Fractional Ownership and Copyright Licensing: Evidence from the Music Industry

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Abstract

Creative content is often the product of collaboration, which may lead to fractional ownership of intellectual property. We study the effect of fractional ownership on the licensing of copyrighted material and its use in follow-on works. To do so, we compile new data on the copyright ownership structure of songs and their licensing for use in movies. We document that fractional song ownership has increased substantially: the mean number of songwriters and publishers per song has tripled between 1958 and 2021. We show that, conditional on a rich set of controls, greater fractionalization is associated with lower likelihood of licensing. We leverage the Sony-led acquisition of EMI Music Publishing in 2012 to obtain within-song variation in ownership and find that consolidating ownership rights significantly increases licensing, beyond any standalone effects of the merger.

Keywords: copyright licensing, ownership fractionalization, music industry

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1 Introduction

Intellectual property (IP) is one the main policy instruments used by governments to increase innovation incentives and creativity. Copyrights and patents, the two most prominent forms of IP, grant owners the right to exclude others from copying protected ideas. At least since Nordhaus (1969), economists have noted that these exclusionary rights may lead to market power which, in turn, may generate product market distortions. On top of this 'static' trade-off, the welfare effects of intellectual property also depend on its impact on follow-on innovators and creators. In cumulative innovation settings, where new ideas build on existing ideas, IP generates additional 'dynamic' trade-offs (Aghion et al., 2001; Acemoglu and Akcigit, 2012). In this context, IP holders may obtain additional rents from follow-on creators and innovators that need a license to develop their ideas. Whether follow-on innovation takes place depends on the ability of subsequent generations of IP holders to reach an agreement on the licensing terms.

The management literature has emphasized the crucial role that IP licensing negotiations play in shaping the diffusion of new knowledge, the incentives to innovate, and vertical specialization (Gans and Stern, 2003; Arora et al., 2004). At the same time, several studies have documented the challenges that firms face when negotiating a licensing deal. For example, survey evidence examined by Agrawal et al. (2015) shows that, on average, technology-oriented organizations successfully conclude only half of the patent license negotiations they start.

Intellectual property licensing negotiations are likely to be particularly problematic when follow-on innovators require permission from multiple IP holders to develop their ideas. The argument is that, in a multilateral negotiation, transaction costs are higher, reaching an agreement may take longer, and the risk of bargaining failure is higher (Heller and Eisenberg, 1998; Shapiro, 2001). These views have shaped policy discussion, suggesting scrutiny of licensing practices for standard essential patents, and supporting the formation of patent pools. Some scholars argue instead that these concerns are excessive, as they rely on specific assumptions about the licensing process (Spulber, 2016).

These conflicting viewpoints highlight the need for empirical work that identifies if, and in what environments, the IP ownership structure may generate frictions in the licensing process. Obtaining such empirical evidence is challenging due to two key issues. The first is measurement. It is typically not feasible to observe on a large scale the set of licenses that follow-on creators need to develop a new idea. Researchers have relied on indirect measures constructed using the degree of concentration in patenting or patent citations (Ziedonis, 2004; Galasso and Schankerman, 2010; Noel and Schankerman, 2013). Measuring cumulativeness directly is also difficult, and researchers often use patent measures as proxies. Even when specific measures of follow-on ideas are available, a key difficulty is to distinguish between cases where IP owners are willing to license (surplus-enhancing follow-on ideas) and those where they are unwilling to license due to rent dissipation (Gaessler et al., 2024).

The second challenge relates to the endogeneity of the IP ownership structure. Specifically, IP inputs with dispersed ownership may differ from others in ways that also affect licensing propensity. For example, collaborative projects may also have higher quality, which leads to greater licensing. Ideally, one would like to observe how licensing outcomes are affected from a change in ownership structure while keeping the underlying protected knowledge fixed.

This paper provides a novel look at the relationship between IP ownership and cumulative use in a setting that allows us to advance on both fronts. Specifically, we examine the use of copyrighted musical compositions as soundtrack in movies. First, we construct a detailed dataset that identifies the use in movies for all songs that appeared in the Billboard weekly charts from 1958 to 2021. Relative to other cumulative innovation settings, the use of a song in a movie is unlikely to generate substantial rent dissipation effects, as the purchase of a song is typically not a substitute for the purchase of a movie. Second, we obtain rich information on copyright ownership for all the songs in our sample, by accessing proprietary data from the Mechanical Licensing Collective (MLC). We show that, for a large fraction of songs, the copyright is co-owned by several music publishers representing the songwriters who created the piece. The variance in co-ownership is substantial, and the extent of fractional ownership has increased considerably over time, especially in the past twenty years. Because movie producers require a license from all co-owning publishers, this data allows us to measure directly the number of negotiations required by follow-on creators.

We use this cross-sectional information to document a robust negative correlation between the fractionalization of copyright ownership and the use of a song as soundtrack in a movie. Our estimates indicate an average reduction in the likelihood of licensing of about 25 percent for the songs with the highest ownership fractionalization, relative to the other songs in our sample.

As a first step to address identification threats from unobserved heterogeneity, we show that the finding is robust to controlling for detailed information about the song. Even in regression models where the identifying variation involves the comparison of songs released by the same performing artist, in the same genre, and with similar performance on the Billboard chart, we still find that ownership fractionalization is associated with lower usage in movies.

We explore several dimensions of heterogeneity to better understand the economic mechanisms at play. In line with the predictions of standard models of product differentiation, we find that the negative association between ownership fractionalization and licensing is more pronounced in settings with higher substitutability between songs, such as the use of pop songs in comedy movies. Conversely, the negative association is not statistically significant in cases where substitutability is likely to be low, such as the use of songs in documentaries about a specific music band.

Our second empirical exercise leverages the 2012 acquisition of EMI Music Publishing by Sony. This acquisition led to a reduction in the negotiations required to license songs that were previously co-owned by EMI and Sony. Exploiting this within-song variation in copyright ownership, we show that the merger led to an increase in the use of previously co-owned songs in movies. Comparing the licensing of co-owned songs with licensing of songs that were exclusively owned by either Sony or EMI, we demonstrate that the result is not merely driven by the standalone effects of the merger. We also show that the effect appears driven by the co-owned songs with the highest degree of fractionalization, which provides further support to the idea that simplifying the copyright ownership structure facilitates licensing.

Finally, we use our parameter estimates to provide a simple quantification of the effect of copyright fractionalization on songwriters and movie producers. Back of the envelope computations linking the estimated effects to publicly available estimates of licensing fees suggest that fractionalization may have a non-trivial effect on licensing revenue and songwriters' income. Conversely, a simple calibration of a nested logit model of demand for song by filmmakers suggests small effects of fractionalization on filmmakers' surplus. While illustrative, these computations are consistent with the idea that filmmakers consider songs as highly substitutable in many circumstances.

From an IP policy perspective, our analysis has implications for the substantial increase in the number of jointly owned patents that the U.S. witnessed during the past decades (Belderbos et al., 2014; Briggs, 2015). This is typically explained by greater collaboration among firms, as well as greater collaboration with universities. For example, U.S. estimates suggest that more than 15 percent of university patents are co-owned with other organizations (Funk, 2013). Taken together, our findings indicate that such an increase in fractionalization of IP may impact the cumulative innovation process. As we discuss in Section 9, our findings also have implications for the proposed revisions of the consent decree with ASCAP and BMI (Department of Justice, 2019).

From a managerial perspective, our results suggest that creators and innovators should take into account the possible trade-offs generated by IP co-ownership. This parallels common warnings given to technology start-ups that badly structured capitalization tables may discourage investors (Kamps, 2024). Moreover, digitization and specialization among songwriters are important drivers of the increase in copyright fractionalization that we observe in the data (Seabrook, 2015). In this respect, our findings suggest that changes in the production function of creative goods may have implications for the functioning of the market for IP and the diffusion of creative content.

The rest of the paper proceeds as follows. Section 2 reviews the related literature and highlights our contributions. Section 3 provides background information about music copyright and movie soundtracks. Section 4 discusses theoretically the link between ownership fractionalization and licensing. Section 5 describes the datasets used. Section 6 presents the cross-sectional analysis establishing a robust correlation between ownership fractionalization and copyright licensing. Section 7 examines several dimensions of heterogeneity. Section 8 presents our panel data analysis based on the Sony-EMI merger. Section 9 discusses the managerial and policy implications of our findings. Brief concluding remarks close the paper.

2 Literature Review

Our paper is related to the literature on the management of IP and the market for patents that examines how licensing shapes the diffusion of new technologies and R&D incentives (Gans and Stern, 2003; Arora et al., 2004). Scholars have identified several factors that affect the propensity of licensing a patent. These include moral hazard (Arora, 1996), incomplete information (Gans et al., 2008; Hegde and Luo, 2018), market thickness (Fosfuri, 2006; Agrawal et al., 2015) and the strength of IP rights (Arora and Ceccagnoli, 2006; Lee, 2023).

More specifically, the paper is connected to studies examining how the dispersion of IP ownership may affect firm strategies. Several theoretical studies suggest that in the presence of multilateral bargaining transaction costs are higher, bargaining delays are longer, and the risk of bargaining failure is higher (Lerner and Tirole, 2004; Lemley and Shapiro, 2006). Spulber (2016) argues instead that these concerns are excessive, as they rely on specific assumptions on licensing negotiations. Empirical work has shown that firms patent more aggressively when ownership of IP is dispersed (Ziedonis, 2004). Galasso and Schankerman (2010) and Von Graevenitz et al. (2013) show that fragmentation of patent ownership affects the rate of litigation and settlement. A key challenge in this line of research has been to identify the set of patent licenses that follow-on innovators need to engage in, and to measure the extent to which these negotiations are difficult (Von Graevenitz et al., 2011). Our paper contributes to this literature exploiting detailed data on fractionalization of IP ownership and providing new evidence that ownership structure affects reuse of creative content.

