatment groups within propensity score matching. This method uses an algorithm that matches a treated song with a non-treated song based on similar attribute levels. These attribute levels represent a song’s characteristics and are used to create almost identical pairs of treatment and control groups. Therefore, the attributes will assist in making sure that the difference between the treatment and control groups is as untroubling as possible. Otherwise, differences in the composition could likely explain differences in behavior instead of the average treatment effect. The audio attributes and their statistics are represented in Table 5.

|  |  |  |
| --- | --- | --- |
| **Audio attributes** | **Mean** | **SD** |
| Danceability | 0.589 | 0.181 |
| Energy | 0.643 | 0.270 |
| Speechiness | 0.051 | 0.170 |
| Acousticness | 0.188 | 0.352 |
| Instrumentalness | 0.002 | 0.369 |
| Liveness | 0.130 | 0.181 |
| Valence | 0.454 | 0.270 |

**Table 5**: The mean and standard deviation of all audio attributes by Chartmetric

## Data preparation

In order to analyze the data; it needs to be transformed. First, the Tunefind dataset is cleaned by removing any duplicates within the web scraping process. Second, the timeline of the Tunefind dataset is adjusted. The Chartmetric dataset only has available data from 2016 to 2021. Thus, the sample size of the Tunefind dataset should consist of episodes that were released during this period, to estimate the effect of the treatment. Third, we refine the sample size to episodes that have more than three songs per episode. By filtering the sample size, we can analyze the moderation effect of the featured song order. Since the moderating effect of the order requires a minimum of three songs (beginning/middle/end), we filter for a minimum of three songs per episode. To validate this data preparation, we performed an analysis with and without refining the sample size for moderation. The results showed that without refining the sample size, the mean of the song order is lower. Indicating that multiple episodes only have a few songs, pressing the mean downward. Therefore, we must filter for a minimum of three songs to prevent bias for the moderating song order effect. Finally, we have removed songs from our sample that were featured at the end of our observation window, as recently featured songs are not able to cause an effect.

To analyze the two datasets, they need to be merged. This research creates a final dataset that demonstrates the music popularity (playlist additions) per week for a song that is featured or is not featured in a TV series. Since both datasets have song titles as their unit of analysis, they are joined on this variable. To ensure correct joining, we also join on artist names, because non-identical songs can have the same song title. During the joining process, we ran into memory issues with many observations and variables. Functions using string distance were not applicable because our analytics tool stores everything in RAM and functions such as fuzzy join (a variation of dplyr’s join operations) use a lot of data on our large dataset. Strings need to match since the representativity would decrease if songs were not joined because of different spellings. For this reason, we chose to make the strings as identical as possible. By setting every string to lower case, non-numerical, and without spacing, we managed to merge the two datasets with a regular join. To validate the merger, we computed the Levenshtein distance to control for string distance. Furthermore, for extra validation, we took a random sample (n=50) and manually checked that the merger succeeded. Appendix D shows the output of our manual validation.

By using propensity score matching, we successfully matched each treated song with a non-treated song. These pairs are defined by a numeric class and are used to compare identical songs and reduce selection bias. The second-stage dataset is designed as a long format where weekly song data serves as the unit of analysis. For each week, each song has a post-treatment variable (0/1), and the post-treatment starts when the episode is released. Thus, an episode released on 1 December 2020 will activate the post-treatment for songs allocated to this episode. Hence, the post-treatment column is added to design the difference-in-differences analysis and compute the average treatment effect after the treatment. At last, we use week-level and song-level fixed effects to control for common time trends, week-to-week fluctuations, and overall liking of music.

## Overview of the final dataset

This section gives a general overview of the merged dataset along the various dimensions of songs that were and were not featured in a TV series. Not all observations from the previous datasets are used, only the ones computed by the propensity score matching. After the propensity score matching, the dataset has 2,420 songs, divided into a balanced sample of 1,210 control and 1,210 treatment observations. Table 7 represents the composition of the groups created by the propensity score matching.

|  |  |  |
| --- | --- | --- |
|  | Control | Treated |
| All | 394,429 | 1,210 |
| Matched | 1,210 | 1,210 |
| Unmatched | 393,219 | 0 |

**Table 7**: A matching overview based on propensity score matching

To visualize the final dataset (see Figure 3), we have plotted the difference between pre-treatment and post-treatment for the treatment group. The plot indicates that music popularity tends to move downward, indicating that music popularity decreases over time. Thus, when a song gets released, it is high in popularity and slowly loses its momentum. Figure 3 shows that for the treated group after the treatment, the short-term trend is still downward. However, after approximately 25 weeks the treated group stabilizes and starts an uptrend. This may be a lagged treatment effect since consumers can watch an episode after the treatment. For a comparison with the control group, we refer to the parallel trends in section 6.4

Chart, line chart

Description automatically generated

**Figure 3**: the plotted difference between pre-treatment and post-treatment in weeks

# Method

This chapter describes the design of the research. The methodology explains the research strategy, its challenges, and how to overcome these. Furthermore, the comparison between treatment and control groups is elaborated on, and the analytical process is described. Based on previous research (Datta et al., 2018), this research uses propensity score matching (PSM) and difference-in-differences (DiD) to estimate a causal relationship.

## Identification strategy

The objective of this research is to identify a causal relationship between a song being featured in a TV series and its music popularity, measured by the number of playlist additions (number of playlists a song is added to per week). There are two major challenges when identifying a causal relationship. First, the data collection process fails to randomly assign observations to treatment and control groups, as we based our treatment and control group on non-random criteria (e.g., being featured is not random). Applying a DiD model without randomization would include endogeneity due to self-selection. Therefore, this research follows a quasi-experimental approach, aiming to identify external events that can approximate random assignment. In our study, being featured in a TV series approximates random assignment. The treatment and control groups need to differ in a way that is as untroubling as possible to mimic random assignment (Goldfarb et al., 2022). The quasi-experimental matching procedure uses a propensity score to equally match songs that have been featured in TV series with similar songs that have not been featured. Appendix E provides the attribute balance after propensity score matching.

