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Let that Sync in: The Effect of Music Reuse on Product Discovery

Abstract

Digitization has importantly expanded the scope for reusing music in movies, a process known as music synchronization. We use panel data on Netflix and Shazam to estimate the causal effect of music synchronization on the discovery of reused songs. Our results show that songs are substantially more likely to be discovered via Shazam's music recognition algorithm when reused in movies that get more Netflix exposure, even after controlling for song quality. We further show evidence of reuse in movies positively affecting song consumption on the Spotify charts, indicating that movies play a significant role in boosting the demand of reused music. These results have important implications for the policy debate on copyright and fair use and can additionally inform the negotiation of licensing rights between movie producers and music rightholders. They additionally improve our understanding of how innovations enabled by digitization can affect the content industries.

Keywords: copyright, reuse, digitization, recorded music, music synchronization.

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1 Introduction

Digitization has drastically affected markets for creative products such as music, movies, and books. By dramatically reducing production and search costs, digital technologies have enabled a massive increase in the production of creative content as well as new opportunities for creators to reuse it in their production process (Waldfogel, 2017; Goldfarb and Tucker, 2019). In the case of music, existing recorded songs can be reused in the context of derivative works, including remixing and digital sampling, or in combination with other forms of creative content.¹ One particularly important avenue for reuse is found in the movie industry, where creators regularly incorporate existing musical works within their audiovisual productions - through a process called "music synchronization" - with the goal of enhancing their creativity and appeal.²

The recent growth of video streaming platforms - combined with the sustained growth in movie production - naturally increased reuse opportunities for musical works. Between 2017 and 2022, synchronization royalties for licensing songs in media - including TV and movies - grew by over 38%. This increase revived interest in the relevance and potential effects of music synchronization for music right-holders and artists.³ Music reuse in movies faces significant transaction costs as it requires the licensing of various copyrights embedded in the underlying musical work to be reused. Because the inclusion of music into a movie requires negotiations between music copyright holders and movie producers, determining whether music synchronization affects the demand for the reused songs becomes particularly relevant to inform the negotiation of licensing rights.

Music synchronization in a movie can draw movie watchers' attention towards reused songs, potentially promoting their discovery and increasing their demand.⁴ Perhaps more

¹Digital sampling is defined as the reuse of a portion (or sample) of a sound recording in another recording.

 $^{^{2}}$ We use the terms "synchronization" and "reuse" interchangeably throughout the paper.

³See, for instance, https://www.billboard.com/pro/music-synch-revenue-tv-film-growing/.

⁴One prominent - and perhaps extreme - example comes from Kate Bush's song "Running Up That Hill" which witnessed a dramatic increase in demand following its appearance on Netflix' fourth season of *Stranger Things*. See, for instance, https://edition.cnn.com/2022/06/23/media/stranger-things-4-netflix-kate-bush/index.html.

importantly, digitization plays a crucial role in the potential effect of music synchronization on the performance of reused songs. Indeed, innovations enabled by digitization have drastically reduced search costs for consumers and improved their ability to discover new music embedded in visual content. In particular, mobile applications that rely on music recognition algorithms (e.g. *Shazam*) allow movie watchers to easily identify songs appearing in a movie by using their smartphone, enabling the discovery of new content.⁵ Such innovation is therefore likely to have increased the potential impact of music reuse on song discovery.

Against this backdrop, this paper estimates the causal effect of music synchronization in movies on the discovery and performance of reused songs. Answering this question is empirically challenging, for two main reasons. The first and major impediment relates to a significant lack of data availability. Indeed, while (some) measures of song performance are readily available, the availability of movie-level consumption data is much more limited. Movie streaming data in particular is typically not accessible as video streaming platforms tend to be very secretive about their data. With a bit of creativity, we are nevertheless able to construct a dataset that is suitable to estimating the causal effect of music reuse in movies on song discovery. More specifically, we combine country-specific movie information on Netflix's Top 10 daily charts with song-level data on the Shazam daily Top 200 charts from July 2020 until December 2022. Given that Shazam is designed to help users identify songs they are currently exposed to, the Shazam Top charts provide a good measure of the outcome of a song discovery process. We additionally rely on the daily Spotify Top 200 charts to assess the effect of reuse on music consumption.

The second challenge we face in identifying the causal effect of music synchronization on discovery relates to the potential endogeneity of both movie and reused songs' performance. To illustrate this point, consider a simple empirical strategy that would consist in asking whether songs reused in movies that get more consumer exposure (e.g. more heavily streamed movies) perform better. While tempting, this approach suffers from an

⁵See https://en.wikipedia.org/wiki/Shazam_(application).

important drawback because songs that appear in movies are not randomly chosen. It is possible that higher quality movies - or movies expected to perform better - are able to include more popular songs, or songs that are expected to become popular. In this case, a simple comparison of songs appearing in movies that stream more with songs that appear in movies that stream less would likely reveal a positive correlation but would fail to identify a causal effect and would lead to biased estimates. The fact that our data include measures of song and movie consumption across countries and over time nevertheless offers the possibility to tackle that empirical challenge. Such panel data structure indeed allow us to control for song fixed effects, effectively asking whether the same song performs better in countries where the movie in which it is reused is streamed more. Put differently, we consider a song to be "treated" with different consumer exposure levels in different countries. Under the assumption that a movie's streaming performance varies across countries for reasons that are unrelated to the popularity of its reused songs, we can measure the causal effect of reuse on song discovery by comparing the Shazam performance of the same song in different countries where the movie in which it is reused obtains different Netflix rankings.

We find several results. We first show that music reuse has a substantial impact on song discovery. A song is over 6 times more likely to appear in the Shazam Top 200 charts when the movie in which it is reused ranks first on Netflix, compared to when the movie ranks tenth. Given Shazam's purpose of helping consumers identify songs they encounter, we interpret these results as evidence of movies positively affecting the discovery of reused songs. Consistent with such mechanism, we identify a substantially larger effect for more recent music, which naturally offers a higher scope for discovery. Using data on worldwide Netflix views and shazams allows us to further confirm the effect of Netflix exposure on Shazam performance. We estimate that an additional million weekly worldwide Netflix views lead to a 3% increase in worldwide Shazams for the reused songs.

We also find positive effects of music synchronization on the Spotify charts appearance, although these are only detectable for more recent music. For the latter group of songs, our estimates indicate that the likelihood of a song appearing in the Spotify Top 200 charts increases by 37% when reused in a movie ranked first on Netflix, compared to when the movie ranks tenth.

Our results have several implications. First, we show that music synchronization in movies, combined with the advent of music recognition algorithms, can serve as a relevant mechanism for the discovery of reused songs by consumers. Second, our results contribute to the policy debate related to copyright and fair use. In the United States, a fundamental consideration when determining whether the use of a work is a fair use relates to how the reuse affects the market for the original work.⁶ In a fair use analysis, courts must therefore review whether the reuse harms the existing or future market of the original work, for instance by displacing its demand. Our results reveal that music synchronization generates a positive effect on the demand for the reused songs and therefore provide direct evidence on this fundamental fair use consideration. Third, and related, these results have important implications for the negotiation of licensing rights between movie producers and music rightholders. When negotiating over copyright licenses, both parties should internalize the fact that synchronization positively affects the market performance of the reused songs. There is, to our knowledge, no evidence that copyright license terms internalize such promotional effect. Finally, our results show how digitization can spur cross-industry complementarities in the case of the movie and music sectors.

The paper proceeds in six sections after the introduction. Section 2 describes the process of music synchronization in movies and documents its growing importance. It also discusses the relevant literature. Section 3 describes the data used in the study and provides descriptive statistics. Section 4 presents our various empirical approaches while Section 5 reports the results of our estimations of the effect of music reuse on song discovery. Section 6 explores the effects of music reuse on song consumption and Section 7 concludes.