Our paper is also related to the literature examining the effects of copyright protection on market outcomes and welfare. Research in this area has shown that copyright affects welfare by shaping product availability and prices (Mortimer, 2007; Li et al., 2018; Reimers, 2018; Giorcelli and Moser, 2020) and the profitability of authorship (MacGarvie and Moser (2013)). In the context of music, several studies have examined the challenges associated with copyright enforcement in the presence of digitization and file sharing technologies (see Waldfogel (2012a,b) and Peukert and Windisch (2023) for recent surveys).

Related to our focus on reuse of creative works, Gans (2015) provides a model where original content can be remixed by follow-on creators and compares several IP regimes, such as fair-use exemptions and remix rights. Heald (2009) compares the use of popular in-copyright and out-of-copyright musical compositions in movies. Biasi and Moser (2021) exploit a reduction in copyrights strength of science books during World War II to show that weaker copyrights encouraged the creation of follow-on science. Nagaraj (2018) examines differences in reuse in Wikipedia between in-copyright and out-of-copyright issues of digitized Baseball Digest magazine and shows that copyright protection negatively affects follow-on reuse. Our paper contributes to this literature by shedding light on the importance of the copyright ownership structure as a determinant of the reuse of content, and by providing new empirical evidence on the issue of anti-commons in IP.

Finally, our paper is related to the literature studying co-ownership of intellectual property. This line of research has typically focused on co-ownership of patents and examined the relation between co-ownership and value (Belderbos et al., 2014; Briggs, 2015). Fosfuri et al. (2017) show that legal rules on shared ownership can shape collaboration and patent assignments decisions. Our paper contributes to this literature by providing novel empirical evidence on co-ownership of copyright and its effect on content re-use.

3 Institutional Background

This section provides background on the use of music in movies, beginning with key terminology used throughout the paper. It then outlines licensing requirements for featuring a song in a movie, and concludes with an examination of the modern songwriting process.

Terminology

In the remainder of the paper, we use the following terminology. A "musical work," or simply "work," refers to the musical composition (musical arrangement, melody, lyrics, etc); a "song" refers to the audio recording of a work. Works are composed by "songwriters," whereas songs are recorded and performed by "performers." Songwriters and performers may not be identical: for example, the work "All Along the Watchtower" was composed by

Bob Dylan in 1967. This work has been recorded by multiple performers, including a song performed by the Jimi Hendrix Experience in 1968.

Movie soundtracks

Music is an important input in movie production. Filmmakers have to select the right music to bring each scene to life. Two major components of film music are the score and the soundtrack. The score is original music composed specifically for the movie to build its atmosphere and emotional landscape, whereas a soundtrack includes pre-existing songs which fit the movie or a particular scene's mood and tone.[1] While both elements are commonly used, this paper focuses on the use of soundtracks in movies. The choice of a soundtrack introduces important copyright considerations, which are essential for legally incorporating music into a movie.

The use of a song in a movie requires a synchronization (or sync) license, which encompasses two main sets of copyrights. The first is the copyright of the underlying musical work, commonly referred to as the "composition" rights. The second is the copyright of the sound recording or song, often referred to as the "master" rights (McKinney, 2020). Typically, master rights are owned by a single record company. Composition rights, instead, are often split between multiple publishers that represent the songwriters that created the piece (Cooke, 2015).[2] To include an original recording of a musical work in a movie, producers need to license both the master rights from the record company and the composition rights from the publishers.

As an example, take the song "A Sky Full of Stars" by the British rock band Coldplay released in May 2014. The recording for this song is owned by the Parlophone record label of the Warner Music Group. The musical work was composed by five songwriters: Christopher Martin, Jonathan Buckland, William Champion, Guy Berryman of Coldplay, and Swedish artist Tim Bergling professionally known as Avicii. These writers are represented by two publishers, Universal Music Publishing and EMI. Universal owns 90% of the copyright of the work and EMI owns 10%.

In the United States, copyright law allows each co-owner to license the work non-exclusively without permission from the other co-owners (Davidson, 1961). Despite this

[1]The term "soundtrack" is sometimes used to refer to the compilation of songs and sounds that comprise all of the movie's music. Celebrated movie score composers include Ennio Morricone (*The Good, the Bad and the Ugly, 1966*), John Williams (*Star Wars, 1977*), and Hans Zimmer (*The Lion King, 1994*).

[2]A publisher is a person or an organization responsible for representing composers, songwriters, and lyricists-—the authors of the musical composition—-ensuring they get compensated for the commercial use of their intellectual property. A publishing deal between a songwriter and a publisher involves transferring a part of the copyright to the publisher. In exchange, the songwriter receives a share of royalties collected by the publisher.

provision, the practice in the movie industry is to negotiate separate synchronization deals with each publishers owning a fraction of the copyright (Cooke, 2015). This occurs for several reasons. First, most international jurisdictions require permission of all co-owners for a non-exclusive license (Gabriel, 2007). This implies that consent by all co-owners is needed to use the licensed work on a global scale. Second, U.S. courts differ in their view of the permissibility of unilateral licenses, especially in the case of retroactive license that permits a previously unauthorized use (Pepe, 2009).

In principle, the multilateral bargaining problem generated by split copyright can be solved by a contractual agreement that grants one of the parties the right to license the song on behalf of the other co-owners. Reaching an agreement on such contract can be challenging, as the parties may have different views on who would be the best administrator. Co-owners may also have idiosyncratic preferences related to the use of songs in movies with specific rating or political messages (Kohn and Kohn (2002)). Indeed, when these contractual agreements are in place, they often include restrictions on the scope of unilateral licenses that can be granted by the administrator (Kushnir (2005)).

Kohn and Kohn (2002) and other industry publications suggest that the norm is to license U.S. synchronization rights with a fixed fee, which often ranges from $20,000 to $200,000 depending on the specific use of the song in the movie (e.g. background vs featured) and other characteristics of the movie (e.g. major studio vs indie).

The songwriting process

Next, we discuss recent trends affecting the songwriting process. In recent decades, songwriting has undergone significant transformations, marked by increasing specialization and fractionalization in ownership. This shift is suggested by the declining trend of solo songwriting. Historically, solo songwriters dominated the music charts, with 44% of Billboard Hot 100 chart-toppers in the 1970s credited to a single writer. This percentage steadily declined over the subsequent decades, falling to 24% in the 1990s and to just 4% in the 2010s (Grein, 2020). This evolution reflects a departure from the traditional singer-songwriter or melody-and-lyrics approaches of writing popular songs, prevalent during the first half of the 20th century (e.g., Tin Pan Alley and Brill Building eras), where typically one or two writers would compose the song with, on occasion, contribution from a lyricist. Since the early 1990s, modern songwriting practices often resemble a segmented production line, where different specialists contribute distinct elements to the final composition. As detailed in Seabrook (2015), in modern popular songwriting, "songs were written more like television shows, by teams of writers who willingly shared credit with one another."

Several factors may have contributed to the rise in songwriting specialization. First, specialization facilitates a more efficient, factory-style production of music, allowing producers, who compose the rhythm and beats, to generate multiple tracks simultaneously and distribute them among various "topliners" such as melodists and lyricists. This method supports the delegation of song components such as verses, hooks, and bridges to specialized writers, increasing productivity (Seabrook, 2015). Technological advancements have further enabled this shift by simplifying remote collaboration and music editing, through tools like digital audio workstations and software (e.g., Cubase, Ableton). Moreover, cultural influences such as the ascent of hip-hop—a genre inherently reliant on collaboration—and the practice of sampling have broadened the scope of credited contributors. Nonetheless, as we document in Section 5, specialization appears to have affected all genres, including more traditional ones such as Country and Rock.

4 Theoretical Considerations

From a microeconomic perspective, fractionalized ownership of a song's copyright implies that the licensees face a multilateral negotiation rather than a bilateral negotiation. Specifically, the problem maps into economic models where one central player (a buyer) has to bargain with a number of other players (sellers) and agreement with all parties is required to generate surplus (trade). Coase (1960) provided one of the first economic analysis of this class of problems, using the example of a railroad expansion project where the railway required permission from several farmers located along the proposed route. Several subsequent papers in economic theory have identified channels through which the multilateral nature of the negotiation leads to delay, or failure, in the negotiation. The initial insight of Coase (1960) related to the presence of transaction costs, which may reduce substantially the profitability of the negotiation when too many parties are involved. Other possible causes of bargaining failure identified in the literature include incomplete information (Mailath and Postlewaite, 1990), hold-up power (Cai, 2000), and overconfidence (Ali, 2006; Galasso, 2010).

Overall, the insights from this body of work suggest that songs with fractionalized ownership are less likely to be licensed. To illustrate, consider the case of a movie producer requiring a song for a new movie. Assume that the preferred song by the movie producer is expected to increase the value of the movie by v_1, and that the second-best song generates a value equal to v_2, with $v_1 > v_2$. If the license fee is the same for the two songs (and is normalized to zero) the producer will license song 1.[3] Consider now the case in which ownership of song 1 is fractionalized, and reaching agreement with all the owners entails

[3]As explained in the previous section, standard industry practice involves licensing songs for a fixed fee, with suggested rates available from several industry publications.

a transaction cost denoted f. If the ownership of song 2 is not fractionalized, the movie producer will license the second song if $v_2 > v_1 - f$. In other words, the transaction costs associated with fractionalization may lead movie producers to license a 'second-best' song to avoid a costly multilateral negotiation.[4]

The parameter f captures the possible channels that make a multilateral licensing negotiation more costly relative to one with a more concentrated ownership. Disentangling the different components of this cost is outside the scope of the paper, as in our empirical context we do not directly observe negotiations and failed licensing.

At the same time, our empirical setting allows us to examine the interplay of fractionalization with other features of the licensing environment. In particular, we investigate heterogeneity in the impact of fractionalization across genres where substitutability between songs is expected to be high and those where it is not. Understanding the interaction between fractionalization and substitutability requires a model of product differentiation.