Second, the matches created by the propensity matching receive treatment at different times since episodes (and their songs) are released on different dates. To create comparability between treatment and control groups, propensity score matching is used to create pairs with similar covariates. Within these pairs, the control observation mirrors the relative treatment time of the treatment observations.

## Treatment and control group

Since this research was conducted as a quasi-experiment, there are concerns about selection bias. The data structure is designed in such a way that the large existing dataset of Chartmetric serves as outcome data (playlist additions) for the treatment and control groups. The treatment is activated when a song makes an appearance in a TV series, and the treatment is derived from songs scraped from Tunefind to overlap with the songs that are imported from Chartmetric. This would divide the Chartmetric data into two groups, one where songs have made an appearance in a TV series, and one in which they have not. This process of creating two groups is used to generate the treatment and control groups. Furthermore, because songs in the treatment and control groups differ in song and featuring characteristics, differences in the composition could likely explain differences in behavior. The difference in characteristics between the treatment and control groups could result in a significant effect, where there actually is none. The group allocation is designed to be as random as possible. However, since the allocation is not completely random, it is possible that unobserved variables influence our outcome variable. To deal with selection effects, two quasi-experimental methods are used. They are explained in the following sections.

## Propensity score matching

Matching methods have been developed such that the outcomes of the treatment group are contrasted only with the outcomes of the comparable control group (Rosenbaum & Rubin, 1983). The general objective of PSM is to estimate a score that realizes a similar variable distribution and behavior among the treatment and control groups (Imbens & Rubin, 2015). In this research, self-selection may arise due to differences in song popularity. It could be that popular songs are more likely to be featured in a TV series due to producers wanting to use songs that will be recognized. We attempt to control for this type of selection by adding song-level and week-level fixed effects to the model. The matching process removes songs from the sample that are likely never to be featured in a TV series. Therefore, the control group aims to resemble the treatment group in every way except for their treatment. Thus, the score-matching process and fixed effects are combined to compare the treatment and control groups as closely as possible (Datta et al. 2018). Our fixed effects are variables that are constant across songs and remain constant over time. These variables remove omitted variable bias by measuring changes within groups across time. In the absence of fixed effects, the concern is that comparisons of treated and control units will not have a credible causal interpretation (Arkhangelsky & Imbens, 2018).

To ensure the best propensity score matching, we have compared multiple logit models (comparison available in Appendix F). Primarily, we have excluded all insignificant variables. Since the insignificant variables from the logistic regression are not different from zero and have therefore no contribution to the treatment assignment. Thereafter, we estimated the model fit by interpreting the log-likelihood. By looking at the lowest AIC value (2K – 2(log-likelihood)), we have chosen the propensity score equation presented below. The predictor variables represent a song's attributes and pre-treatment music popularity. Therefore, these variables matter since are likely to predict treatment and determine matching control observations.

This research estimates the propensity score of each song being added to a playlist as a function of observed variables (Rosenbaum & Rubin, 1983). We predict the propensity score per song with a model that considers audio attributes, the number of playlists, and Spotify popularity per song at the start of the observation window (2016). The speechiness, liveness, and instrumentalness represent the significant audio attributes per song and are used to match songs that are alike in music characteristics. The number of playlists and Spotify popularity represent the music popularity and ensure matching the treatment and control observations on similar popularity before the treatment. Therefore, the computed score prediction is based on covariates that represent the song's attributes and initial music popularity in 2016. These variables predict the treatment since they estimate the likelihood of a song being featured in a TV series. A song with certain audio features (e.g., high liveness) and a certain music popularity may be more likely to be featured in a TV series. Appendix G represents summary statistics of the propensity score matching. It illustrates the pair difference between the treatment and control groups and indicates that the matching procedure went well.

Additionally, by computing the propensity score as linear regression, we gain insight into the coefficient, standard errors, and significance of the observed variables. We use the binary treatment as our dependent variable and regress our predictor variables. The explanatory power of the linear regression can be calculated with the use of R². Our model has an R² of 0.16, which indicates that our independent variable does not explain much of the variation of our dependent variable. However, according to Imai et al. (2008), propensity score matching is only used to design balanced groups on a set of covariates. Therefore, the R², the creditability of our selection model, is a poor method of assessing the effectiveness of the matching procedure and is close to irrelevant (Ho et al., 2007). Furthermore, all the variables are significant (*p* <2e-16) and therefore selected in the model. Table 8 below illustrates the output of the propensity score regression. The coefficients represent the impact a variable has on treatment allocation. Overall, the predictor variables do not have much influence on the treatment allocation. Nevertheless, if a variable has a positive coefficient, this variable is likely to predict that a song will be featured in a TV series since the treatment allocation is our dependent variable. Thus, songs that are high in popularity are more likely to predict treatment and are therefore more likely to be featured in a TV series. In addition, songs that are high in speechiness have a negative influence on the treatment.

Table

Description automatically generated

**Table 8:** Summary statistics of the coefficients PSM linear regression

For further comparability, this research makes sure that matched treatment and control pairs have the same observation window. If treated songs were matched with control songs in a different observation window, any estimated treatment effect could not directly be linked to the treatment effect but could arise from timing differences. Our propensity score algorithm uses a nearest-neighbor technique to match songs that are closest together in terms of distance measured by our logit model (Datta et al. 2018).

After matching, both treatment and control songs are alike in terms of their propensities (see Figure 5), observation window, and observed attributes (see Appendix G). Our matching algorithm computes a treatment and control group, which accounts for observed audio features and pre-treatment music popularity. Although the treatment and control groups were previously unbalanced, they are now almost identical. Figure 4 below represents the propensity score distribution for treated and untreated observations. It illustrates the comparison between the distribution of the covariates in the treatment group and in the matched control group (Austin, 2009). Since the propensity score represents the probability of treatment assignment, it is logical that the propensity score is skewed (more to the right) for the treatment group. Therefore, the observed baseline characteristics predict treatment well. By plotting the density, we can visualize the region of common support (where the density of the estimated propensity scores overlaps). No conclusion can be made about the average treatment effects for a treated observation with no available comparison. Therefore, common support is used to select observations for the second-stage sample (Imbens, 2004).