⁶This is one of the four factors considered in the US fair use legal doctrine, as outlined in the Section 107 of the US Copyright Act. See https://www.copyright.gov/fair-use/.

2 Background

2.1 Music Synchronization

Music is an essential component of many forms of visual content and is repeatedly reused in movies, TV shows, video games, and commercial advertising, where it is synchronized with moving visual media. In all of these channels, the use of music is indispensable to set the tone, to create a certain atmosphere, and to evoke viewers' emotions.

Movie productions typically involve a music supervisor in charge of selecting the music to be synchronized, and the process of music selection involves various steps and the negotiation of licensing terms. After identifying the songs they need, music supervisors would reach to rightholders (e.g. an artist's publishing company) to negotiate the licensing terms necessary to clear the various copyrights protecting music.⁷ A song is generally protected by two copyrights. The first one is owned by the songwriters and is based on the song composition (melodies and lyrics). The second copyright is based on the sound recording, usually in the hands of a record label. Two types of licenses are therefore involved in the synchronization of pre-recorded songs: a synchronization license that grants permission to use the composition, and a master use license that permits usage of the master recording (Johnson, 2008).

The sustained growth in both movie and music production has – together with the growth in video streaming platforms – increased opportunities for music reuse in movie productions. This has led, in turn, to an increase in the relative importance of synchronization for the music industry. Figure 1 reports the evolution of movie production along with the growth in music synchronization in the US. Setting aside the years 2020-2021 where production came to a halt due to the COVID-19 pandemic, movie production has witnessed a sustained increase, generating growing opportunities for music to be reused. And indeed, revenues coming from music synchronization have followed a similar increasing trend.

⁷The terms of synchronization licenses are generally determined on a case-by-case basis through negotiation and depend on a variety of factors, including the duration of the music used, the number and type of scenes the music appears, the territories the movie will be distributed in, etc. (Passman, 2014).

Over the five-year period between 2017 and 2022, synchronization revenue increased by over 38%. The increasing importance of music synchronization has also been highlighted by industry participants and observers. Reservoir Media, an independent music company based in New York, saw its sync revenue grew 70% in the second quarter of 2022. Its CEO, Golnar Khosrowshahi, notes that "as the film and TV industries [...] thrived in an era where consumption has grown significantly, the music industry has also benefited from this upswing." Christine Barnum, chief revenue officer at CD Baby, also highlights that "[video streaming] services are spending money on sync alongside all this new content they're creating to attract new subscribers."⁸



Source. INDU and FIRA. NOVIES are defined as reactined finits. Revenue is expressed in minions of 2022 USD.

Figure 1: Evolution of Movie Releases and U.S. Music Syncronization Revenue.

Music reuse in movies can generate revenues via two main channels. First, synchronization licenses generate direct revenues for artists and rightholders. Second, music reuse in movies can additionally have promotional effects for the synchronized musical works. The potential of the latter effect has especially been highlighted by the spectacular success

⁸See https://www.billboard.com/pro/music-synch-revenue-tv-film-growing/.

obtained by Kate Bush's "Running Up That Hill" following its appearance in Netflix's TV show *Stranger Things.*⁹ According to Tim Miles, SVP at Warner Music Group, this event has "shown some of our artists just how powerful TV and film can be for them, and how in the age of streaming a spark from sync can cause a forest fire - that wasn't possible 10 years ago. In that sense, I think it will have a really powerful legacy."¹⁰ While the growing importance of sync for the recorded music industry is undeniable, there is currently no systematic evidence on the question of how music synchronization further affects revenue through its impact on song success. Our paper sheds direct light on this effect by identifying the causal impact of music synchronization on the discovery of reused songs.

2.2 Existing Literature

Our paper relates and contributes to four streams of literature. First, we contribute to the literature on the management and economics of product discovery (Sorensen, 2017). More specifically, there is an important and growing literature showing how new technologies enabled by digitization can act as product discovery tools (Godinho de Matos et al., 2016; Aguiar, 2017; Datta et al., 2018; Aguiar and Waldfogel, 2021; Reimers and Waldfogel, 2021; Cabral et al., 2021; Sim et al., 2022; Peukert and Reimers, 2022). We show how innovation in the form of music recognition algorithms can stimulate the demand for musical works reused within movies through a product discovery process. Because our empirical approach relies on charts data to measure the effect of music synchronization on song discovery, our paper also relates to existing work on the impact of best-seller lists on sales and product variety (Sorensen, 2007; Carare, 2012; Cabral and Natividad, 2016). From an econometric perspective, our approach of exploiting cross-country differences in Netflix ranks to identify their effects on song success relates to the approach taken in

⁹See, for instance, https://edition.cnn.com/2022/06/23/media/stranger-things-4-netflix-kate-bush/index.html.

¹⁰See the International Federation of the Phonographic Industry's "Global Music Report 2023", available at https://www.ifpi.org/ifpi-global-music-report-global-recorded-music-revenues-grew-9-in-2022/.

Aguiar and Waldfogel (2021) to identify the effect of Spotify's New Music Friday playlist rankings on song streaming performance.

Second, our study relates to the large literature exploring cross-channel effects in the content industries. Existing studies have typically focused on the effect of a given consumption channel on another, within a same industry. For instance, several studies have estimated the impact of music streaming and music videos on direct music sales (Wlömert and Papies, 2016; Aguiar and Waldfogel, 2018; Kretschmer and Peukert, 2020), as well as the impact of digital distribution on physical sales in movies (Danaher et al., 2010) and in books (Forman et al., 2009; Chen et al., 2019). Nagaraj and Reimers (2023) find that the digitization of books can boost sales of physical editions via a product discovery process. We contribute to this strand of literature by showing that consumption through an industry-specific channel (movies streaming) can affect product discovery in another industry (music).

Third, our paper relates to the large literature on the management and economics of intellectual property. In particular, our study relates to a large strand of literature focusing on the various effects of copyright (Heald, 2014; Reimers, 2019; Biasi and Moser, 2021; Watson et al., 2023) and more specifically to the literature that explores the effect of intellectual property on reuse (Gans, 2015; Nagaraj, 2018; Kaiser et al., 2023; Cuntz, 2023). Perhaps most related to our paper, Watson (2017) shows that digital sampling causes a significant increase in the streaming consumption of reused songs. Consistent with an advertising effect of reuse, this effect is significantly larger for lesser known reused artists. Schuster et al. (2019) similarly report a positive relationship between songs appearing in the Billboard Hot 100 charts and the sales of the songs they sample. We contribute to this literature by showing that music reuse within movies positively affects the discovery of the reused songs, therefore further informing rights-holders' licensing decisions as well as the public policy debate surrounding copyright and fair use.

Fourth, our paper relates to a large literature on the effects of advertisement on product performance. Within the context of the content industries – and similar to our empirical

approach of relying on cross-country variation in movie exposure – Stephens-Davidowitz et al. (2017) estimate the causal effect of advertisement on movie demand by exploiting US cross-city variation in Super Bowl ad exposure. Our paper also naturally relates to Hendricks and Sorensen (2009), who have reported significant advertisement effects in the context of new music album releases.

3 Data and Descriptives

The underlying data used in this study consist in two main datasets that are constructed from four separate sources. Our first dataset provides country-specific information on movies' daily Netflix performance, as well as on the performance of the songs they reuse. Our second dataset includes more detailed information on movie and song performance at the global and weekly level. We now describe the construction of these datasets and provide some basic descriptive statistics.