To this end, consider a Hotelling framework where the two songs are located at the end points of the unit interval, and movie producers are distributed uniformly over $[0, 1]$. As standard in horizonal differentiation models, we assume that to license the song a movie producer needs to pay a transportation cost which increases linearly with the distance from the song. Specifically, if the producer is located at $x \in [0, 1]$, it sustains a travel cost tx to reach song 1, and $t(1 - x)$ to reach song 2. The parameter $t > 0$ captures the degree of substitutability between the songs, and lower t maps to lower product differentiation and greater ability of movie producers to replace song 1 with song 2.

The marginal movie producer indifferent between the two songs is located at $\widehat{x}$ such that

$$v_1 - f - t\widehat{x} = v_2 - t(1 - \widehat{x})$$

which gives a market share for song 1 equal to

$$s_1 = \frac{1}{2t}(v_1 - f - v_2 + t).$$

From the above formula it is immediate to see that

$$\frac{\partial s_1}{\partial f} = -\frac{1}{2t} < 0$$

and that

$$\frac{\partial^2 s_1}{\partial t \partial f} = \frac{1}{2t^2} > 0.$$

[4]In theory, these transaction costs can be reduced by the copyright holders through a contract that grants one of the owners the right to license the song on behalf of the others. In the previous section, we discussed why reaching such agreement is challenging in our empirical context.

The first derivative shows that a marginal increase in f reduces the licensing share of the song, which confirms the negative effect of fractionalization discussed above. The second derivative implies that the negative effect of fractionalization is larger when substitutability between the songs is higher (i.e. t is lower). This is a prediction that we will examine in our empirical analysis. In Appendix A, we show that these empirical predictions can also be derived in a logit demand model. A movie producer is less likely to choose the 'best-match' song as the cost associated with fractionalization increases, and the effect is stronger when products are less differentiated and the set of available songs to choose from is large.

5 Data Sources and Descriptive Statistics

This section describes the main data sources used in our analysis and presents summary statistics and key trends.

5.1 Data Sources

Our main sample consists of songs that appear on the Billboard Hot 100 weekly record charts between August 1958 and November 2021.[5] Every week, the chart ranks the 100 most popular songs in the US based on sales (physical and digital), online streaming (since 2007), and radio airplay. The Billboard Hot 100 chart is the music industry standard by which a song's popularity is measured. For each song that appears on the chart in a given week, we observe its title, the name of the performer, and its rank. We construct proxies for a song's popularity by computing the number of weeks the song appears on the charts and its highest rank (across all weeks).

We supplement the Billboard data with additional song-level information from MusicBrainz, an online collaborative music encyclopedia, and from the Spotify API.[6] From MusicBrainz, we obtain information on a song's first release date, and on performer and song genres. From the Spotify API, we obtain information on the performer's genre (songs are not classified by genre in the Spotify API). We provide additional details on the construction of artist and song genres in Appendix B.

Data on the copyright ownership structure of musical works is obtained from the Mechanical Licensing Collective (MLC).[7] The MLC is a nonprofit organization designated by

[5] The charts can be accessed at: https://www.billboard.com/charts/hot-100/ [Accessed on April 22nd, 2024].

[6] See https://musicbrainz.org/ and https://developer.spotify.com/documentation/web-api [Accessed on April 22nd, 2024].

[7] See https://www.themlc.com/ [Accessed on April 22nd, 2024].

the US Copyright Office pursuant to the Music Modernization Act of 2018. The MLC administers licenses to streaming and download services (e.g., Spotify, Apple Music), collects the royalties under those licenses, and pays songwriters and music publishers. The MLC provides a publicly accessible musical works database that songwriters and music publishers use to submit and maintain their musical works data. For each musical work, the MLC data contains the list of "parties" (songwriters and publishers) associated with the work. For each work-publisher pair, we observe the publisher's ownership share of the work: this is the share of licensing royalties collected by the publisher and split with the songwriter(s) they represent.[8] The data also contains the list of all songs (title and performer as they appear on streaming services) associated with the musical work. For each musical work, we compute the number of songwriters, the number of publishers, and the Herfindahl–Hirschman index (HHI) from ownership shares. The HHI is computed as the sum of squared ownership shares.

Finally, we build a dataset of movie soundtracks from the Internet Movie Database (IMDb), an online database of information related to movies and television series.[9] For each year between 2000 and 2021, we select the top 500 feature films by US box office revenue. These movies account for the quasi-entirety of US domestic box office revenue.[10] For each movie, we extract information on the movie soundtrack including: song title, performers, songwriters, and publishers. This dataset allows us to directly measure the licensing of songs in movies. We also collect additional movie-level information including the movie budget, box office revenue (in the US and worldwide), country of origin, production companies, genre, number of awards nominations, number of awards won, and movie ratings (metacritc score, IMDb rating, the number of IMDb votes).

Two important considerations are worth highlighting when it comes to our data source choices. First, although movie soundtracks often include songs not appearing on the Billboard charts, we focus on Billboard songs for several reasons. The universe of songs available for licensing in movies is very large: e.g., the entire MLC database contains more than 32 million copyrighted musical works, many of which are relatively obscure and with little "economic" value (from a soundtrack perspective). The Billboard charts allow us to construct a sample of songs and measure their popularity in an internally consistent way over several decades. Moreover, because Billboard songs are more visible, we expect licensing frictions to be lower compared to less popular songs, which would make our estimates conservative.

[8] We do not observe how the share collected by a publisher is split with the songwriter they represent. A songwriter typically receives between 50% and 75% of the royalties collected, depending on how well-established they are.

[9] See https://www.imdb.com/.

[10] For example, in 2010, the top 175 movies accounted for 94.5% of domestic box office revenue (based on data from https://www.the-numbers.com/market/2010/summary).

Second, we focus on the licensing of songs in movies—sync licenses—instead of other types of licenses such as mechanical licenses for music streaming or public performance rights for radio play.[11] We do so because sync licenses target a specific piece of music, whereas mechanical and public performance licenses are typically "blanket" licenses covering entire libraries of songs. Sync licenses are negotiated at the song-level by music users (e.g., filmmakers) and copyright owners, making licensing frictions a first-order consideration.

Our final sample is obtained by merging the sample of Billboard songs with copyright ownership information from the MLC and with soundtrack data from IMDb. While there exists an industry code identifying unique musical works—the International Standard Musical Work Code (ISWC)—this code is reported in the MLC data only, but not in our other data sources. Therefore, we merge the datasets based on song titles and artist names. Merging datasets based on non-standardized string variables presents known challenges, which we overcome by standardizing the song titles and artist names in various ways.[12]

Our initial sample consists of 29,672 unique songs appearing in the Billboard data. We are able to recover copyright ownership information for the associated musical works for 78% of Billboard songs,[13] then we match these songs with the IMDb soundtrack data. Our final sample consists of 23,189 songs. For each song, we identify all movies (if any) in which the song is part of the soundtrack. The Billboard songs for which we are able to recover copyright ownership from the MLC do not differ significantly from the full Billboard sample: they have similar average release year (1986.7 v. 1985.8), average peak rank (46.71 v. 45.24), and average number of weeks on the charts (11.1 v. 11.4).

5.2 Descriptive Statistics

Table 1 shows summary statistics for the variables used in the analysis. The average number of songwriters and publishers are similar (2.53 and 2.47). A song remains on the billboard

[11] Public performance royalties are paid for the right to play a composition in public, mechanical royalties are paid for the right to reproduce a composition through the process of recording, manufacturing, and distributing the work. For music streaming, the difference between the two types of royalties is user choice: if the user chooses a song on an on-demand platform (e.g., Spotify), then public performance royalties and mechanical royalties are paid out. If a song is played on a non-interactive platform (such as Pandora's free radio), only performance royalties are paid out. Technically, if a song is part of a movie soundtrack, the copyright owner receives sync royalties, as well as public performance royalties whenever the movie is publicly broadcast.

[12] For example, the datasets differ in the way artist names or song titles are recorded. We remove terms such as "feat.", "featuring" in artist names, which may differ across datasets. Song titles sometimes use "&" or "+" instead of "and", or use parenthesis for part of the title.

[13] This is done in two steps. First, we merge the Billboard songs with *songs* in the MLC data. Second, we use the mapping from MLC songs to MLC works provided by the MLC to retrieve the underlying musical work corresponding to each Billboard song. Non-matched Billboard songs are songs for which neither the song title nor the performer name matches the way these are recorded in the MLC data.

charts for 11.4 weeks on average. The average number of licenses (across all songs) is 0.29 and 14.6% of all songs are licensed in a movie at least once.[14]

A small fraction of works (6.4%) is associated with more than one song. For example, "Stand by Me" composed by Ben E. King, Jerry Leiber, and Mike Stoller has been recorded by 7 different performers whose version of the work appeared on Billboard charts (these include the versions by John Lennon, Ben E. King, or Maurice White). The top most licensed performers are the British rock band Queen, the American singer-songwriter Marvin Gaye, and the American rock band Blondie. The top most licensed songs include "Let's Get It On" performed by Marvin Gaye, "Dance Hall Days" performed by Wang Chung, and "Push It" performed by Salt-N-Pepa.

Table 1: Summary Statistics

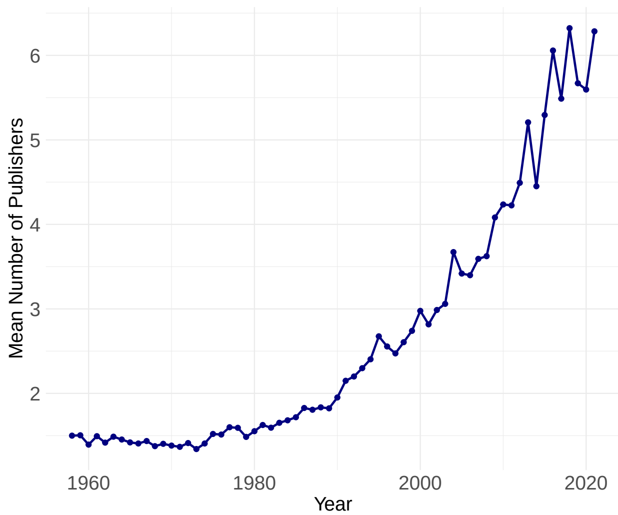
Variable	Observations	Mean	Std. Dev.	Min	Max
Songwriters	23,189	2.53	1.83	1	28
Publishers	23,189	2.47	2.30	0	30
HHI	23,189	0.651	0.33	0	1
Release Year	23,189	1985.85	19.13	1958	2021
Peak Rank	23,189	45.24	30.27	1	100
Weeks on Billboard	23,189	11.41	8.24	1	90
Ever Licensed	23,189	0.146	0.35	0	1
Licenses	23,189	0.29	0.99	0	21

Note: Song-level summary statistics. Licenses corresponds to the total number of licenses in movies over the period 2000-2021. Ever licensed is a dummy for whether a song was ever licensed in movies over the period 2000-2021.