Chart, histogram

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**Figure 4**: the plotted density of the treatment and control group after matching

After all observations have been matched based on their propensity score, the matched treatment and control observations are given the same numeric subclass to represent each other. By dropping all the other observations that did not qualify for the matching, the dataset is cleaned and serves an equal number of treatment and control observations. Figure 5 below shows an example of how the propensity score matching filters for observations that have similarities in popularity. Therefore, this technique flattens out the difference between observations and can compare observations based on observed characteristics.

Chart

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**Figure 5**: Before (left) and after (right) for propensity score matching.

## Difference in Differences

A difference-in-differences analysis compares the treatment and control group before and after the treatment is activated. The DiD method creates a baseline for comparison between the treatment and control group and enables control for sources of heterogeneity across groups (Goldfarb et al., 2022). This research uses a DiD approach to estimate the average effect of a song being featured in a TV series on its music popularity. By comparing music popularity of songs before and after their treatment with those of matched control songs, the following model is estimated:

Where Yit is the dependent variable representing music popularity per individual song in a TV series (i) per week (t). Furthermore, is a song-level fixed effect that controls for overall music popularity. As popular songs could be more likely to receive treatment. Next, represents the week-level fixed effect, which controls for the increase/decrease in music popularity over time. Overall, songs can increase in music popularity because Spotify streams are growing (IFPI, 2022). Alternatively, music popularity can also decrease over time, as songs slowly become less popular and are replaced by new songs. This two-way fixed effect formula represents time-invariant song characteristics, such as song popularity and overall liking of music. Therefore, this formula accounts for variation in the treatment period and overall fixed effects (Datta et al. 2018). Furthermore, the formula accounts for an average effect. The delta represents the average treatment effect of the main effect. It explains how big the difference is between before and after for treated vs untreated. When interpreting, this number gives the gain or loss in music popularity (number of playlists) when a song is featured in a TV series.

We also investigate how long changes in music popularity last. During the data inspection progress, we have seen that music popularity can decrease over time (Figure 3). To capture these effects and to better understand the timing of the treatment interaction, we introduce three timeframes. We examine the effect of a song being featured in a TV series on music popularity in the short-term (0-4 weeks), medium-term (5-25 weeks), and long-term (>25 weeks). By expanding the previous two-way fixed effect formula with multiple timeframes, we estimate the following model:

Where Yit is the dependent variable representing the music popularity of each individual song in a TV series (i) per week (t). The previously mentioned two-way fixed effects and control for music popularity and its changes over time. The indicator variables such as I(weeks since treatment) are dummy variables and are assigned as 1 if the weeks since treatment for consumer i are within the indicated range. Therefore, the model differentiates between short-term (0-4 weeks), medium-term (5-25 weeks), and long-term (>25 weeks) effects. Furthermore, we assume that the standard error terms (ε­­it) are uncorrelated with the indicator variables (Datta et al., 2018). In addition, we use robust standard errors clustered at the song level (track ID) to account for any serial correlation (Bertrand et al. 2004). By clustering our standard errors at the song level, we control for heterogeneity within groups.

## Heterogeneity in treatment effects

The impact on a song’s popularity of being featured in a TV series may depend on certain individual characteristics and circumstances. Therefore, we consider two potential song-level moderators that can influence the impact on music popularity: (1) featured song order and (2) featured song duration. As mentioned before, the research available on these effects is mainly psychological and not centered on music popularity. Our discussion is therefore broadly investigative. First, the effect of song featuring on music popularity may differ according to song order. A song at the beginning of an episode may prompt greater awareness than a song in the middle, but consumers may not be ready to shazam songs at the beginning of an episode. A song at the end of an episode may be higher in emotion due to a cliffhanger effect (Feigenbaum & Simon, 1962; Fredrickson & Branigan, 2005). We study this moderation effect by estimating the interaction of the main effect with a mean-centered song order. To determine a mean-centered song order, we subtracted the mean from each value and divided this by its standard deviation.

Second, we are interested in the moderating effect of featured song duration. If a featured song is played for longer, it has a greater chance of being noticed and this increases the chance of the song being ‘shazamed’. In addition, longer song duration and higher emotion progress in tandem (Bachorik et al., 2009). We study this moderation effect by estimating the interaction of the main effect with a mean-centered song duration. Once more, we subtracted the mean from each value and divided this by its standard deviation. We incorporate both components as moderators for the effect on music popularity. To avoid cluttering, we do not distinguish between short-, medium-, and long-term effects, but instead, use the overall main effect. By adding moderating effects, we extend the main overall DiD formula:

To correctly use the DiD analysis, the parallel trends assumption needs to be satisfied. This involves demonstrating that the behavior of the treatment and control group were similar before treatment (Goldfarb et al., 2022). To test this assumption, this research uses the pre-treatment to visualize pre-treatment trends. By plotting the trends of the control and treatment groups, this can be visually controlled. The parallel trends are further discussed in the robustness of the results.

Concisely, this research combines propensity score matching with a DiD approach. The PSM model selects non-treatment songs that are likely to get the treatment and uses this in the DiD equation. The reported effects from the DiD regression are interpreted as the average treatment effect on songs that are featured in a TV series.

# Results

In this section, we present the analyses' results using the model specification described in the previous section. First, we describe the model fit of our main model. Second, we elaborate on the results regarding the main effect of a song being featured in a TV series on its music popularity. Third, we investigate the moderating effects on music popularity of (1) featured song duration and (2) featured song order. Finally, we conduct robustness checks to validate our research and outcomes. All statistical tables are also provided in Appendix H

## Model fit

As mentioned before, we utilized a quasi-experimental approach to test the causal relationship between a song being featured in a TV series and its music popularity, and whether this relationship is influenced by song duration and song order. By conducting a difference in differences analysis, we have estimated regression results. Since our outcome variable is continuous over time, we can estimate effects in different timeframes. If a song receives treatment, the effect may not be immediately registered. Consumers can watch an episode after the treatment has been activated. Therefore, the effect can be perceived through different timeframes. Hence, when presenting our results, we make a distinction between (1) short-term (0-4 weeks), (2) medium-term (5-25 weeks), and (3) long-term (>25 weeks) effects.