To construct our first country-level dataset, we first obtained data on the daily Netflix Top 10 movie charts from flixpatrol.com, a third-party website that collects daily countryspecific charts for a variety of streaming platforms.¹¹ Flixpatrol archives the daily Netflix charts directly from the "Top 10 Movies in [country name] Today" section in Netflix, and we obtained these charts for the period ranging from July 7, 2020 to December 6, 2022 for a set of 38 countries.¹² We then obtain the list of songs that appear in these movies from two distinct sources: tunefind.com and what-song.com.¹³

Next, we obtain measures of song performance from chartmetric.com, a third-party ag-

¹¹See www.flixpatrol.com.

¹²The countries included in the sample are: Argentina, Australia, Australia, Belgium, Brazil, Bulgaria, Canada, Chile, Colombia, Costa-Rica, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Mexico, Morocco, Netherlands, New-Zealand, Norway, Peru, Poland, Portugal, Romania, Singapore, Spain, Sweden, Switzerland, Taiwan, Turkey, United Kingdom, United States, and Uruguay.

¹³Both websites provide soundtrack listings of every songs heard in movies and TV shows. In the case of tunefind, song listings "come from Music Supervisors - the professionals responsible for selecting music for TV shows and movies - or may be submitted by users." See https://www.tunefind.com/about. In the case of what-song, their content is generated from a combination of their admins as well as users. See https://www.what-song.com/about.

gregator of music data.¹⁴ For the same period and set of 38 countries listed above, we collect the country-specific daily Top 200 Shazam charts to measure song discovery. As an additional measure of song performance based on consumption rather than discovery, we additionally obtain the daily and country-specific Top 200 Spotify charts.

Finally, we also obtain information on song and movie characteristics. In particular, we observe the release date of each song, which allows us to construct measure of the song's age when the movie in which it is synchronized appears on Netflix's top charts. The Netflix data also allows us to identify whether a given movie is a Netflix original productions. We also obtain the origin country of production as well as the release date of each movie from IMDb.

Our final country-level dataset includes 1,914 distinct movies and 20,296 distinct songs observed across 38 countries' Netflix daily top 10 charts over the period ranging from July 7, 2020 and December 6, 2022.¹⁵ This amounts to a total of 2,341,613 observations.¹⁶ Panel I of Table 1 provides sample statistics on our daily country-level sample. Of all the daily Netflix chart entries in our sample, about 1.9% appear in the Shazam daily top 200 charts, and 0.27% appear in the Spotify daily top 200 charts. Songs are, on average, 15 years old when appearing in movies that make the Netflix charts. The second part of the table presents movie-specific statistics. Movies synchronize an average of 10.6 songs, and out of the 1,914 movies that appear in our final sample, 270 (14.1%) are Netflix originals.

Our second dataset includes worldwide movie and song performance at the weekly level.

 $^{^{14}\}mathrm{See}$ www.chartmetric.com.

¹⁵Because we are interested in the effect of song reuse, we exclude songs that are specifically written for a movie from our sample. Identifying the causal effect of synchronization for songs that are specifically written for a movie may also prove to be more challenging. In particular, unobserved promotion efforts around both the song and the movie may bias estimates. To drop them from our sample, we identify these specific songs by comparing their release date with the release date of the movie in which they appear. We consider a song to have been written specifically for a movie if these two dates coincide.

¹⁶Because our measure of song performance only varies at the song level, and given that our empirical strategy exploits variation in a song's movie exposure based on Netflix ranks, we exclude songs that are reused in multiple movies from the sample. Note that 91.7% of the 22,136 songs in our original sample appear in a single movie. 5.6 percent appear in two movies, and 1.6 percent appear in 3 distinct movies. Less than 0.5 percent appear in more than 3 movies. We obtain almost identical results if we include these observations in our sample.

	Mean	Std. Dev.	Min	Max	Ν
I. Country-Level Data					
a. Netflix Charts Entries					
Is in Shazam Top 200 Charts Is in Spotify Top 200 Charts Song Age	$1.89 \\ 0.27 \\ 5,529.04$	$13.62 \\ 5.22 \\ 5,893.07$	$egin{array}{c} 0 \ 0 \ 2 \end{array}$	$100 \\ 100 \\ 44,859$	2,341,613 2,341,613 2,341,613
b. Movies					
# of Songs Synchronized Is Netflix Exclusive II. Global Data	$10.60 \\ 14.11$	9.43 34.82	$\begin{array}{c} 1 \\ 0 \end{array}$	59 100	$1,914 \\ 1,914$
a. Netflix Charts Entries					
Is in Shazam Top 200 Charts Song Age Netflix weekly views Number of weekly Shazams	$\begin{array}{r} 3.48\\941.55\\10.59\\7,404.33\end{array}$	$18.33 \\888.36 \\10.20 \\17,148.59$	0 1 2 0	$ 100 \\ 6,386 \\ 76 \\ 293,255 $	6,433 6,433 495 2,627
b. Movies					
# of Songs Synchronized Is Netflix Exclusive	$\begin{array}{c} 12.26 \\ 60.13 \end{array}$	$10.45 \\ 49.12$	$\begin{array}{c} 1 \\ 0 \end{array}$	54 100	$\frac{158}{158}$

Table 1: Descriptive Statistics.[†]

[†] Song age is measured in days for the country-level data and in weeks for the global data. Netflix weekly worldwide views are measured in million and measure the global number of views obtained by movies on Netflix. We obtain data on the global weekly Top 10 Netflix movie charts from Netflix.com.¹⁷ Compared to the country-level Netflix charts, these have the advantage of providing information on the weekly number of worldwide Netflix views for the charted movies. We recover these data for English-speaking movies for the period between July 4, 2021 and December 18, 2022 and merge them with the tunefind and what-song data to obtain the list of reused songs in each charted movie. As a measure of song discovery, we again rely on the global Shazam charts. Going beyond rank measures, our global Shazam data also allow us to obtain measures of the total weekly number of times a song is shazamed globally.¹⁸ This second dataset therefore includes weekly measures of both Netflix and Shazam global consumption. Despite their advantage, the higher frequency of these data imply a much smaller number of observations, and our final global sample only includes 158 movies and 1,934 songs, corresponding to about 9% of the country-level sample.

Panel II of Table 1 provides sample statistics on our weekly global dataset. Of all the weekly Netflix chart entries in our sample, 3.5% appear in the Shazam weekly global top 200 charts.¹⁹ Songs are, on average, over 18 years old when appearing in movies that make the Netflix global charts. Movies that appear on the weekly Netflix global Top 10 receive an average of 10.6 million views worldwide. The songs reused in these movies are shazamed an average of 7,404 times every week, worldwide. Movies synchronize an average of 12.3 songs, and out of the 158 movies that appear in the final sample, 95 (60.13%) are Netflix originals.

4 Empirical Approaches

To estimate the effect of music synchronization on the discovery of reused songs, our empirical approach consists in asking whether songs are more likely to be discovered (i.e.

¹⁷See https://www.netflix.com/tudum/top10/.

¹⁸Note that this variable is only available for a subset of songs in our sample. In particular, the size of this subsample is 40% of our main sample.

¹⁹Because we observe the Shazam global top charts at the daily level, we define a song as making the top charts during a given week if the song appeared at least once in the daily global top charts during that week.

"shazamed") when the movie in which they are reused gets more consumer exposure (i.e. streams more on Netflix). We first implement this empirical strategy using the country-level data described above and then rely on our global data to implement a similar approach. We present these separate approaches below.