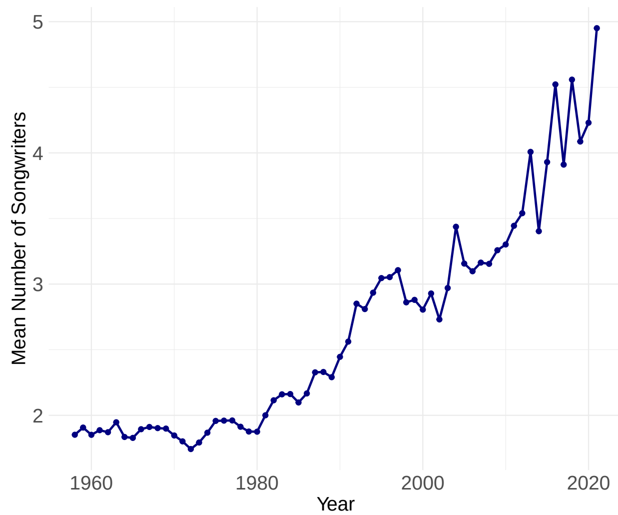
To document how the ownership structure of songs evolved over the past six decades, we compute the average number of publishers and songwriters per song for every year and plot the time series in Figure 1. The figures point to increasing fractional ownership over time and, in particular, starting from the 1980s. These trends are also observed when computing the average HHI per song using the ownership shares. Over our sample period, the average number of publishers and songwriters increase from 1.5 to 6 and from 2 to 5 respectively, and the HHI decreases from roughly 0.8 to 0.3. In Appendix Figure A1, we show that these trends are not driven by compositional changes in the mix of genres (e.g., hip hop/rap, an inherently more collaborative genre, becoming more popular in the 1980s) but are in fact observed across all music genres.

[14]The minimum number of publishers is zero. This is due to a small number of songs (0.6% of the sample) for which the MLC data contains only information on the songwriters but not the publishers. Also, in rare cases, the number of publishers is higher than the number of songwriters: this occurs when a songwriter has multiple publishing deals and is represented by more than one publisher.

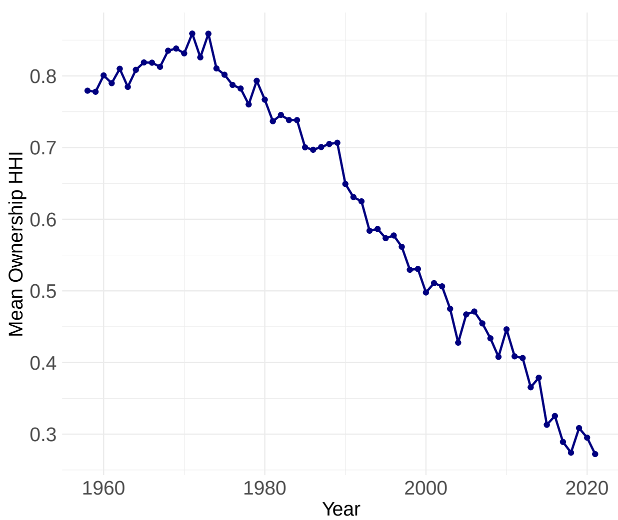
Figure 1: Fractionalization Increases Over Time



(a) Publishers per Song



(b) Songwriters per Song



(c) HHI per Song

Notes: The figures show the average number of publishers, songwriters, and the HHI per song in each year from 1958 to 2021.

Finally, we examine the association between fractional ownership and licensing propensity. Simple mean comparisons show that songs that are licensed (at least once) have on average fewer publishers (2.32 vs 2.50) and higher HHI (0.68 vs 0.65) than never licensed songs. These differences are statistically significant. However, we cannot reject the equality of means for the number of songwriters between licensed and never licensed songs. This suggests that licensing frictions, if present, are mostly associated with the number of entities in charge of the licensing process, i.e., the publishers rather than the songwriters.

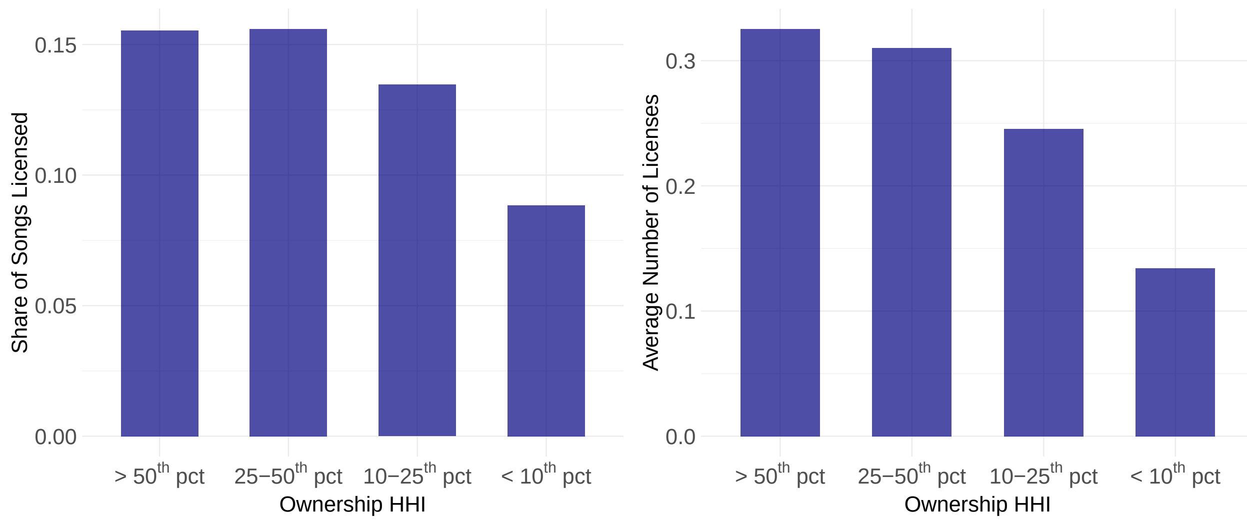
We also consider how ownership is associated with the extensive and intensive margins of licensing. In anticipation of the analysis in Section 6, we focus on the HHI as our measure of fractionalization and plot the probability of licensing (extensive margin) and the number of licenses per song (intensive margin) for different quantiles of the HHI distribution. Figure 2 shows the results. For songs with HHI above the first quartile (25th pct), the licensing probability is 0.15. For the bottom 10% of songs by HHI, i.e., the most fragmented songs, the licensing probability drops to 0.08 and is statistically different from the average licensing probability in other groups. At the intensive margin, the difference is even starker: for the most fragmented songs by HHI, the average number of licenses is 0.13 per song, which is 2.5 times smaller (and statistically different) than for songs above the 25th percentile by HHI (0.32 licenses per song).

The correlation between ownership fractionalization and licensing is likely partly driven by confounders. For instance, more recent songs are more fractionalized (Figure 1) and may be licensed less often either because they face more substitutes—the total stock of songs available for licensing grows over time—or because they have fewer opportunities of being licensed—a song released in 2010 can only be licensed by movies released in 2010 or later. It is therefore important to control for these potential confounders: for instance, by exploiting variation in fragmentation across songs released in the same year. In the next section, we unpack the relationship between fractional ownership and licensing by considering rich sets of controls and specifications.

6 Cross-Sectional Analysis

In this section we examine the cross-sectional association between copyright ownership fractionalization and follow-on use of songs in movies. We provide a baseline estimation of the correlation and document its robustness to the use of several alternative specifications that account for possible selections and measurement concerns. We then present heterogenous effects across several characteristics of movies and songs.

In our main specification, we estimate the following model



(a) Share of Songs Licensed

(b) Number of licenses

Figure 2: The left figure shows the share of songs licensed for different values of the HHI. The right figure shows the average total number of licenses (across movies released in 2000-2021) per song for different values of the HHI. "Pct" stands for percentile.

$$Y_i = \beta HHI_i + \alpha' \mathbf{X}_i + \gamma_{t(i)} + \gamma_{g(i)} + \epsilon_i \tag{1}$$

where i indexes songs, Y_i is a dummy for whether song i was ever licensed (or the total number of licenses), HHI_i equals $\sum_j s_{ij}^2$ where s_{ij} is the ownership share of publisher j in song i, $\mathbf{X}_i$ are controls (weeks on board, peak rank, number of songwriters, etc.), $\gamma_{t(i)}$ and $\gamma_{g(i)}$ are release year and genre fixed effects.[15]

6.1 Baseline Estimates

Table 2 provides the first battery of regression results documenting a negative association between high fractional copyright ownership and soundtrack licensing. Column (1) shows the negative correlation between the number of publishers co-owning a song and the likelihood the song is ever licensed. Column (2) reports the positive association between the HHI of publishers' copyright shares and licensing. Both regressions indicate that the likelihood of licensing decreases as ownership becomes more fractionalized.

Column (3), in a model which includes year and song genre fixed effects, introduces

[15]Due to imperfect matching between the Billboard and MusicBrainz databases, the release year of a song (from MusicBrainz) is only available for 14,855 Billboard songs. For this subsample, the correlation between the release year of the song and the first year it enters the Billboard charts is 0.99, e.g., virtually all songs enter the Billboard charts on the year they are released. For this reason, we treat the year of entry on the Billboard charts (which is available for the entire sample) as being identical to the release year.