Our regression indicates that the independent variables explain 96% of the variance in music popularity ( = 0.96476). The adjusted R² gives a penalty for adding extra variables. A benchmark for a strong effect size is an R² of > 0.7 (Moore et al., 2013). Although this high R² value seems sufficient, we have reason to believe that our model is overfitting. Our regression coefficients therefore represent random noise rather than the actual relationship. Since our R² is artificially inflated, this reduces the generalizability outside the original sample (Hawkins, 2004). The overfitting is caused by the song-level fixed effect in our model. The fixed effect explains almost all variance in the dependent variable, music popularity. By removing the song-level fixed effect the adjusted R² drops to 4%. Moreover, by investigating the residuals, we conclude that the residuals do not form randomly around the zero line. There is a non-random linear pattern that indicates a bad fit despite a high R². We provide a general overview of the residual analysis in Appendix I.

However, since our methodology is based on two-way fixed effects. The within R² is of main interest, as fixed effects are known as the within estimator. This indicates how well our independent variables account for changes in music popularity within each song over time (Torres-Reyna, 2007). Our within R² has an insufficiently low value of 0.00361, which is less than 1% of the within variance explained. Nevertheless, this shows a more realistic distribution of the variance in our model. To additionally validate our model, we examine the RMSE. The RMSE ( = 0.26751) indicates the absolute fit of the model to the data. This tells us how close the observed data points are to the model's predicted values. The RMSE is normally sufficient when it is close to zero. However, this depends on the range of the dependent variable. Our dependent variable the number of playlists has a range from 1 to 2,788. Therefore, our RMSE of 0.27 is indeed low, indicating that our model could estimate the number of playlists accurately.

In general, we can conclude that the suggested methodology does not perform well. The model does not correctly represent the relationship in the population. However, our robustness checks indicate that the within-sample results are valid. Therefore, we continue presenting our results in the following sections and, in the end, propose a new model for further research.

## Main effect

In this section, we describe the results of the DiD analysis regarding the relationship between a song being featured in a TV series and its music popularity. Table 9 represents the statistical output of our main model with our song-level and week-level fixed effects. These fixed effects allow the intercept to vary freely across individuals. Therefore, our fixed effects are variables that are constant across individuals and remain constant over time. Thus, when estimating the main effect, we account for week and popularity differences. In addition, we use robust standard errors clustered at the track level to account for any serial correlation (Bertrand et al., 2004). Our dataset has an observation window of 200 weeks before and 200 weeks after the relative treatment period. However, to minimize the noise of other events that could influence the treatment (e.g., a concert or an album release), we have shortened the observation window to 50 weeks before and 50 weeks after the relative treatment. In addition, we have transformed our dependent variable into a logarithmic function for interpreting percentages (formula: exp(beta)-1).

First, we examine the overall main effect. We have hypothesized that the popularity of a song increases on condition that the song is featured in a TV series. Contrary to our expectations, the featuring of a song has a negative effect on its music popularity. The interaction effect accounting for the difference in difference has a negative significant value (beta = -0.052, *p* = 0.001). This indicates that the treatment group has a 5.07% lower average number of playlists after the treatment, compared to the control group. It may be that our expected relationship does not exist in our sample, since each song is featured in a different setting. Therefore, regular treatment, simply getting featured, is not enough to generate a positive main effect. Only songs with the right featuring characteristics (e.g., the right atmosphere around the song) can generate a significant positive effect. Furthermore, it may be that the relationship does not exist in our sample since the desired effect only occurs for popular TV series. Just as product placement is more effective in popular TV series (Charry, 2014). We have used a broad sample of popular and unpopular TV series. Therefore, the effect may not be visible. However, the unconfirmed hypothesis could also be due to a measurement issue. The overfitting model has caused the regression coefficient to represent random noise rather than the actual effect. Therefore, the generalizability outside our sample is low and the coefficients are not trustworthy.

Table

Description automatically generated

**Table 9:** Statistical output of the overall main effect

Since we are also interested in the short-term (0-4 weeks), medium-term (5-25 weeks), and long-term (>25 weeks) effects, we have created three dummy variables to represent the timeframes. They equal 1 if the relative treatment time is within the timeframe, and otherwise 0. Table 10 below represents the output of the main effect including the timeframes. As mentioned before, we hypothesized that the popularity of a song increases when it is featured in a TV series. Once again, we cannot confirm this and examine that the featuring of a song has a negative effect on its music popularity. For all three timeframes ((1) short, (2) medium, and (3) long), the interaction term is significantly negative ((1) beta = -0.038, *p* = 0.003, (2) beta = -0.064, p < 0.001), (3) beta = -0.043, *p* = 0.025). Therefore, when we observe the short-term treatment effects, we see that a treated song appears on average in 3.73% fewer playlists after being featured in a TV series. The interaction term decreases even further in the medium term. The medium-term treatment effect results on average in a 6.20% decrease in the number of playlists for the treatment group, compared to the control group. Moreover, the long-term treatment interaction has a negative effect of 4.21%, indicating that on average the treatment group also performs less well in the long term compared to the control group. These findings do not support our expectations, since there is no positive relationship in our sample. Equivalent to the overall main effect, it may be that simply being featured in a TV series is not enough to generate a gain in music popularity. Furthermore, the negative interaction effect may derive from treated songs declining at a faster pace. Music popularity for the treated group has always been higher (see Figure 6, parallel trends). Therefore, higher popularity may result in a steeper drop compared to the less popular control group. However, since our model does not perform well, the unconfirmed hypothesis could also be explained by a measurement issue. The overfitting model does not correctly represent the relationship and is therefore not generalizable to the population.