4.1 Approach Using the Country-level Data

To illustrate the intuition behind our empirical approach relying on the country-level data, Figure 2 reports the share of reused songs at each Netflix Top 10 rank that ultimately appears in the corresponding countries' top 200 Shazam charts. The figure shows that songs reused in movies better ranked on the Netflix charts are more likely to appear in the daily Shazam top 200 charts. Close to 6 percent of the songs reused in movies ranked first in a country's Netflix charts end up appearing on the country's Shazam charts. Close to 3.5 percent of those reused in movies ranked second do so, and this share declines monotonically with the Netflix ranking, reaching only slightly more than 0.5 percent for synchronized songs whose movie is ranked 9 or 10 in the charts. The figure reports very similar patterns when focusing on the Shazam Top 100 or Shazam Top 50 charts.

While the relationship reported in Figure 2 suggests that music reuse matters for song discovery, it naturally does not provide evidence of a causal effect. Indeed, if more popular movies are able to reuse more popular songs, then we would observe a positive correlation between movie and song success even in the absence of any causal effect of music reuse on song discovery.



Figure 2: Netflix Rank and Song Shazam Performance.

To control for this unobserved heterogeneity in song quality, our empirical approach relies on the panel nature of our data. Because we observe a movie's Netflix ranking across countries and over time, we can control for song fixed effects and exploit the within-song variation in Netflix rankings. In other words, controlling for unobserved song quality, we can ask whether the *same song* performs better in countries and days where the movie in which it is reused obtains better Netflix rankings. Our identification assumption is therefore that the cross-country variation in Netflix ranks is exogenous to the popularity of the songs it reuses. Put differently, we assume that the cross-country differences in a movie's Netflix ranking are not driven by the popularity of the songs it reuses. This seems like a reasonable assumption given that consumers' choices of which movie to watch are unlikely to be related to the songs that are reused in the movie. This is naturally true in the case of songs that have yet to be discovered by consumers.

Figure 3a provides some descriptives on the within movie cross-country variation in Netflix ranks by showing the average daily Netflix rank differentials between a given country pair

(the U.S. and Spain) for the overall sample period. For the movies that appear on both countries' charts, the mean rank differential is zero – meaning that a movie gets the same rank in both countries – but there is still significant variation. Likewise, Figure 3b reports a measure of the within-movie variation in Netflix ranks over time.²⁰ We rely on this variation in Netflix charts to identify the causal effect of music reuse on song discovery.

To implement our empirical approach, we define D_{ict} as an indicator variable equal to 1 if song *i* appears in country *c*'s Shazam Top 200 charts on day *t*. Additionally, we define $NetflixRank_{mct}^{r}$ as an indicator equal to 1 when movie *m* in which song *i* is reused is ranked r^{th} in country *c*'s Netflix Top 10 charts on day *t*. We then estimate models of the following form:

$$D_{ict} = \beta_r Net flix Rank_{mct}^r + age_{it} + \mu_i + \eta_c + \lambda_t + \varepsilon_{imct}, \tag{1}$$

where age_{it} measures the age (in years) of song *i* on day *t*, μ_i are song fixed effects, η_c are country fixed effects, and λ_t is a set of day-of-the-year fixed effects.²¹ To simplify the readability of the results, we multiply the dependent variable D_{ict} by 100 when estimating (1). Using β_{10} as the reference group, each β_r coefficient is therefore directly interpreted as a song's percentage point difference in making the Shazam Top 200 charts when the movie in which it is reused is ranked r^{th} , compared to when the movie is ranked 10^{th} . Taking the view that a movie's Netflix ranking varies for reasons that are unrelated to the popularity of the songs that it reuses, the coefficients β_r provide evidence of the causal effect of Netflix exposure on the Shazam performance of reused songs. Given that we observe songs both across countries and over time, we can go a step further and include country-specific song fixed effects in (1). Instead of assuming that the unobserved appeal or quality of song *i* is the same across countries, this allows to further control for the fact

²⁰More specifically, the figure reports the day-to-day change in Netflix ranking averaged across all movies and countries in the sample. Positive values therefore correspond to increase in ranks (i.e. worse positions) whereas negative values correspond to rank improvements.

²¹We construct each song's age as the difference between date t and the release date of the song.



(a) Netflix Top 10 Rank Differentials for the U.S. and Spain.



(b) Day-to-day Same-song Netflix Top 10 Rank Differentials.

Figure 3: Variation in Movies' Netflix Rankings across Countries and Over Time.

that song quality may differ across countries (e.g. a Spanish song is likely to have higher appeal in Spain than in the U.S.).

4.2 Approach Using the Global Data

Beyond providing information on its daily Top 10 charts by country, Netflix also provides information on its weekly Global Top 10 charts. These data do not allow us to rely on cross-country variation in movie exposure to identify the effect of reuse, but they provide information on weekly worldwide views for the movies making the Netflix Global Top 10 charts as well as a measure of songs' weekly worldwide number of shazams.²² While the lack of country variation and the lower frequency of the data imply a much smaller sample of movies and songs, these data provide an additional opportunity to estimate the effect of reuse using information on the intensity of both Netflix and Shazam performance at the global level.

Following a similar empirical strategy, we can rely on within-song variation in Netflix global exposure over time to identify the effect of reuse on Shazam global performance. In other words, we can ask whether a song reused in a given movie performs better on Shazam globally during weeks in which the movie performs better on Netflix. Similar to equation (1), we can start by estimating specifications of the following form:

$$Y_{it} = \beta_r Net flix Rank_{mt}^r + age_{it} + \mu_i + \lambda_t + \varepsilon_{imt}, \qquad (2)$$

where Y_{it} measures the Shazam global performance of song *i* during week *t*, and $NetflixRank_{mt}^{r}$ is equal to 1 when movie *m* in which song *i* is reused is ranked r^{th} in Netflix Global Top 10 charts on week *t*. The variable age_{it} measures the age (in years) of song *i* on day *t*, and we control for song quality via the inclusion of song fixed effects μ_i , and λ_t is a set of week-of-the-year fixed effects.

²²See https://www.netflix.com/tudum/top10/. The worldwide number of Shazams is provided by Chartmetric. Note that this information is only provided for a subset of songs.

We use two distinct measures of performance, Y_{it} . First, we use an indicator for whether song *i* appears in the Shazam Top 200 charts during week *t*. More precisely, because we have access to the Shazam daily global Top charts, we define D_{it} as an indicator for whether song *i* reused in movie *m* appears at least once in the daily global Top Shazam charts during week t.²³ Second, we use the logarithm of the weekly worldwide shazams obtained by song *i* in week *t*.

Using the same two Shazam performance measures, we can further use the intensity of Netflix consumption at the global level to estimate the impact of additional Netflix views on Shazam performance. More specifically, we estimate the following:

$$Y_{it} = \delta Net flix Views_{mt} + age_{it} + \mu_i + \lambda_t + \varepsilon_{imt}, \tag{3}$$

where the variable $NetflixViews_{mt}$ now measures the number of worldwide Netflix views (in millions) of movie m in which song i is reused during week t. Under the assumption that song fixed effects allow us to control for unobserved song heterogeneity, δ provides the causal effect of an additional million Netflix views on Shazam performance.

5 Effect of Reuse on Song Discovery

5.1 Results Using the Country-Level Data

Figure 4 reports the estimated parameters β_r (with β_{10} as the reference group) when estimating various specifications of equation (1). Controlling for day and country fixed effects exclusively - a specification we simply label "No Song FEs" in the figure - the estimated parameters indicate that songs that are reused in movies ranked number 1 on the Netflix charts are about 5 percentage points more likely to appear on the Shazam

²³Note that this definition of Shazam success is therefore slightly different from the one used in Section 4.1 above. In particular, it implies that the β_r coefficients should be interpreted as a song's percentage point difference in making the daily Shazam global charts at least once in week t when the movie in which it is reused is ranked r^{th} , compared to when the movie is ranked 10^{th} .

charts than songs synced in a movie ranked 10^{th} .