Table 2: Main Estimation Results

	Dep. variable: Ever Licensed				
	(1)	(2)	(3)	(4)	(5)
Publishers	-0.004***				
	(0.001)				
HHI		0.038***			
		(0.007)			
HHI $<$ 10pct			-0.029***	-0.030***	-0.040***
			(0.008)	(0.007)	(0.007)
10pct $\leq$ HHI $<$ 25pct			-0.007		
			(0.008)		
25pct $\leq$ HHI $<$ 50pct			0.006		
			(0.006)		
Peak Rank				-0.002***	-0.002***
				(0.000)	(0.000)
Weeks on Billboard				0.007***	0.007***
				(0.001)	(0.001)
Songwriters					0.005***
					(0.002)
Release Year FEs	No	No	Yes	Yes	Yes
Genre FEs	No	No	Yes	Yes	Yes
R^2	0.00080	0.0013	0.061	0.12	0.12
Adjusted R^2	0.00076	0.0013	0.058	0.12	0.12
Observations	23189	23189	23188	23188	23188

*Note: The unit of analysis is a song. Robust standard errors are used and shown in parenthesis. Columns (3) to (5) control for whether a Billboard songs matches multiple works in the MLC data. Significance levels are given by: * 0.10 ** 0.05 *** 0.01.*

dummies to distinguish between songs with different levels of fractionalization. Specifically, we distinguish between songs with HHI in the first decile, those with HHI between the 10th -25th percentile, and those with HHI between the 25th percentile and the median, with the omitted category being songs with HHI above the median. In line with the pattern presented in Figure 2, the regression shows that the drop in licensing appears concentrated at the highest level of fractionalization. Only the dummy capturing songs in the first decile of the HHI distribution is statistically significant.

Column (4) presents our baseline model, which includes year and genre fixed effects as well as two variables capturing the performance of the song in the Billboard chart: the peak rank achieved by the song and the number of weeks the song appeared on the chart. The regression confirms a lower likelihood of licensing for songs that have a highly fractionalized ownership.

Column (5) further expands the model introducing a control for the number of songwriters. The correlation between the number of songwriters and licensing is positive, but adding this variable does not affect the coefficient on the dummy for the song with the lowest levels of HHI. We note that that the number of publishers rather than the number of songwriters is the likely driver of bargaining difficulties, as songwriters are typically represented by publishers in copyright negotiations. One possible explanation for the positive coefficient is that songs with more songwriters may be of higher quality and therefore more likely to be used in movies.

To have a sense of the magnitude of the effect, notice that about 15 percent of the songs with HHI above the first decile are licensed in at least one movie. Relative to this baseline, the estimate in column (5) suggests a reduction in the likelihood of licensing of about 25 percent for songs that are highly fractionalized.

6.2 Robustness and Extensions

In the remainder of this section, we show that our main finding is robust to alternative specifications and extensions. We also present empirical exercises related to possible concerns of sample selection and mismeasurement of copyright ownership and song popularity. All regression tables are included in Appendix D.

Alternative econometric specifications

Appendix Table A1 presents our first set of robustness tests. These results confirm that the negative association uncovered in Table 3 can be observed in alternative econometric models and specifications.

We first extend our baseline model to include performer fixed effects. This demanding specification relies on variation across songs performed by the same artist that enter the Billboard chart in the same year and have similar chart performance. Even in this case, we find that songs whose copyright ownership is highly fractionalized are less likely to be used in movies.

We then show that results are robust to using as dependent variable the total number of licenses rather than a dummy for being licensed at least once. We confirm our finding using this alternative metric, both in OLS and in Poisson specifications respectively. Appendix Table A1 also shows robustness of the main results to dropping songs that are associated with multiple works. The estimated coefficient on low HHI is essentially the same as the one in our baseline.

Finally, we show that results are robust to considering only songs released over the time period 1980-2018. Dropping the earlier sample years allows us to examine the effect on more modern music production which relies more substantially on collaboration and division of labor (Seabrook, 2015). Dropping the period after 2019 addresses the concern that several aspects of movie production and music consumption may have changed during the COVID-19 pandemic.

Popularity and sample selection

In Table A2, we tackle concerns around sample selection. First, if licensing in movies increases a song's likelihood of entering the Billboard charts, then conditioning on the Billboard sample may bias our estimate of the effect of fractionalization. To address this concern, we restrict the sample to songs released after the year 2000, for which we observe the full licensing history. We then drop from this sample the songs for which the first license in a movie occurs either before or within 3 months after the song first entered the Billboard charts and show that the result hold with this subsample.[16]

Second, if licensing in movies improves a song's ranking and number of weeks in the chart, our Popularity controls may create a spurious correlation between licensing and HHI (i.e., a case of "bad controls"). To address this concern, we use the same sample as above but compute the popularity controls (peak rank and number of weeks on charts) using only weeks at least 3 months before the song was first licensed in a movie. Results are robust to using these pre-licensing popularity measure. Overall, these results alleviate concerns that the association between licensing and HHI is due to sample selection or mismeasurement of

[16]We experiment with other cutoffs, e.g., 6 months, and find similar results. There are 144 songs which were licensed before they entered the Billboard charts, and 266 songs that were licensed either before or within 3 months after entering the Billboard charts.

song popularity.

Measurement of ownership

Another concern with our cross-sectional analysis is that ownership may be mismeasured because the MLC data only contains song ownership information at the time we accessed the data (August 2023). The concern is that a song's ownership, say, in 2005 may be different from its ownership in 2023.[17] In this respect it is important to notice that, in most music publishing contracts, copyright ownership is fully transferred to the publishers (Kohn and Kohn, 2002). This implies that a publisher's share is typically stable over time, and does not change when songwriters die or re-assign their royalty rights to third parties.

Changes in copyright ownership are certainly possible in the case of mergers and acquisitions between publishers. Indeed, we exploit a prominent M&A in the empirical exercise presented in Section 8. Nonetheless, during the period of our study the majority of mergers and acquisitions between publishers were small in size, involving only a small share of co-owned songs between the merging parties. Therefore, the fraction of songs for which the HHI changes because of mergers and acquisitions (that is, co-owned songs between merging parties) is relatively small.

To address this concern more constructively, in Table A2, we verify that the association uncovered in our baseline regression remains qualitatively similar when the dependent variable only includes licensing in movies released over the period 2018-2021. Measurement errors in ownership shares are unlikely in this subsample, which considers licenses that take place close to our date of access to the MLC data.

Number of publishers vs. HHI

Thus far, our analysis has documented a robust negative association between high fractionalization of copyright ownership and the use of a song in movies. We constructed our measure of fractionalization exploiting the HHI, a common index used in industrial organization studies on market structure. A key feature of the HHI index is that it does not rely only on the number of co-owners but it also considers the asymmetry in their shares. For example, for a copyright owned by two publishers, the HHI is lower in the case in which they have equal share ($0.5 = 0.5^2 + 0.5^2$) rather than the case in which one publisher owns 80 percent of the copyright ($0.68 = 0.8^2 + 0.2^2$).

A natural question to ask is whether the asymmetry of ownership shares does matter in our setting. On the one hand, as discussed in Section 3, obtaining global synchronization

[17] The MLC publishes historical snapshots of the data, unfortunately these snapshots only go back to 2021.

rights typically requires consent by all parties. This suggests that bargaining frictions may be only driven by the number of publishers, independently of their specific shares. On the other hand, it may also be the case that when some publishers own very small copyright fractions, private contracting may assign the management of licensing rights to those owning larger shares. Kohn and Kohn (2002) indeed suggest that agreeing on the allocation of administrative control is easier when a party has much greater ownership share than the others. If this is the case, HHI may provide a better measure for the complexity of the negotiation problem.

Appendix Table A3 investigates this issue with several empirical exercises. First, we compare the estimate of our baseline model with the one obtained adding a control for the number of publishers. We find that the magnitude and the statistical significance of the coefficient for the dummy capturing low-HHI ownership is unaffected when we control for the number of publishers. On the other hand, the coefficient on the number of publishers is small and statistically insignificant. This suggests that the fractionalization of shares, rather than the sheer number of publishers appears to be the key driver of the results. The table provides further support for this idea in models that jointly control for HHI and number of publishers using dummies or continuous measures. Across the specifications, we find that the measures that rely on the HHI are strongly correlated with licensing, whereas those that use only the number of publishers are not. While these results should be interpreted with caution given the high correlation between HHI and number of publishers (about 0.68), the table is consistent with the idea that intellectual property negotiations are more complex when co-owners have relative symmetric size compared to the case in which some of them have much larger shares than others.

7 Heterogeneity analysis

We have shown that copyrights with high ownership fractionalization are, on average, associated with lower usage in movies. In this section, we unbundle the average effect and explore several dimensions of heterogeneity.

Genre and substitutability

We begin distinguishing between songs of different genres. Specifically, in Table 3, we split our sample distinguishing between Pop and Rock songs (column 1) and songs in other music genres (column 2). These regressions show that the negative association between high fractionalization and licensing is more pronounced in Pop and Rock relative to other genres.

The magnitude of the coefficient is larger for the first sample, as well as its implied elasticity. Specifically, the estimates show that high fractionalization is associated with about 27 percent less licensing for Pop and Rock songs, and roughly 15 percent less licensing for other genres.[18]

These results are consistent with the idea that there is greater substitutability among Pop and Rock compositions relative to songs in other genres. As discussed in the theoretical framework presented in Section 4, licensing rates are likely to be lower for fractionalized songs when it is easier for movie producers to find substitutes. This also resonates with the views of several industry commentators who have argued that the commodification of modern pop and rock music has led to greater formulaic production and standardization of songs (Seabrook, 2015). Indeed, industry experts often warn copyright owners that their music may be more substitutable than they think. For example, McKinney (2020) writes:

> "*Music supervisors working on films and TV shows have thousands of songs to choose from, and usually have several songs in mind for each use. If an [copyright] administrator is too aggressive, the music supervisor will likely move to the next candidate.*"

To provide further support to the idea that fractionalization is more salient when songs are highly substitutable, Table 3 further distinguishes between the use of Pop and Rock songs in comedy movies (column 3) and in movies that focus on music, such as musicals, music dramas or music documentaries about a particular artist or band (column 4). Examples include "A Star Is Born" and "Sunshine Daydream." Intuitively, we expect a high substitution rate between songs used in comedy but much lower substitutability for the use in movies more focused on music. Consistent with this idea, we find a large negative association between high fractionalization and licensing in comedies, but no statistically significant association in music-focused movies.[19]

Artist and song popularity

In Appendix Table A4, we examine additional potential sources of heterogeneity related to the popularity of the artists and the songs. First, we distinguish between more and less prominent artists using information on the number of times they appeared on the Billboard

[18] In unreported regression, we further distinguished across the other music genres aggregated in column 2. We find no effect for Country music and coefficients smaller in magnitude and more noisily estimated for Hip Hop and R&B.