Table

Description automatically generated

**Table 10:** Statistical output of the overall main effect, with timeframes.

## Moderating effect

There are negative short-term, medium-term, and long-term effects on music popularity of a song being featured in a TV series. We also explore how the overall main effect differs across featuring characteristics. To avoid cluttering, we do not distinguish between short-, medium-, and long-term effects, but use the overall main effect. As mentioned before, we investigate the moderating effect of featured song order and featured song duration. To ensure the correct interpretation of these coefficients, we have mean-centered the values. Without this, comparing values for the featured song order would be unfair because not every episode has the same number of songs. In addition, we have not used a logarithmic function for the dependent variable since our calculations are interpreted as above or below the average number of playlists due to mean centering.

Table 11 below represents the moderating effects. First, we examine the moderating effect of the featured song order. We hypothesized that the relationship between a featured song and its music popularity is stronger for songs that are played at the beginning/ending compared to songs that are played in the middle of a TV series. Indeed, the featured song order has a significant moderating effect (beta = -6.770, *p* = 0.019). Therefore, a song with an above-average order has less music popularity. This negative coefficient supports the hypothesis that the effect on music popularity of songs being featured is stronger for songs at the beginning of an episode. This negative effect is therefore consistent with the notion that intro songs gain more in popularity because they attract more attention and are memorized better.

Second, we examine the moderating effect of featured song duration. We expected that the music popularity of featured songs would increase with a longer featured song duration in seconds. We found an insignificant moderating effect for featured song duration (beta = -0.105, *p* = 0.937). Since the effect is not significant, we cannot make any statements about this coefficient and are not able to reject the null hypothesis. The effect might not exist since the literature mentions opposing arguments. Bigand et al. (2005) mentioned that it takes less than 1 second of a featured song to create an emotional response. Therefore, the duration in seconds may have no influence on the awareness and memory of the consumers (Blanchette & Richards 2003; Nabi 2003; Niedenthal & Setterlund 1994; Richards et al. 2002). And, in turn, may have no influence on music discovery and music popularity.

Table

Description automatically generated

**Table 11:** Statistical output of the moderating effect.

## Robustness check

In this section, we are investigating whether our results are robust to the possibility that one of our assumptions might not be true. If the treatment group is systematically different from the control group in a way that is not captured in the matching procedure but affects our dependent variables, our estimated treatment effect may be biased (Datta et al., 2018). We estimate the parallel trends as a robustness check to control for this. We satisfy the parallel trends assumption to visually show that in absence of the treatment group, the difference between the treatment and control group is constant over time (Goldfarb et al., 2022). In Figure 6, we illustrate that the trends of the treatment and control groups are similar before the treatment. After satisfying the parallel trends assumption, we can estimate and make inferences about causal claims (Marcus & Sant’Anna, 2021).

Chart, line chart

Description automatically generated

**Figure 6**: Before (left) and after (right) for propensity score matching on observed variables.

Second, we perform a placebo test in which we estimate an additional DiD by using a fake treatment group. To implement this, we move the relative treatment time to the time before the actual treatment time. Therefore, the treatment does not occur and should result in a zero or insignificant effect. Next, we construct a two-way fixed effect DiD estimator by **r**eiterating the overall main effect. To compare significant results with insignificant results, we implement the placebo effect on the overall main effect. By lagging the relative treatment time, we can investigate our placebo estimates. We have examined the placebo effect within multiple lagged timeframes to increase validity (e.g., 25 weeks, 30 weeks, 35 weeks, 40 weeks). We fail to reject the null hypothesis of no treatment effect for the placebo treatments for each lagged result. In Appendix J we have grouped multiple tables to support our outcome. Our results provide further support that our matching procedure is free from selection of unobservables (Datta et al., 2018).

# Discussion

In this research, we examined the influence of a song being featured in a TV series on its music popularity. We showed that the main effect differs between timeframes, and therefore changes over time. The following sections provide a conclusion of our results, supply implications, elaborate on the limitations of our research and propose further research.

## Summary of main findings

We have obtained insights into how a song featured in a TV series affects music popularity. We conclude that for the overall main effect, the average treatment estimator has a significant negative effect, which indicates that a featured song has lower music popularity than a non-featured song. By expanding the model with timing effects, we conclude that the treatment interaction differs according to the number of weeks. Nevertheless, our results show that the interaction effect is negative for all the timeframes (short-term: -3.73%, medium-term: -6.20%, and long-term: -4.21%). This finding is contrary to the flow of this research, which suggests that being featured in a TV series increases exposure and results in enhanced music popularity. There are two possible explanations for this contradictory finding. First, it is possible that the relationship does not exist in our sample, in which we inspected a relationship on a large scale. Each treated song is featured in a different setting, with different characteristics. Therefore, not all songs have the potential to gain in music popularity. This depends on the way in which the song is used in the TV series: the scene gives meaning to the song. The gain in music popularity may therefore depend on the atmosphere around the song. Second, it is possible that our model is unable to measure the relationship. Due to overfitting, our model represents random noise rather than the actual relationship. Therefore, our results are not generalizable to the population and may be untrustworthy. Nonetheless, our robustness checks indicate that the results are valid. The pre-treatment trends are parallel, and the placebo treatment presents multiple insignificant effects.

Furthermore, we expected the moderating effect of featured song order to be stronger for songs that are at the beginning or end of an episode, and we found support for this expectation. Our results show a significant negative interaction effect, indicating that the moderating effect is stronger for songs at the beginning. This effect is therefore consistent with the notion that intro songs gain more in popularity. A possible explanation is that intro songs create recognizability for the TV series and therefore have a different relationship.

## Theoretical and managerial takeaways

Previous research has made it clear that movie- and TV soundtracks serve as a marketing tool to increase music popularity (Beaster-Jones, 2009; Lee & Kim, 2022; Tepper & Hargittai, 2009). Based on these findings, we expected the featuring of a song in a TV series to have a positive overall effect on its music popularity. Although our main overall effect is significantly negative, we add to the literature by finding that there is a significant difference between the short-term (0-4 weeks), medium-term (5-25 weeks), and long-term (>25 weeks) effects on music popularity of a song that is featured. Since all the timeframe effects are significantly negative, this implies that spending time and resources on making sure a song is featured in a TV series will likely not pay off. However, the results leading to this implication may be biased. As mentioned before, we have estimated an overfitting model, causing the measurement of the relationship to be inaccurate. Although this research shows that featuring a song does not increase music popularity, we continue to have confidence in the existence of a positive effect, because our model does not correctly represent the relationship the population.