Note: The "Song FEs" estimates presents β_r coefficients obtained from estimating equation (1) in the text. The "No Song FEs" estimates come from a similar specification that excludes song fixed effects. The "Song-Country FEs" estimates additionally control for country-specific song fixed effects. Shaded areas represent 95% confidence bands. Standard errors are clustered at the country level.

Figure 4: Effect of Appearing in Netflix Top Charts on Shazam Top 200 Chart Appearance.

Including song fixed effects – a specification we label "Song FEs" in the figure – leads to a substantial decrease in the size of the effects of Netflix ranking, especially for the highest ranks. This is consistent with the idea that part of the relationship between Netflix ranks and song success depicted in Figure 2 results from more popular movies reusing more popular songs, rather than solely reflecting a causal effect of reuse on song discovery. The estimated coefficients nevertheless remain of significance, both economically and statistically. Further controlling for country-specific song fixed-effects – a specification we label "Song-Country FEs" in the figure – leads to very similar estimates. More specifically, the likelihood of a song making the Top Shazam charts increases by 3 percentage points when reused in a movie ranked first on Netflix, compared to when the movie ranks 10^{th} .

Given that only 0.49 percent of the songs reused in movies ranked 10^{th} ultimately reach the Shazam Top 200 charts (see Figure 2), this difference corresponds to a more than 6-fold increase in the likelihood of being discovered. The effect of reuse also falls quite sharply with the Netflix rank. The effect of being ranked 1^{st} is over 35 percent larger than the effect of being ranked 2^{nd} , and 75 percent larger than being ranked 3^{rd} . Note, however, that the estimates still remain statistically significant at lower ranks.

5.1.1 Robustness Checks

Even after controlling for country-specific song fixed effects, it is useful to think about specific instances where our identification assumption may not hold. We now look at these to test the robustness of our results.

Cross-country Differences in Netflix Catalogs

Two aspects of subscription video on-demand (SVOD) platforms may affect the results presented above. First, the rights to distribute content are typically acquired by SVOD platforms on a country-specific basis. This means that some movies could be available in a given country's Netflix catalog but not others. Second, movies available in a given country's Netflix catalog are not necessarily exclusive to the platform. This means that a given movie – even if available in the Netflix catalog of every country – may also be available on competing platforms in some countries. Both of these aspects could affect our results given that our estimation strategy relies on cross-country variation in Netflix exposure. To remedy this, we restrict our sample to the subset of Netflix original movies appearing within the daily Netflix Top 10 charts. This approach guarantees that any movie in our restricted sample is available in every country's Netflix catalog and does not appear on any alternative SVOD platform.

Table 2 reports the results of performing this exercise. As a reference, column (1) presents the results of estimating equation (1) when relying on the full sample, which corresponds

to the estimates shown in Figure 4. Column (2) deals with the concern that movie catalogs may vary across countries by restricting the sample to the subset of Netflix original movies. While the results show a similar pattern as the one reported in column (1), the coefficients are all larger in magnitude. For instance, songs appearing on a Netflix original movie ranked first see their probability of appearing in the Shazam daily top 200 charts increase by over 4.4 percentage points, compared to an estimate of about 3 percentage points when considering all movies. The effect of reuse similarly falls quite sharply with the Netflix rank. One reason why the coefficients in specification (2) are larger lies in the fact that the songs that appear in Netflix original movies tend to be younger on average.²⁴ All else equal, more recent songs present more scope for discovery, which may lead to the larger effects reported.²⁵ Overall, we take the results presented in column (2) as evidence of the robustness of our main results.

Country-Specific Preferences

As noted above, a potential issue with our empirical approach is the existence of countrydifferences in song appeal. While our specifications include country-specific song fixed effects to directly deal with this concern, Netflix ranks may still vary across countries for endogenous reasons. In particular, both movies and the music they reuse might be expected to perform better in their home country than abroad. If domestic music is more likely to be reused in domestic movies, then we would observe a positive relationship between Netflix rankings and song performance, but not because better Netflix exposure causes higher song performance. For instance, Spanish songs would obtain more exposure via Spanish movies in Spain and would also perform better on the Spanish Shazam charts, even if better Netflix exposure had no effect on song discovery. To deal with this concern, we further remove domestic movies from each country. Column (3) of Table 2 reports the

²⁴Songs that appear in Netflix original movies are 11.3 years old, on average, while the corresponding figure is 17.7 for movies that are not Netflix originals.

 $^{^{25}\}mathrm{We}$ explore the differentiated effect of reuse on songs of different age more in detail in Section 5.1.2 below.

				Netflix Movies,
	All Movies	Netflix Movies	No Domestic	No Domestic
	(1)	(2)	(3)	(4)
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Netflix Rank: 1	3.002***	4.426^{***}	2.907^{***}	4.272^{***}
	(0.247)	(0.315)	(0.253)	(0.326)
Netflix Rank: 2	2.203^{***}	3.808^{***}	2.156^{***}	3.677^{***}
	(0.154)	(0.274)	(0.156)	(0.274)
Netflix Rank: 3	1.719^{***}	3.221^{***}	1.675^{***}	3.090^{***}
	(0.126)	(0.253)	(0.122)	(0.242)
Netflix Rank: 4	1.227^{***}	2.507^{***}	1.198^{***}	2.431^{***}
	(0.098)	(0.223)	(0.099)	(0.223)
Netflix Rank: 5	0.849***	1.945^{***}	0.839^{***}	1.868^{***}
	(0.076)	(0.192)	(0.074)	(0.188)
Netflix Rank: 6	0.555***	1.366^{***}	0.563^{***}	1.325***
	(0.054)	(0.142)	(0.055)	(0.142)
Netflix Rank: 7	0.357^{***}	0.900***	0.375^{***}	0.931^{***}
	(0.056)	(0.146)	(0.056)	(0.142)
Netflix Rank: 8	0.247^{***}	0.679^{***}	0.247^{***}	0.659^{***}
	(0.044)	(0.128)	(0.045)	(0.129)
Netflix Rank: 9	0.108^{***}	0.334^{***}	0.101^{**}	0.302^{**}
	(0.038)	(0.112)	(0.040)	(0.112)
Song Age	-0.611^{***}	-1.937^{***}	-0.649***	-2.139***
	(0.194)	(0.249)	(0.197)	(0.231)
Day-of-the-Year Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark
Song-Country Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark
$Adjusted-R^2$	0.642	0.653	0.643	0.653
N	2341613	937908	2256624	910115

Table 2: Netflix Movie Rank Effects on Song Shazam Performance. [†]

[†] The table reports the results of estimating equation (1) in the text. The dependent variable is equal to 100 if a synchronized song appears in the Shazam Top 200 charts and 0 otherwise. The reference group is defined by movies ranked 10^{th} on the Netflix charts. Each coefficient is therefore interpreted as a song's percentage point difference in making the Shazam Top 200 charts when the movie in which it is reused is ranked r^{th} , compared to when the movie is ranked 10^{th} . Standard errors are clustered at the country level and reported in parenthesis.

 \ast Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

results of estimating equation (1) excluding domestic movies from the sample. The results are very similar to the results for the full sample presented in column (1). Specification (4) additionally removes domestic movies from the sample of Netflix original movies. Compared to specification (2), the estimates are again virtually unchanged. Overall, Table 2 therefore provides support to the validity of our empirical approach and the robustness of our estimates of the causal effect of music reuse on song discovery.