[19] Data on movie genre is from IMDb, which assigns up to three genres per movie. The list and definition of each genre can be found at: https://help.imdb.com/article/contribution/titles/genres/GZDRMS6R742JRGAG# [Accessed on: September 8th, 2024]. The most popular genres are Comedy, Drama, and Romance. The genre Music/Musical is assigned to movies containing significant music-related elements.

Table 3: Estimation Results: Licensing by Song and Movie Genres

	Ever Licensed			
	(1) Rock/Pop	(2) Other genres	(3) Comedy	(4) Music/Musical
HHI < 10pct	-0.050***	-0.017**	-0.034***	-0.002
	(0.013)	(0.008)	(0.012)	(0.005)
Release Year FEs	Yes	Yes	Yes	Yes
Song Genre FEs	Yes	Yes	Yes	Yes
Popularity Controls	Yes	Yes	Yes	Yes
Mean Outcome	0.18	0.11	0.14	0.025
R^2	0.12	0.13	0.10	0.028
Adjusted R^2	0.11	0.12	0.096	0.022
Observations	11289	11899	11289	11289

*Note: The unit of analysis is a song. Robust standard errors are used and shown in parenthesis. Popularity Controls include the song's peak rank and number of weeks on the Billboard charts. Significance levels are given by: * 0.10 ** 0.05 *** 0.01*

chart during our sample period. While the magnitude of the negative association between fractionalization and licensing is larger for songs by less prominent performers, we find that it is present also in the sample of songs by performers with many hits. This suggests that ownership fractionalization is not only an issue for songs by less prominent performers, as it also affects the most successful and experienced performers.[20]

We then examine differences across more and less successful songs. Specifically, we distinguish between songs that are above and below the median in terms of weeks of presence in the Billboard chart. Here the results, also presented in Table A4, are more striking. Even if the degree of high fractionalization appears similar across the two samples, the negative association with licensing is exclusively driven by the most popular song. The coefficient on the songs that remain fewer weeks on the chart is small and statistically insignificant, whereas the estimate for the songs that are more popular is large and highly significant. Table A4 also confirms that this differential effect holds if we define popularity using the weeks on the chart before a song is first licensed in a movie and focusing on songs released after the year 2000 for which the full licensing history is known.

This differential effect is consistent with the interpretation that popular songs are less likely to be included in a movie for their 'fit' with the plot or themes of the movie, but

[20] On average, songs in our sample are performed by artists that have appeared in the Billboard chart 14 times, but this distribution is highly skewed. There are 6,450 artists in our sample, and more than half of them appear on the billboard chart only once. Only 10 percent of the artists appear on the chart 8 times or more (the cutoff we used in Appendix Table A4), but these artists account for about half of the songs in our sample.

rather because they are familiar to the audience. In line with our theoretical framework, we expect popular songs to be more substitutable than others from the perspective of the movie directors. In turn, this would lead to fewer licenses when the transaction costs are high, as in the case of fractional copyright ownership.

Movie budget and nationality

One important variable that may affect music licensing choices is the movie budget. To examine this aspect, we exploit movie budget information which is available for 4,821 US-produced movies over the period 2000-2021. We deflate movie budgets to 2010 US$ and distinguish two groups of movies. "Low budget" movies are defined as movies with budget in the bottom 25% of the distribution. "High budget" movies are defined as movies with budget in the top 25% of the distribution. Industry reports indicate that the music budget is a relatively small fraction of total movie budget (between 2% and 5%). Therefore, the choice of music per se is unlikely to change whether a movie is classified as low or high budget under our definitions. This alleviates concerns of reverse causality (i.e., licensing costly fractionalized songs makes a movie "high budget").[21] Appendix Table A5 presents split sample regressions that contrast the association between fractionalization and licensing between low budget and high budget movie. Our analysis shows that the most fractionalized songs are less likely to be licensed by both low and high budget movies. The magnitude of the effect is slightly smaller for high budget movies, but we cannot reject equality between the two estimates.

Appendix Table A5 also distinguishes between US movies (i.e., movies with at least one US producer) and foreign movies. In this case, too, fractionalization is found to have a negative and significant association with licensing for both movie types. The most fractionalized songs are 20% less likely to be licensed in US-produced movies than average, whereas they are 33% less likely to be licensed in foreign produced movies than average. While this differential magnitude may reflect the higher transactions costs faced by foreign movie producers when licensing Billboard songs, which are typically owned by US music publishers, we interpret this difference with caution as we cannot reject equality between the two estimates.

[21] In this part of the analysis, we focus on music licensing in US-produced movies. As we discuss below, foreign-produced movies (released in the US) have typically lower budgets compared to US-produced movies, and may face other frictions in licensing unrelated to budget.

8 Panel Data Analysis

It is difficult to conclude from the cross-sectional analysis alone that differences in ownership structure are the primary driver of different licensing propensities. Songs involving more publishers may differ in unobserved dimensions that could potentially make them more appropriate for inclusion in movies. In this section, we use the panel structure of our data to provide causal evidence on the effect of ownership fractionalization on licensing. Specifically, we leverage the acquisition of EMI Music Publishing by Sony in 2012 as a source of within-song variation in ownership fractionalization and compare the licensing of songs with different degrees of ownership fractionalization, before and after the acquisition.

8.1 The Sony-Led Acquisition of EMI Music Publishing

In 2011, the music publishing industry was dominated by four companies: Universal Music Publishing Group, EMI Music Publishing, Warner Chappell Music, and Sony/ATV Music Publishing.[22] The top four music publishers collectively accounted for approximately 69% of the global market: Universal Music Publishing Group was the market leader with a 23% market share, EMI Music Publishing was the second largest publisher with a 20% share, followed by Warner Chappell Music at 14%, and Sony/ATV Music Publishing at 13% (Warner Music Group, 2012).

In November 2011, EMI was put up for sale due to a series of financial difficulties and mismanagement issues following its 2007 acquisition by private equity firm Terra Firma. Forde (2019) offers a book-length treatment of the EMI sale. EMI's financial difficulties concerned its recording business, not its publishing business, which were run as separate entities. The following quotes, from Forde (2019), provide support for this point:

> "*Publishing had not been affected by digital disruption to anything approaching the level of recorded music. EMI Music Publishing had long been a profit centre for the company and Terra Firma's time at EMI left it pretty much unscathed - in part because it was carrying on and making money as usual, and also because the enormity of the job facing Terra Firma with recorded music seemed to double in size every time they dug into it and they thought they had got a handle on it.*"

> "*Terra Firma's logic was that it was buying a business where one half (publishing) came with virtually no risk while the other (recorded music), because of the reconstructive surgery it was planning, was almost all risk.*"

[22] Sony/ATV was a joint venture of Sony Music Publishing and ATV (Associated Television) formed in 1995. ATV is a British publishing company, most notably known as the publisher of the Lennon–McCartney song catalogue, and is owned by the Michael Jackson estate since 1985.

"*Hands [Terra Firma's CEO] says that Terra Firma knew that EMI Music Publishing was a robust business that ran efficiently and this could be the part of the company used to regenerate the struggling recorded music side.*"

By 2011, Terra Firma could no longer service EMI's debt, leading Citigroup to foreclose on the company. The sale was driven by the need to offload the struggling company's assets and stabilize its financial situation. On June 29, 2012, an investor consortium led by Sony/ATV Music Publishing acquired EMI Music Publishing for $2.2 billion (Sony Corporation, 2012). In addition to Sony, the consortium included the estate of Michael Jackson, Abu Dhabi state-owned investment fund Mubadala, Jynwel Capital Limited, US investment firm Blackstone, and David Geffen.[23] EMI's recording business was acquired by Universal Music Group in September 2012.

Sony acquired approximately 30% of the equity interest in EMI Music Publishing and paid aggregate cash contributions of $320 million. At the time of the acquisition, EMI Music Publishing owned over 1.3 million copyrights, including the greatest hits of Motown and classic film and television scores, and Sony owned more than 750,000 copyrights, including songs by the Beatles and the Leiber Stoller catalog. The EMI Music Publishing acquisition made Sony the largest music publisher and administrator in the industry.

Importantly, while Sony acquired only 30% of EMI Music Publishing, it put up a much lower cash contribution in exchange of *administering the entire catalog of EMI*. Sony management announced it will operate the two publishing portfolios as one company (Christman, 2013).

In July 2018, Sony bought out the Jackson estate's 10% stake in EMI Music Publishing. In November 2018, Sony acquired the remaining 60% equity interest in EMI from the Mubadala Investment fund and other investors, resulting in EMI becoming a wholly-owned subsidiary of Sony (Sony Corporation, 2018).

While there were other mergers and acquisition over our sample period, the EMI-Sony acquisition was the largest. Other mergers and acquisition were much smaller in size and involved small shares of co-owned songs between the merging parties. This feature of the Sony-EMI acquisition is important as it provides us with a sufficiently large sample of treated (co-owned) songs, as explained in the next section.

[23]The deal received European Union approval in April 2012, on condition that some catalogs be divested. The publishing rights for Famous Music UK and Virgin Music were sold to BMG Rights Management in December 2012 for $150 million. We account for these divestment choices in the analysis below.