In addition, we found that treated songs have always been more popular, even after the matching procedure. The parallel trends (Figure 6) illustrate that the treatment group remains above the control group during the whole observation window. Therefore, a treated song might not gain in music popularity but is still more likely to be treated/featured in the future.

Moreover, in our analysis, we found that a song featured at the beginning of an episode has the greatest effect on music popularity. Thus, being featured as the introductory song of an episode brings great value to a song’s music popularity.

From a practical point of view, this research provides insights into the featuring song order that will increase music popularity, in addition to the possible negative effect of being featured in the first place. Music labels can use these insights to make sound arrangements with the movie industry regarding song usage. Although being featured in a TV series once might not have large benefits, featuring a song in a TV series generates exposure, and implementing this, should produce an effect.

In addition, the effect that song featuring has on music popularity may be dependent on the atmosphere around the song. Each song has a different setting and not every song has the same potential to gain in music popularity.

## Limitations

Our research has several limitations. First, the number of playlists is not the perfect proxy for music popularity. It shows us how many times the song is added to a playlist, but it does not tell us how many consumers listen to this playlist. The number of listeners or the number of online streams per song would be a better measurement of music popularity. Since this precisely tells us how many customers listen to a song and gives a more accurate representation of music popularity over time. Unfortunately, the existing Chartmetric dataset lacked time series data on this measurement. Second, the songs that received the treatment are not validated. On Tunefind, every individual can add any song to an episode, whether or not that song was actually featured. Therefore, some songs may have received a false treatment, unintentionally influencing our outcome variable. This cannot be checked on a large scale and is therefore a limitation of the research. Third, some data have been excluded from the second-stage dataset. The Tunefind data gathered does not have moderating values on all observations. Tunefind provides us with the duration of a song during a scene, but this is not available for every song. Therefore, to incorporate moderation of duration, we have excluded all the observations of the treatment group that had no available values. Since some observations were excluded in the data aggregation process due to missing position data, the outcome may vary according to the population. Next, our results are not based on cross-validation. A resampling method uses different proportions of the data to validate the outcomes (Berrar, 2019). Therefore, the outcome of our sample may be partially based on luck and would therefore not be generalizable to the whole population. Finally, due to the overfitting of our model, we provide inaccurate results that are not generalizable to the population.

## Future research

Our research is the first to investigate the way in which featuring a song in a TV series affects that song’s music popularity and it leaves multiple possibilities for further research. First, we have seen that music popularity tends to trend downwards as time passes. Therefore, a simple treatment might not be enough to increase music popularity significantly. A song will need to satisfy multiple conditions to greatly increase its music popularity. History shows us that some songs gain short-term popularity because of being featured in a movie or TV series (e.g., “Running Up That Hill” by Kate Bush in Stranger Things, “Dreams” by Fleetwood Mac on TikTok, or “Something in the Way” by Nirvana in The Batman). These songs have some characteristics that enable them to gain exceptional popularity, and this could be researched and explained. We have used a broad sample with featured songs in different settings, instead of a concentrated sample with songs that have similar settings. Therefore, not every song has the same potential to gain music popularity. By examining what condition a featured song has to meet in order to gain music popularity, music labels and the movie industry can gain insights that they can apply in their strategic implications.

Furthermore, we have researched the influence of on-demand platforms and TV series on music popularity. However, new platforms such as TikTok are becoming increasingly important in creating an environment in which songs can increase their music popularity. For a music artist, being featured in a TikTok video may also have a promotional effect and influence our outcome variable, music popularity.

Because our suggested methodology does not perform well and the model does not correctly represent the relationship in our sample, we want to propose a new model for further research. We examined that the song-level fixed effect explains almost all variance in our dependent variable and therefore produces an overfitting model. Since the song-level fixed effect accounts for popularity differences between songs, an alternative would be to remove song-level fixed effects and add a control variable for popularity. A drawback of this alternative is that it eliminates the two-way fixed effects and therefore weakens causal claims, because the research would no longer account for unobserved song-level and week-level effects at the same time. If we implement the new model, the R² drops to a more reasonable 49% and presents an insignificant but positive main effect (beta = 0.049, *p* = 0.215). However, when we examine the short-term effect, there is a significant positive effect (beta = 0.079, *p* = 0.051). Therefore, our confidence in a positive effect is not groundless. Appendix K provides a representation of the model and its coefficients. Finally, we would like to emphasize that the popularity of a TV series may have influenced the treatment effect. Just as product placement is more effective in popular TV series (Charry, 2014), the treatment effect could be more effective in popular TV series. Therefore, we suggest adding TV series popularity as a moderator in further research.

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# Appendices

Appendix A Literature overview

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | *Main literature streams* | | *Secondary literature streams* | | | *Effect on* |
| Author | Film soundtrack | Music marketing | Change of perceptions | Technology | Product placement |
| Beaster-Jones (2009) | x | x |  |  |  | Music popularity |
| Frith (2002) | x |  | x |  |  | Music culture |
| D'Astous & Chartier (2012) |  | x | x |  | x | Evaluations, Memory |
| Wilson & Till (2011) |  | x | x |  | x | Evaluations, Memory |
| Panda (2004) |  | x | x |  | x | Evaluations, Memory |
| Lee & Kim (2022) | x | x |  | x |  | Music popularity |
| Nugent (2018) | x | x | x |  |  | Music popularity |
| Cayari (2011) |  | x | x | x |  | Music consumption |
| Wiles & Danielova (2009) |  | x | x |  | x | Evaluations, Memory |
| Abel et al. (2010) | ± | x | x | x |  | Music popularity |
| Dewan (2014) | ± | x |  | x |  | Music sales |
| Negus (2002) | x | x | x |  |  | Music popularity |
| Tepper & Hargittai (2009) | x | x |  | x |  | Music discovery |
| Datta et al. (2018) |  |  |  | x |  | Music discovery |
| THIS STUDY | x | x | x | x | ± | Music popularity |