Alternative Definitions of Song Performance

Our measure of song performance relies on whether a given song ultimately appears in the Shazam Top 200 charts. To further test the robustness of our results, we implement our estimation approach using alternative cutoff values for the Shazam Top charts. More specifically, we restrict our attention to the Top 100, Top 50, and Top 10 Shazam charts to ask whether reuse also has an effect on these more restrictive discovery measures. Figure 5 reports the results of estimating equation (1) when using these three alternative definitions of discovery, controlling for country-specific song fixed effects. As expected, the effect of music synchronization are smaller when relying on more restrictive discovery measure of song performance, but we still observe significant effects even when focusing on the Shazam Top 10. For instance, the likelihood of a song appearing in the Shazam Top 10 charts increases by 0.2 percentage points when the movie in which it is reused ranks first on Netflix, compared to when the movie ranks tenth. The corresponding effect increases to about 1.2 percentage points when focusing on the Shazam Top 50 charts, and to 2.2 percentage points when focusing on the Top 100.



Figure 5: Netflix Rank Effects on Shazam Song Performance.

Note: The figures present the results from estimating equation (1) in the text, using various dependent measure of Shazam performance as the dependent variable and controlling for country-specific song fixed effects. The dependent variable is equal to 100 if the song appears in the corresponding Shazam charts and 0 otherwise. Shaded areas represent 95% confidence bands. Standard errors are clustered at the country level.

5.1.2 Effect on Frontline vs Catalog Songs

We have reported a significant causal effect of music reuse on song discovery. To provide further evidence on the mechanisms driving this effect, we now explore the differential effect of music reuse on songs of different age. All else equal, recent songs offer a higher degree of product discovery relative to older songs that are more likely to be known. If the estimates presented above result from product discovery, then we should observe stronger effects for more recently released music. Following the music industry convention, we start by distinguishing between "frontline" and "catalog" music, the former being defined as music that is 18 months old or younger.²⁶ We explore the differential effect of music

 $^{^{26}\}mathrm{Within}$ our sample, 12.9% of the Netflix charts entries correspond to frontline songs.

reuse on these two groups of songs by interacting the Netflix rank variables in equation (1) with an indicator variable for frontline songs.

Figure 6 reports the results of these estimations, again controlling for country-specific song fixed effects. Consistent with the outcome of a product discovery process, the estimates are substantially larger when focusing on frontline songs. Relative to being reused in a movie ranked 10^{th} on the Netflix charts, appearing in a movie ranked first increase frontline songs' likelihood of making the Shazam Top 200 charts by 8.5 percentage points. This effect is over four times larger than for catalog music.



Note: The reported estimates correspond to the coefficients on the Netflix rank variables interacted with an indicator variable for frontline and catalog songs in equation (1), controlling for country-specific song fixed effects. Shaded areas represent 95% confidence bands. Standard errors are clustered at the country level.

Figure 6: Netflix Rank Effects on Shazam Performance for Frontline and Catalog Songs.

Note that the effects for catalog music are still significant and substantial. For catalog songs, appearing in a movie ranked first on Netflix still increases the likelihood of making the Shazam charts by close to 2 percentage points relative to the movie being ranked tenth.

While more recent songs, by definition, offer a higher likelihood of being discovered, this result indicates that reuse can also be beneficial for the discovery of older songs.

Table 3 reports the results of estimating similar specifications where a continuous measure of song's age is interacted with the Netflix rank variables. Following the structure of Table 2, the table presents four specifications that are each based on different samples. Column (1) considers the full set of movies while column (2) focuses on the subsample of Netflix original movies. Column (3) excludes domestic movies, and column (4) excludes domestic movies from the restricted sample of Netflix original movies. Consistent with the estimates presented in Figure 6, all three specifications reveal that older songs obtain a significantly lower likelihood of making the Shazam top charts at every Netflix rank.

5.2 Results Using the Global Data

While the lack of cross-country variation and the lower frequency of our weekly global data results in a much smaller sample of movies and songs, they offer an alternative to estimate the effect of reuse using information on the intensity of both Netflix and Shazam performance.

Figure 7 presents the results of estimating equation (2) using our two measures of global Shazam performance. The left-hand panel of the figure reports the results of using the appearance on the Shazam global weekly Top 200 charts as a dependent variable. Once again, the results show that better Netflix ranks lead to a significantly higher likelihood of making the Shazam Top charts for reused songs. After controlling for song fixed-effects, being reused in a movie ranked first on the Netflix weekly global charts increases the song's likelihood of making the daily Shazam global charts at least once in that week by close to 12 percentage points, relative to the movie being ranked 10^{th} .

The right-hand panel of Figure 7 reports the results of using the logarithm of the weekly worldwide shazams as a measure of performance. The results show similar patterns and

				Netflix Movies,
	All Movies	Netflix Movies	No Domestic	No Domestic
	(1)	(2)	(3)	(4)
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Netflix Rank: 1	3.989***	5.264***	3.877***	5.087***
	(0.344)	(0.415)	(0.353)	(0.431)
Netflix Rank: 2	3.114***	4.651***	3.065^{***}	4.508***
	(0.210)	(0.338)	(0.213)	(0.339)
Netflix Rank: 3	2.499***	3.938^{***}	2.430***	3.770***
	(0.175)	(0.299)	(0.174)	(0.294)
Netflix Rank: 4	1.803***	3.028***	1.769^{***}	2.934^{***}
	(0.147)	(0.270)	(0.150)	(0.271)
Netflix Rank: 5	1.391***	2.501^{***}	1.367^{***}	2.405^{***}
	(0.125)	(0.250)	(0.125)	(0.247)
Netflix Rank: 6	0.968^{***}	1.761^{***}	0.959^{***}	1.715***
	(0.087)	(0.187)	(0.090)	(0.186)
Netflix Rank: 7	0.643^{***}	1.140^{***}	0.671^{***}	1.182^{***}
	(0.099)	(0.198)	(0.098)	(0.189)
Netflix Rank: 8	0.465^{***}	0.879^{***}	0.461^{***}	0.842^{***}
	(0.073)	(0.172)	(0.074)	(0.172)
Netflix Rank: 9	0.226^{***}	0.437^{***}	0.216^{***}	0.391^{***}
	(0.061)	(0.141)	(0.063)	(0.141)
Netflix Rank: $1 \times \text{Song Age}$	-0.070***	-0.072***	-0.069***	-0.070***
	(0.008)	(0.011)	(0.009)	(0.012)
Netflix Rank: $2 \times \text{Song Age}$	-0.062***	-0.073***	-0.063***	-0.072***
	(0.005)	(0.008)	(0.005)	(0.008)
Netflix Rank: $3 \times \text{Song Age}$	-0.052***	-0.062***	-0.051^{***}	-0.059***
	(0.004)	(0.007)	(0.004)	(0.008)
Netflix Rank: $4 \times \text{Song Age}$	-0.038***	-0.045***	-0.038***	-0.043***
	(0.004)	(0.007)	(0.004)	(0.007)
Netflix Rank: $5 \times \text{Song Age}$	-0.035***	-0.048***	-0.034^{***}	-0.047***
	(0.004)	(0.006)	(0.004)	(0.006)
Netflix Rank: $6 \times \text{Song Age}$	-0.026***	-0.034***	-0.025***	-0.034***
	(0.003)	(0.006)	(0.003)	(0.006)
Netflix Rank: $7 \times \text{Song Age}$	-0.018***	-0.021***	-0.019^{***}	-0.022***
	(0.003)	(0.006)	(0.003)	(0.006)
Netflix Rank: $8 \times \text{Song Age}$	-0.013***	-0.017^{***}	-0.013***	-0.016***
	(0.002)	(0.005)	(0.002)	(0.005)
Netflix Rank: $9 \times \text{Song Age}$	-0.007***	-0.009**	-0.007***	-0.008^{*}
	(0.002)	(0.004)	(0.002)	(0.004)
Song Age	-0.612^{***}	-1.900***	-0.649^{***}	-2.100***
	(0.192)	(0.249)	(0.195)	(0.232)
Day-of-the-Year Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark
Song-Country Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark
$\operatorname{Adjusted} - R^2$	0.642	0.654	0.643	0.653
N	2341613	937908	2256624	910115

Table 3: Netflix Movie Rank Effects on Song Shazam Performance. [†]

[†] The dependent variable is equal to 100 if a synchronized song appears in the Shazam Top 200 charts and 0 otherwise. The reference group is defined by movies ranked 10th on the Netflix charts. Song age is measured in years. Standard errors are clustered at the country level and reported in parenthesis.

 * Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

indicate that higher Netflix exposure leads to a significant increase in shazams. In particular, a song reused in a movie ranked first on the global charts is shazamed over 170%more than if the movie were ranked 10^{th} .²⁷



Graph by Performance Measure

Note: The "Song FEs" specifications report the β_r coefficients obtained from estimating equation (2) in the text. The "No Song FEs" estimates come from a similar specification that excludes song fixed effects. The left-hand figure reports estimates that rely on a dependent variable equal to 100 if the song appears in the Shazam Top 200 charts and 0 otherwise. The right-hand figure reports estimates using the log of the total number of global shazams as a dependent variable. Shaded areas represent 95% confidence bands. Standard errors are clustered at the song level.

Figure 7: Global Netflix Rank and Song Shazam Performance.

Table 4 presents the results of estimating equation (3), using our two measures of shazam performance. Columns (1) and (2) consider appearance in the Shazam charts as a measure of song discovery. The estimates indicate that an additional million worldwide Netflix views – a ten percent increase relative to the sample average, see Table 1 – leads to an increase of 0.4 percentage points in the probability of appearing in the Shazam global

²⁷Given that the coefficient on the dummy for songs ranked first is equal to 1.022, we calculate this effect as $100 \times (e^{1.022} - 1)$.

Top 200 for reused songs. Specifications (3) and (4) use the logarithm of the number of shazams as the dependent variable. Focusing on the subsample of original Netflix movies, the estimate indicates that an additional million global Netflix views leads to an increase in worldwide shazams of about 3 percent for the reused songs.

Dependent Variable:	Appearing in	Shazam Top 200	log(Number	• of Shazams)
	(1)	(2)	(3)	(4)
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Netflix Weekly Views	0 433***	0 414***	0 044***	0 030***
rectilit weekly views	(0.075)	(0.070)	(0.006)	(0.003)
Song Age	-0.064***	-5.717	-0.027***	-0.436
	(0.024)	(3.722)	(0.008)	(0.300)
Week-of-the-year Fixed Effects	\checkmark	\checkmark	\checkmark	\checkmark
Song Fixed Effects	×	\checkmark	×	\checkmark
$Adjusted-R^2$	0.087	0.639	0.114	0.980
N	6433	6433	2627	2627

Table 4: Netflix Streaming Effects on Song Shazam Performance. [†]

[†] Netflix weekly views are measured in millions. Standard errors are clustered at the song level and reported in parenthesis.

* Significant at the 10% level.

 ** Significant at the 5% level.

*** Significant at the 1% level.

6 Effect of Reuse on Song Consumption

After documenting a positive effect of music reuse on song discovery, it is perhaps reasonable to expect a positive effect of reuse on music consumption, for at least two reasons. First, users may decide to further listen to a song on a music streaming platform like Spotify after they discover it through Shazam. Second, users may also decide to directly search for a reused song on a music streaming platform after hearing it in a movie.

Using the same empirical approach as above, we can rely on the Spotify daily Top 200

charts to test whether music synchrnization in movies affects the consumption of reused songs. At the outset, we note that measuring this effect is challenging given the nature of the Spotify data. In particular, the Spotify charts only provide consumption measures for the most popular songs, whose demand is driven by many additional factors besides exposure through movies. This can potentially challenge our ability to detect an effect of reuse on consumption given that this effect would have to be large enough to be detectable within the Top 200 Spotify charts.²⁸

Keeping this caveat in mind, the left-hand panel of Figure 8 reports the share of reused songs at each Netflix Top 10 rank that ultimately appears in the corresponding countries' Top 200 Spotify charts. Much like the relationship presented in Figure 2, the figure indicates that songs reused in movies that perform better on Netflix tend to perform better on Spotify as well. Note, however, that the magnitude of the shares are much smaller than in the case of Shazam. Less than 0.5 percent of the songs that appear in a movie ranked first or second on the Netflix charts end up appearing in the Spotify Top 200 charts. As discussed above, this is perhaps unsurprising given that the demand for the Top 200 most popular songs is driven by multiple factors besides exposure through movies. The right-hand panel of Figure 8 reports a similar relationship when using the log of Spotify streams as a measure of song performance.

 $^{^{28}}$ Additionally, note that the temporal effects of reuse on discovery may differ from the ones on consumption. While the effect of reuse on discovery materializes instantaneously via Shazam – by definition, a song can only be shazamed at the exact time at which the user hears it – a user's Spotify consumption decisions can take place long after they discovered a song through Shazam.



Figure 8: Netflix Rank and Song Spotify Performance.

Following a similar approach as the one presented in Section 4.1, we can estimate specifications of equation (1) relying on two measures of Spotify performance. The left panel of Figure 9 reports the estimated parameters β_r when using the appearance on the Spotify charts as a measure of music consumption. Mimicking the results from Figure 8, the specification that does not control for song fixed effects – labeled "No Song FEs" in the figure – shows that songs appearing in better ranked movies are more likely to appear on the Spotify charts. Controlling for country-specific song fixed effects, however, substantially decreases the coefficients which nevertheless remain statistically significant up to rank 5. The right panel of the figure performs a similar exercise using the logarithm of the Spotify streams as a dependent variable, and the reported estimates present a very similar pattern.



Note: The "Song-Country FEs" estimates presents β_r coefficients obtained from estimating equation (1) in the text. The "No Song FEs" estimates come from a similar specification that excludes song fixed effects. For the left-hand panel, song performance is based on appearance on the Spotify Top 200 charts. For the right-hand panel, song performance is based on the logarithm of Spotify streams. Shaded areas represent 95% confidence bands. Standard errors are clustered at the country level.

Figure 9: Effect of Appearing in Netflix Top Charts on Spotify Performance.

Following the robustness tests presented in Section 5.1.1, Table 5 reports the results of estimating similar specifications on the subset of Netflix original movies. As indicated in specifications (2) and (6), the estimates are larger in magnitude when relying on the set of Netflix original movies. Additionally restricting the sample to exclude domestic movies – in specifications (4) and (8) – does not further affect the estimates. As mentioned in Section 5.1.1, a factor that might be driving the difference in coefficients when relying on the sample of Netflix original movies is that the latter tend to reuse more recent songs, which also make for the lion's share of the Spotify Top 200 charts.²⁹ This further suggests that performing our analysis by differentiating between catalog and frontline

²⁹For the country and time period that correspond to our sample, the share of frontline songs within the Spotify Top 200 charts is equal to 70%, and the average song age is equal to 3.1 years.

music is likely more amenable to identify the effect of reuse on consumption.