8.2 Difference-in-Difference Analysis

Our identification strategy is a difference-in-difference analysis that compares the licensing of songs (and associated works) with different exposures to the Sony-EMI merger, before and after the merger. The approach allows us to exploit within-song variation in ownership and control for persistent unobserved heterogeneity that may be correlated with ownership and affect licensing.

Figure 3 schematically represents our treatment and control groups. We define the treatment group as songs that were co-owned by Sony and EMI publishers before the acquisition and became administered by Sony post-acquisition. Next, we define several potential control groups: "Control 1" is the group of songs that were owned by EMI but not Sony pre-acquisition and became administered by Sony post-acquisition. "Control 2" is the group of songs that were owned by Sony before and after the acquisition. Finally, "Control 3" is the group of songs that are owned by neither Sony nor EMI.

Distinguishing between these different control groups allows us to identify the effect of ownership consolidation separately from the effect of the merger per se (e.g., Sony being "better" than EMI at handling movie soundtrack licensing), or the effect of time-varying shocks that may affect Sony post-merger (e.g., Sony dedicating more resources to movie soundtrack licensing post-acquisition).

Three important points are worth nothing. First, the MLC data allows us to identify songs that are in the treatment group because each MLC page lists the publisher(s) currently owning the rights (EMI), as well as, the publisher(s) currently administering the rights (Sony). Therefore, the MLC page for (a musical work with) a song in the treatment group would list both Sony and EMI publishers as owner of the composition rights, but would show only Sony as the contact publisher administering the rights. Second, in addition to Sony and EMI, the treatment and control groups (1 and 2) may contain other publishers (e.g., Universal). Third, Sony and EMI operate multiple subsidiaries (e.g., EMI Blackwood Music, EMI April Music, Sony/ATV Tunes LLC, Sony/ATV Tree Publishing) which we manually classify into their corresponding parent companies to define the treatment and control groups. Figure A2 in Appendix D shows a screenshot of a song page in the MLC database illustrating the previous two points.

On average, treatment songs tend to have more publishers than control songs. This is expected given that, by definition, treatment songs have at least two publishers (Sony and EMI). Treatment songs also tend to be more recent and have fewer licenses than control songs. This is consistent with the descriptive analysis in Sections 5 and 6: fractional ownership has increased over time and is negatively associated with licensing. We provide more detailed descriptive statistics about the treatment and control groups in Table A6 of Appendix D.

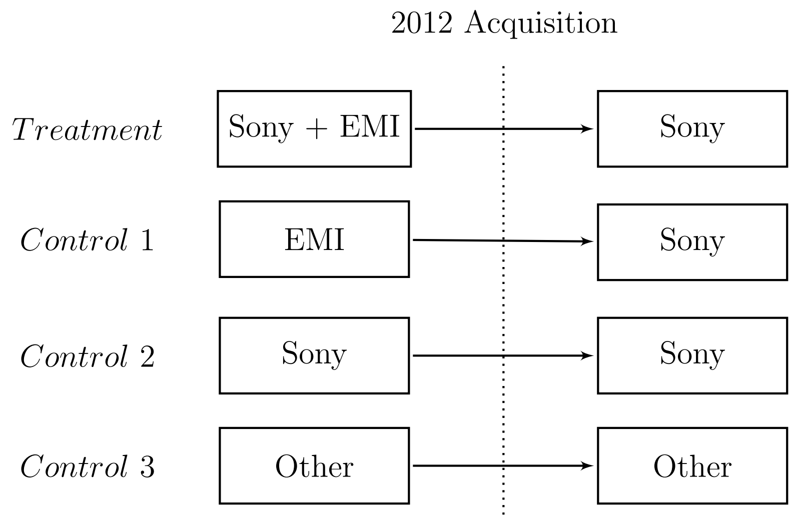


Figure 3: Definition of the Treatment and Control Songs

We estimate versions of the following difference-in-difference specification

$$\begin{aligned} Licensed_{it} = \alpha &+ \beta_T \times Treatment_i \times Post_t \\ &+ \beta_{C1} \times Control1_i \times Post_t + \beta_{C2} \times Control2_i \times Post_t \\ &+ \gamma_i + \delta_t + \epsilon_{it} \end{aligned} \tag{2}$$

where $Licensed_{it}$ is a dummy for whether song i is licensed (at least once) in year t. The variables $Treatment_i$, $Control1_i$, and $Control2_i$ are dummies for whether song i in the treatment or control 1 or 2 groups. $Post_t$ is a dummy for whether the year t is strictly greater than 2012 (acqusition year). Finally, γ_i and δ_t are song and year fixed effects. The omitted reference category is Control 3.

Table 4 shows the results from the main specification. Column (1) estimates Equation (2) exactly. Relative to the omitted category (Control 3), treated songs experience an increase in licensing propensity following the acquisition. Interestingly, songs in Control 1, which were owned by EMI but not Sony pre-acqusition, also see an increase, albeit smaller than the effect on the treatment group. This indicates that the consolidation of ownership rights is associated with an increase in licensing beyond the effects of the acquisition per se. This is further confirmed by the results in Column (2) where we break down the treatment group into songs with high versus low HHI (HHI $<$ 10 pct). The most fragmented treatment songs are the ones that experience a significant increase in licensing propensity.

To quantify this increase, we compute the probability that a song is licensed at least once over a 10-year period. For the average song pre-acquisition, this probability is 18%. For treatment songs post-acquisition, the probability increases to 23%. For treatment songs with low HHI post-acquisition, the licensing probability increases to 28%. Therefore, the consolidation of ownership rights from the Sony–EMI merger increased the licensing probability (over a 10-year period) from 18% to 28%.

Column (3) uses only the sample of songs in the Treatment and Control 3 groups, whereas Column (4) uses only the sample of songs in the Treatment and Control 1 and 2 groups (with Control 2 being the omitted category). In all specifications, we find that the co-owned songs (and particularly highly fragmented ones) are more likely to be licensed following the acquisition.

In the last column, we consider licensing only in movies where Sony is not a producer.[24] This specification alleviates concerns that, post-merger, Sony may have favored newly acquired songs in the movies it produces.[25] We find that, across specifications, the results remain quantitatively similar. We show the baseline specification in column (5) under this more restrictive definition of the dependent variable.

Table 4: DiD Analysis: Main Results

	Dep. Variable: Licensed in Year t				
	(1)	(2)	(3)	(4)	(5)
Treatment (EMI & Sony) × Post	0.007*				0.007**
	(0.004)				(0.003)
Control 1 (EMI) × Post	0.004*	0.004*		0.003	0.004**
	(0.002)	(0.002)		(0.003)	(0.002)
Control 2 (Sony) × Post	0.002	0.002			0.002
	(0.003)	(0.003)			(0.002)
Treatment (EMI & Sony) (Low HHI)× Post		0.013**	0.013**	0.011*	
		(0.006)	(0.006)	(0.006)	
Treatment (EMI & Sony) (High HHI) × Post		0.004	0.004	0.003	
		(0.005)	(0.005)	(0.005)	
Year FEs	Yes	Yes	Yes	Yes	Yes
Song FEs	Yes	Yes	Yes	Yes	Yes
Mean Pre-Merger	0.020	0.020	0.020	0.020	0.017
R^2	0.11	0.11	0.10	0.11	0.099
Adjusted R^2	0.056	0.056	0.052	0.061	0.046
Observations	76325	76325	47889	32659	76325

*Note: The unit of analysis is a song-year. Standard errors are clustered at the song-level and shown in parenthesis. All columns use the cohorts of songs released between 1995 and 2010. Column (3) uses only songs in the Treatment and Control 3 groups. Column (4) uses only songs in the Treatment and Control 1 and 2 groups. Column (5) considers licensing only in movies where Sony is not a producer. Significance levels are given by: * 0.10 ** 0.05 *** 0.01.*

Several robustness tests are presented in the Appendix. In particular, Appendix Table

[24] Sony Entertainment is the parent company, with ventures in the music industry (Sony Music Publishing and Sony Music Entertainment) and in the movie industry (Sony Pictures Entertainment).

[25] Over our sample period, Sony Pictures Entertainment and its subsidiaries (Columbia, Screen Gems, TriStar, etc.) produced 25 movies per year on average.

A7 confirms our findings using a split-sample approach. The table shows that treatment songs experience an increase in licensing that is statistically larger than the one experienced by Control 1 songs with high level of fractionalization after the merger. The same table also shows no differential effect for the songs with lower fractionalization.

In Appendix Table A8, we further exploit alternative sub-samples and controls. We vary the size of the cohort of songs used in the analysis: the results remain qualitatively similar whether we consider the cohorts of songs released over 1995-2010, over 2000-2010, and over 1995-2021.[26] We also replace the year fixed effects with "year by music genre" fixed effects (in column (2)) to capture time-varying trends at a more granular level. Overall, the results remain quantitatively similar.

8.3 Event Study Analysis

We use an event study framework to unpack the dynamic pre- and post-treatment effects documented in the previous section. We run the following regression using the song panel data:

$$\begin{aligned} Licensed_{it} = & \sum_{\tau \in \{-m,\dots,0,\dots,n\}} E_{t-\tau} \left(\beta_{T,\tau} \times Treatment_i + \beta_{C1,\tau} \times Control1_i + \beta_{C2,\tau} \times Control2_i \right) \\ & + \gamma_i + \delta_t + \epsilon_{it} \end{aligned} \tag{3}$$

where $E_{t-\tau}$ is an indicator variable for event time τ, where τ is time-since-acquisition; this dummy equals 1 if $t = 2012 + \tau$ and zero otherwise. The rest of the variables are defined as in Equation (2).