Appendix B Variable operationalization

|  |  |  |
| --- | --- | --- |
| **Variable** | | **Operationalization** |
| **Tracks** | Track ID | Unique song identifier by Chartmetric |
|  | Track title | Given title of the track |
|  | Track artist | Artist(s) who perform(s) the track |
|  | Track genre | Which genre(s) the track belongs to |
|  | Featured track duration | Number of seconds the track is featured in a TV series |
|  | Featured track order | The numerical order in which songs are played within an episode |
|  | Livenessa | The presence of an audience in the recording |
|  | Speechinessa | The presence of spoken words in a track. |
|  | Instrumentalnessa | Prediction of whether a track contains no vocals |
|  |  |  |
| **DiD** | Treatment | Dummy variable for allocated treatment (0/1) |
|  | Post treatment | Dummy variable for indicating after treatment (0/1) |
|  |  |  |
| **Music popularity** | N playlists | Number of playlists to which a track is added |
|  | Spotify Popularity | Generated ratio number of music popularity (0-100) |
|  |  |  |
| **Dates** | Release date episode | Release date of the episode |
|  | Date | The long format of dates during the observation window |

aThese dimensions are measured on a scale from 0 to 1. The closer the value is to 1, the higher the confidence the track loads highly onto this attribute.

Appendix C Tunefind statistics

**Top 10 representing the number of times a soundtrack is listed on Tunefind**

|  |  |  |
| --- | --- | --- |
| # | Soundtrack Title | Number of observations |
| 1 | The Tonight Show Starring Jimmy Fallon | 1994 |
| 2 | Love Island UK | 1696 |
| 3 | Shameless | 971 |
| 4 | Teen Mom OG | 634 |
| 5 | Jersey Shore: Family Vacation | 591 |
| 6 | Teen Mom 2 | 543 |
| 7 | The Challenge | 543 |
| 8 | Lucifer | 463 |
| 9 | Riverdale | 431 |
| 10 | Empire | 387 |

**Top 10 representing the number of times a song is listed on Tunefind**

|  |  |  |  |
| --- | --- | --- | --- |
| # | Song Title | Name of the artist | Number of observations |
| 1 | Cover Girl | RuPaul | 85 |
| 2 | Dexter Main Title | Rolfe Kent | 60 |
| 3 | Midnight City | M83 | 44 |
| 4 | The Fall | Blake Leyh | 44 |
| 5 | Walking on Sunshine | Katrina & The Waves | 44 |
| 6 | At Last | Etta James | 41 |
| 7 | Rise Up | Andra Day | 40 |
| 8 | Juice | Lizzo | 38 |
| 9 | Celebration | Kool & The Gang | 37 |
| 10 | Push It | Salt-N-Pepa | 36 |

Appendix D Merge validation

The song title and song artist belong to Tunefind, and the name and artist names belong to Chartmetric. As shown, the merger of the two datasets went well.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| track\_id | song\_title | song\_artist | name | artist\_names |
| 3978092 | imafraidtogohome | brianhyland | imafraidtogohome | brianhyland |
| 1139305 | mymancalledme | bigmamathornton | mymancalledme | bigmamathornton |
| 199390 | platoon | jungle | platoon | jungle |
| 31603 | anhonestman | fantasticnegrito | anhonestman | fantasticnegrito |
| 16229082 | beautifulbad | grahamcoxon | beautifulbad | grahamcoxon |
| 3790959 | beautifulgirl | jimmiethompson | beautifulgirl | jimmiethompson |
| 22817 | cantleavethenight | badbadnotgood | cantleavethenight | badbadnotgood |
| 2427083 | takeaslice | glassanimals | takeaslice | glassanimals |
| 3538269 | hawaiianbaby | thespinanes | hawaiianbaby | thespinanes |
| 1633277 | thistimeimgoneforgood | bobbybluebland | thistimeimgoneforgood | bobbybluebland |
| 3808535 | 125yards | bearmccreary | 125yards | bearmccreary |
| 13587725 | indigo | alicegray | indigo | alicegray |
| 13574506 | water | coldway | water | coldway |
| 86590 | dirtyblvd | loureed | dirtyblvd | loureed |
| 294120 | guidinglight | television | guidinglight | television |
| 4991180 | thefirstnoel | dinahshore | thefirstnoel | dinahshore |
| 3768 | wonderwallremastered | oasis | wonderwallremastered | oasis |
| 14771780 | youcouldntbecuter | margaretwhiting | youcouldntbecuter | margaretwhiting |
| 8843 | twofingers | jakebugg | twofingers | jakebugg |
| 5616114 | 196nothingisrealra | macquayle | 196nothingisrealra | macquayle |
| 94598 | santaclausiscomingtotown | franksinatra | santaclausiscomingtotown | franksinatra |
| 18385553 | onetime | dcf | onetime | dcf |
| 9886765 | hehadme | carlyvanskaik | hehadme | carlyvanskaik |
| 47461 | iwillrememberyoulive | sarahmclachlan | iwillrememberyoulive | sarahmclachlan |
| 47518 | lettersfromthesky | civiltwilight | lettersfromthesky | civiltwilight |
| 816352 | itstime | nickwaterhouse | itstime | nickwaterhouse |
| 15950 | icanseeclearlynow | jimmycliff | icanseeclearlynow | jimmycliff |
| 2085404 | makealittlemoney | royaldeluxe | makealittlemoney | royaldeluxe |
| 199744 | playthatfunkymusic | vanillaice | playthatfunkymusic | vanillaice |
| 18002088 | hereiamagain | yerinbaek | hereiamagain | yerinbaek |
| 711142 | somebodyelse | jjgreymofro | somebodyelse | jjgreymofro |
| 88847 | ohdaddy | fleetwoodmac | ohdaddy | fleetwoodmac |
| 17678203 | onelessangel | shybaldwin | onelessangel | shybaldwin |
| 13813887 | socialnationalists | grossnet | socialnationalists | grossnet |
| 9777557 | iamthemainbitch | casbah73 | iamthemainbitch | casbah73 |
| 6828017 | lafoule | youssoupha | lafoule | youssoupha |
| 115437 | words | seinabosey | words | seinabosey |
| 22715 | smother | daughter | smother | daughter |
| 4744405 | thenwebegin | alfa9 | thenwebegin | alfa9 |
| 5028 | sexonfire | kingsofleon | sexonfire | kingsofleon |
| 6977595 | isitandwonder | elgoodo | isitandwonder | elgoodo |
| 1699090 | lonesomeinmyhome | juniorkimbrough | lonesomeinmyhome | juniorkimbrough |
| 698635 | 1998paulvandykremix | binaryfinary | 1998paulvandykremix | binaryfinary |
| 205709 | alwaysbewithyou | walkingoncars | alwaysbewithyou | walkingoncars |
| 179638 | bigshot | billyjoel | bigshot | billyjoel |
| 144760 | songformyfather | horacesilver | songformyfather | horacesilver |
| 7286 | indiansummer | jaiwolf | indiansummer | jaiwolf |
| 7202746 | jamessession | harryjames | jamessession | harryjames |
| 6856699 | offthefloor | arcaneroots | offthefloor | arcaneroots |
| 659957 | poormum | mollydrake | poormum | mollydrake |