Figure 10 reports our estimation results when differentiating between catalog and frontline music and controlling for country-specific song fixed effects. The left-hand panel of the figure show the corresponding estimates when using the appearance on the Spotify charts as a measure of song performance. While we are indeed unable to detect a significant effect of reuse on consumption for catalog songs, there is a positive and significant effect for frontline music. Relative to being reused in a movie ranked 10^{th} on the Netflix charts, appearing in a movie ranked first increase frontline songs' likelihood of making the Spotify Top 200 charts by 0.35 percentage points. Given that 0.94 percent of frontline songs reused in movies ranked 10^{th} make the Spotify charts, this effect corresponds to a 37% increase in the likelihood of making the Spotify charts. The right-hand side of the figure reports the results of using the log of Spotify streams as the dependent variable. Again, we are unable to detect an effect of reuse on consumption for catalog songs but a clear positive effect is found for frontline music. Relative to being reused in a movie ranked 10^{th} on the Netflix charts, appearing in a movie ranked first increase frontline songs' Spotify streams by 3.6 percent. These results clearly indicate that reuse in movies positively affect consumption within the set of frontline songs.

Due to the limitations associated with the Spotify Top 200 charts data – in particular the fact that it mostly contains recent music – we are reluctant to interpret the insignificance of our catalog estimates as evidence of lack of an effect of reuse on older music. Rather, we believe that more comprehensive consumption data would be useful to identify the effect of reuse on consumption for catalog music.

Table 5: Netflix Movie Rank Effects on Song Spotify Performance. †

Dependent Variable:		Appearing in	Spotify Top 200			log(St	treams)	
	All Movies	Netflix Movies	No Domestic	Netflix Movies, No Domestic	All Movies	Netflix Movies	No Domestic	Netflix Movies, No Domestic
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Netflix Rank: 1	0.041^{***}	0.123^{***}	0.040^{***}	0.115^{***}	0.004^{***}	0.012^{***}	0.004^{***}	0.011^{***}
	(0.014)	(0.021)	(0.013)	(0.019)	(0.001)	(0.002)	(0.001)	(0.002)
Netflix Rank: 2	0.035^{***}	0.115^{***}	0.038^{***}	0.112^{***}	0.004^{***}	0.011^{***}	0.004^{***}	0.011^{***}
	(0.010)	(0.018)	(0.010)	(0.018)	(0.001)	(0.002)	(0.001)	(0.002)
Netflix Rank: 3	0.040^{***}	0.114^{***}	0.039^{***}	0.105^{***}	0.004^{***}	0.011^{***}	0.004^{***}	0.010^{***}
	(0.011)	(0.022)	(0.010)	(0.020)	(0.001)	(0.002)	(0.001)	(0.002)
Netflix Rank: 4	0.025^{**}	0.095^{***}	0.024^{**}	0.087^{***}	0.003^{**}	0.009^{***}	0.003^{**}	0.008^{***}
	(0.011)	(0.021)	(0.010)	(0.020)	(0.001)	(0.002)	(0.001)	(0.002)
Netflix Rank: 5	0.023^{***}	0.098^{***}	0.021^{***}	0.091^{***}	0.002^{***}	0.010^{***}	0.002^{***}	0.009^{***}
	(0.008)	(0.022)	(0.00)	(0.021)	(0.001)	(0.002)	(0.001)	(0.002)
Netflix Rank: 6	0.008	0.071^{***}	0.007	0.066^{***}	0.001	0.007^{***}	0.001	0.006^{***}
	(0.007)	(0.021)	(0.007)	(0.021)	(0.001)	(0.002)	(0.001)	(0.002)
Netflix Rank: 7	0.005	0.049^{**}	0.002	0.045^{**}	0.000	0.005^{**}	0.000	0.004^{**}
	(0.007)	(0.021)	(0.007)	(0.021)	(0.001)	(0.002)	(0.001)	(0.002)
Netflix Rank: 8	0.005	0.040^{**}	0.005	0.037^{*}	0.001	0.004^{**}	0.000	0.004^{**}
	(0.007)	(0.018)	(0.008)	(0.019)	(0.001)	(0.002)	(0.001)	(0.002)
Netflix Rank: 9	-0.004	0.013	-0.005	0.015	-0.000	0.001	-0.001	0.001
	(0.006)	(0.015)	(0.006)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)
Song Age	-0.075^{*}	0.383^{***}	-0.082^{*}	0.345^{***}	-0.006	0.039^{***}	-0.007*	0.034^{***}
	(0.044)	(0.107)	(0.044)	(0.104)	(0.004)	(0.011)	(0.004)	(0.010)
Day-of-the-Year FEs	>	∕	>	>	>	>	>	>
Song-Country FEs	>	>	>	>	>	>	>	>
$\operatorname{Adjusted} R^2$	0.881	0.912	0.883	0.912	0.882	0.913	0.885	0.915
N	2341613	937908	2256624	910115	2341613	937908	2256624	910115
[†] The table reports the	results of esti-	mating equation (1	l) in the text. The	ie dependent varial ranked 10 th on the	ole is equal to Notfliv chart	100 if a synchroniz	ed song appears is therefore inte	in the Spotify Top
percentage point diffe	rrence in makin	ng the Spotify Top	200 charts when	tanked to on the the movie in which	ch it is reused	is ranked r^{th} , com	is unerelore inter- pared to when t	tpreted as a soug s he movie is ranked
10^{th} Standard errors	s are clustered	at the country leve	el and reported ir	n parenthesis.		<i>l</i>		

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.



Note: The reported estimates correspond to the coefficients on the Netflix rank variables interacted with an indicator variable for frontline and catalog songs in equation (1). For the left-hand panel, song performance is based on appearance on the Spotify Top 200 charts. For the right-hand panel, song performance is based on the logarithm of Spotify streams. Shaded areas represent 95% confidence bands. Standard errors are clustered at the country level.

Figure 10: Netflix Rank Effects on Spotify Performance for Frontline and Catalog Songs among all movies.

7 Conclusion

The sustained growth in movie production enabled by digitization has importantly expanded the scope for reusing music in movies. Despite the growing importance of music synchronization, there is limited empirical evidence on its effects on song performance.

Using data on movies' Netflix performance, we shed light on this question by identifying the causal impact of music reuse on song discovery. Our results show that even after controlling for country-specific song quality, the likelihood of a song appearing in the Shazam Top 200 charts increases more than 6 times when the movie in which it is reused ranks first on Netflix, compared to when the movie ranks tenth. Given Shazam's purpose of helping consumers identify songs they are exposed to, we interpret these results as evidence of movies positively affecting the discovery of music they reuse. Consistent with such mechanism, we further show that this effect is more pronounced for more recent music, which naturally offers a higher scope for discovery. We further estimate that an additional million worldwide Netflix views leads to an increase of 3% in worldwide shazams for reused songs.

Our analysis also reveals positive effects of synchronization on music consumption, although these are more modest in magnitude and only detectable for more recent music. This is perhaps unsurprising given that the Spotify Top 200 charts only provide information on the most popular songs, whose demand is driven by many other factors than exposure through movies. Our estimates indicate that the likelihood of a frontline song appearing in the Spotify Top 200 charts increases by 37% when reused in a movie ranked first on Netflix, compared to when the movie ranks tenth. We highlight that more comprehensive consumption data would be needed to identify the effect of reuse on consumption for older music.

Our results have several implications. First, they show that music synchronization in movies – combined with the advent of music recognition algorithms enabled by digitization – can serve as a relevant channel for the discovery of reused songs. Second, we contribute to the policy debate on copyright and fair use. Specifically, we provide direct evidence on a key factor of the U.S. fair use doctrine by showing that music reuse in movies does not directly harm, and may even enhance, the market for the original work. These results complement previous findings on music sampling (Watson, 2017; Schuster et al., 2019) and suggest that music reuse in movies can directly benefit copyright holders, potentially supporting its consideration as fair use in certain contexts. Third, these results can inform the negotiation of licensing rights between movie producers and music rightholders. Finally, our results show how new technologies enabled by digitization can spur cross-industry complementarities.

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