Appendix E Propensity score matching

Graphical user interface

Description automatically generated with medium confidence

Appendix F Logit model comparison

1. All matching variables

m\_ps1 <-

glm(treatment ~ danceability + speechiness + + valence + loudness + liveness + energy + acousticness + instrumentalness + tempo + nplaylists + spotify\_popularity, family = binomial(), data = match\_join\_nomiss)

1. **Without non-significant variables**

**m\_ps2 <-**

**glm(treatment ~ speechiness + liveness + instrumentalness + nplaylists + spotify\_popularity, family = binomial(), data = match\_join\_nomiss)**

1. Spotify popularity for popularity metric

m\_ps3 <-

glm(treatment ~ speechiness + liveness + instrumentalness + spotify\_popularity, family = binomial(), data = match\_join\_nomiss)

1. Number of playlists for popularity metric

m\_ps4 <-

glm(treatment ~ speechiness + liveness + instrumentalness + nplaylists, family = binomial(), data = match\_join\_nomiss)

1. Without speechiness

m\_ps5 <-

glm(treatment ~ liveness + instrumentalness + nplaylists + spotify\_popularity, family = binomial(), data = match\_join\_nomiss)

summary(m\_ps5)

1. Without speechiness and liveness

m\_ps6 <-

glm(treatment ~ instrumentalness + nplaylists + spotify\_popularity, family = binomial(), data = match\_join\_nomiss)

1. Popularity only

m\_ps7 <-

glm(treatment ~ nplaylists + spotify\_popularity, family = binomial(), data = match\_join\_nomiss)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| *Model* | *AIC* | *BIC* | *McFadden* | *Cox and Snell* | *Nagelkerke* | *P-value* |
| 1 | 16180 | 16320 | 0.05680 | 0.0019660 | 0.05774 | < 0.001 |
| 2 | **16240** | **16320** | **0.05256** | **0.0018190** | **0.05343** | **< 0.001** |
| 3 | 16330 | 16400 | 0.04700 | 0.0016270 | 0.04778 | < 0.001 |
| 4 | 16660 | 16720 | 0.02796 | 0.0009682 | 0.02843 | < 0.001 |
| 5 | 16370 | 16440 | 0.04466 | 0.0015460 | 0.04540 | < 0.001 |
| 6 | 16380 | 16430 | 0.04407 | 0.0015260 | 0.04480 | < 0.001 |
| 7 | 16380 | 16420 | 0.04405 | 0.0015250 | 0.04478 | < 0.001 |

Appendix G Summary of balance for all data vs matched data

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Before** | Treated Mean | Control Mean | Std. Mean Diff. | Var. Ratio |  |
| Distance | 0.0104 | 0.0030 | 0.1665 | 64.6798 |  |
| Speechiness | 0.0694 | 0.1137 | -0.6269 | 0.1724 |  |
| Liveness | 0.1948 | 0.2088 | -0.0940 | 0.6772 |  |
| Instrumentalness | 0.2073 | 0.2576 | -0.1496 | 0.8303 |  |
| Nplaylists | 56.4934 | 5.2537 | 0.2411 | 48.5129 |  |
| Spotify popularity | 19.2471 | 8.7410 | 0.5406 | 2.4998 |  |
| **After** | *Treated Mean* | *Control Mean* | *Std. Mean Diff.* | *Var. Ratio* | ***Std. Pair Dist.*** |
| Distance | 0.0104 | 0.0104 | -0.0001 | 0.9830 | 0.0032 |
| Speechiness | 0.0694 | 0.0719 | -0.0355 | 1.0253 | 0.6129 |
| Liveness | 0.1948 | 0.1984 | -0.0241 | 0.8097 | 0.9837 |
| Instrumentalness | 0.2073 | 0.1899 | 0.0519 | 1.0309 | 0.7306 |
| Nplaylists | 56.4934 | 41.1380 | 0.0722 | 1.0913 | 0.1522 |
| Spotify popularity | 19.2471 | 20.0380 | -0.0407 | 0.9884 | 0.2244 |

Appendix H Statistical output

Statistical output of the overall main effect

Table

Description automatically generated

Statistical output of the overall main effect, with timeframes.

Table

Description automatically generated

Statistical output of the moderating effect.

Table

Description automatically generated

Appendix I Residual analysis

QQ-plot

Chart, line chart

Description automatically generated

Residual versus fit plot

Chart

Description automatically generated

Appendix J Placebo treatment

25 weeks lagged treatment

Table

Description automatically generated

30 weeks lagged treatment

Table

Description automatically generated

35 weeks lagged treatment

Table

Description automatically generated

40 weeks lagged treatment

Table

Description automatically generated

Appendix K Future research

Week-level fixed effects and popularity control of the main effect.

Table

Description automatically generated

Week-level fixed effects and popularity control of the main effect with timeframes.

**Table

Description automatically generated**