Equation (3) differs from the specification in Equation (2) in that now the coefficients on post-acquisition by treatment/control are subscripted by τ, the difference in years measured relative to the acquisition date. This allows for both dynamic effects, such as a delay in the effect of the acquisition as Sony and EMI operations are integrated, and for detecting the presence of pre-trends in licensing prior to the acquisition. The coefficients after the acquisition has occurred ($\beta_{T,\tau}$ for $\tau \geq 0$) capture the dynamic effects of ownership consolidation on licensing. The terms $\beta_{T,\tau}$ before the event has occurred (for $\tau < 0$) provide a placebo test. In the absence of anticipation effects, model misspecification, or omitted confounding variables, these pre-event terms should not have a trend in τ. When implementing this specification, the omitted category is $\tau = -1$ so that all cumulative effects are relative to the year before

[26] We note that in the latter specification, songs released post-acquisition do not contribute to the treatment effect estimates, however, they may improve the precision of post-acquisition fixed effects.

the acquisition. We set $m = 4$ and $n = 7$, such that the effects for periods $\tau \leq -4$ are pooled into coefficient indexed by $\tau = -4$ and the effects for periods $\tau \geq 7$ are pooled into the coefficient index by $\tau = 7$.

Figure 4 shows the results separately for the coefficients $\beta_{T,\tau}$, $\beta_{C1,\tau}$, and $\beta_{C2,\tau}$ for $\tau \in \{-m, \ldots, 0, \ldots, n\}$. Consistent with the static difference-in-difference analysis of the previous section, we find that licensing increases post-acquisition for treatment songs. We cannot detect significant changes for songs owned either by Sony or EMI (Controls 1 and 2) relative to the reference category (Control 3). The effect on treatment songs appears to increase over time, although confidence bands are wide due to the relatively smaller sample size. Relative to the reference category, the treatment group does not show differing pre-trends prior to the acquisition: a Wald test of no pre-trends ($\beta_{T,\tau} = 0$) for $\tau < 0$ cannot reject the null hypothesis (the p-value is 0.30). These results suggest that the observed changes in licensing post-acquisition materializes specifically for songs that were co-owned by EMI and Sony, but not other songs in their portfolios, highlighting the role of ownership consolidation as an important driver of licensing.

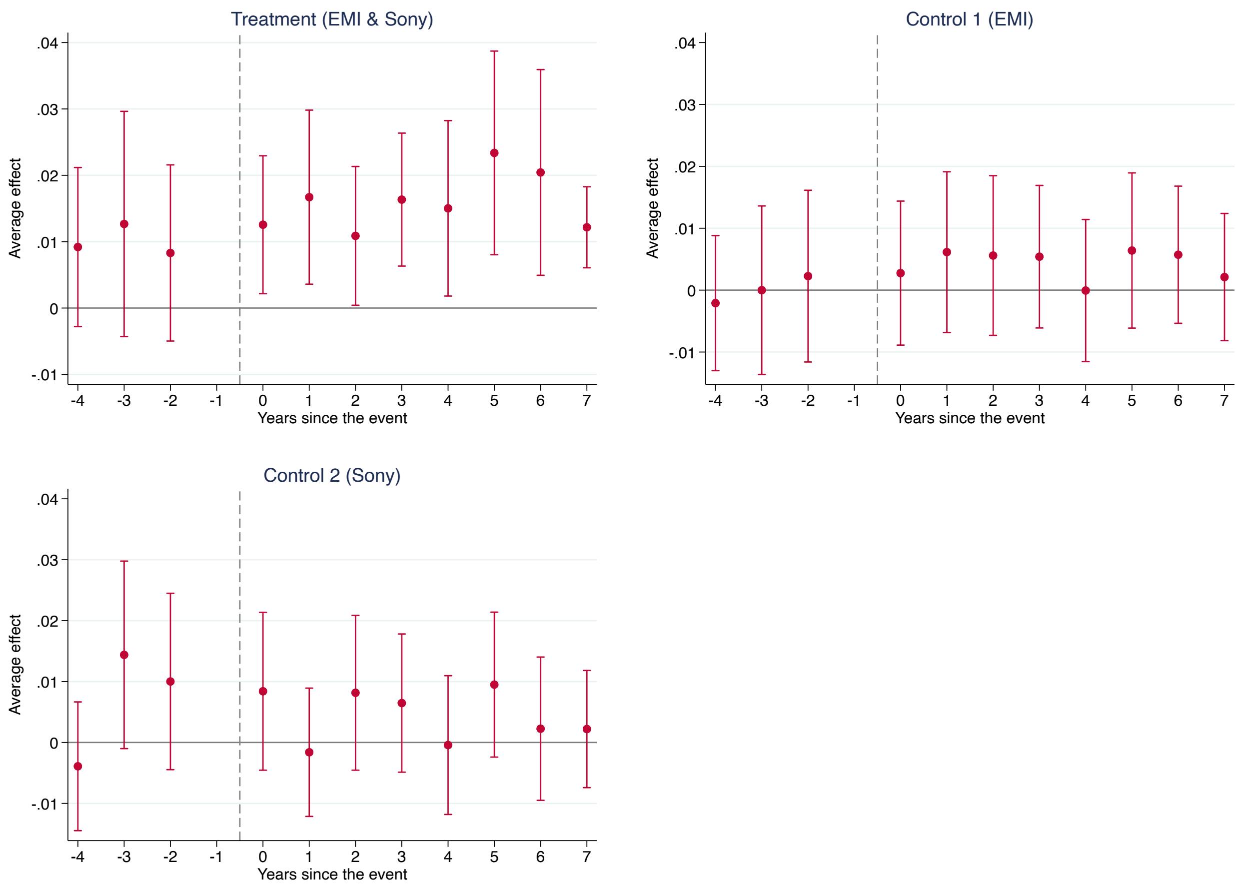
8.4 Addressing Alternative Explanations

We interpret our finding that the merger between Sony and EMI increased licensing of co-owned songs as evidence that the bargaining frictions generated by ownership fractionalization render licensing more difficult. However, there are two possible reasons for believing that this interpretation of our results may lead us to overestimate the degree to which fractionalization reduces licensing. Rather than lower bargaining frictions, the post-merger increase in licensing could reflect: 1) greater investment by Sony to manage its portfolio of co-owned songs; or 2) spillover effects between EMI-Sony songs and other songs. In this subsection we address each of these arguments.

Management of co-owned songs

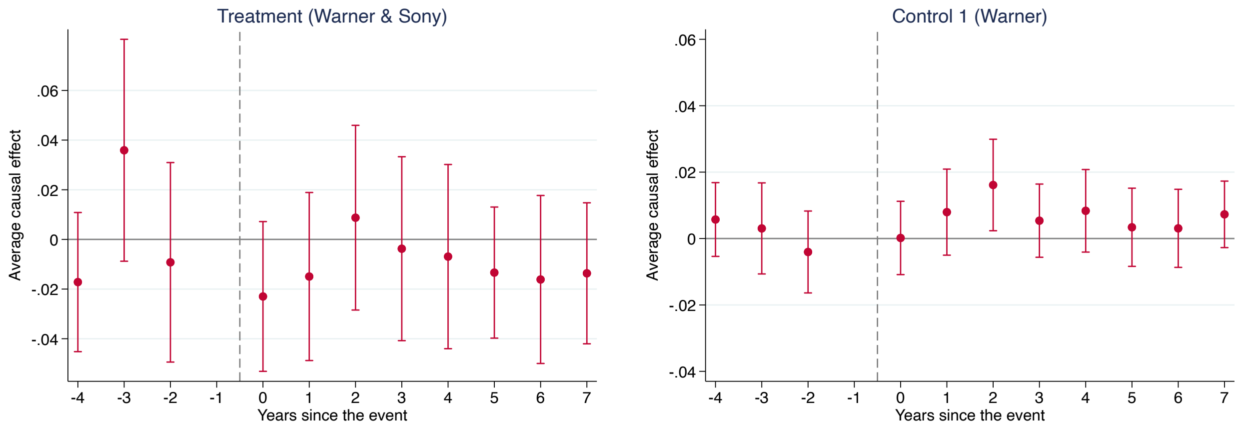
While the inclusion of control 2 (Sony-owned songs) accounts for possible changes in management style for the entire Sony IP portfolio after the merger, a threat to our identification strategy is that Sony may have devoted more resources to the licensing of its co-owned songs post-acquisition. Under this hypothesis, one would expect licensing to increase for all songs co-owned by Sony—for reasons that are unrelated to the consolidation in ownership rights. To rule out this alternative explanation, we conduct a placebo test where we construct treatment and control groups following the approach described in Figure 3, but replace EMI with another publisher, Warner Chappell Music, that was not involved in the acquisition.

Figure 4: Event Study Analysis: Main Results



Notes: The effects of the 2012 Sony acquisition of EMI on song licensing in years before and after the event. Song and year fixed effects are included. Estimates are relative to the reference category which are songs that are not owned by either Sony or EMI. 95% confidence interval are shown as vertical segments.

Figure 5: Event Study Analysis: Placebo Test



Notes: The placebo analysis considers the licensing of songs co-owned by Sony and Warner Chappell Music before and after the Sony acquisition of EMI. Song and year fixed effects are included. Estimates are relative to the reference category which are songs that are not owned by either Sony or Warner. 95% confidence interval are shown as vertical segments.

Specifically, we construct a "fake" treatment group formed of songs co-owned by Sony and Warner, but not EMI. We then compare the licensing of these songs before and after 2012 to a control group of songs owned by Warner but not Sony, and a control group of songs owned by neither Sony nor Warner.[27] Because Warner was not involved in the acquisition, the ownership of Sony–Warner songs does not change around the acquisition year, and therefore, absent confounders, we should not detect any change in the licensing for this group of songs. The results of the placebo test are shown in Figure 5. We do not find any change in the licensing of songs co-owned by Warner and Sony post-2012. These results provide additional support for the positive effect of ownership consolidation on licensing estimated above.

Spillover effects

A second threat to the interpretation of our difference-in-differences estimates is that songs in the control groups may have experienced a reduction in their licensing propensity as a result of the merger. Specifically, in line with the predictions of our theoretical framework, the decrease in ownership fractionalization affecting songs co-owned by Sony and EMI may have induced moviemakers to substitute songs of other publishers with Sony-EMI songs. If the magnitude of this substitution effect is substantial, it would generate a violation of the Stable Unit Treatment Value (SUTVA) assumption, as the control group would be affected by a negative spillover (Rubin, 2005). In turn, this would lead us to overestimate the positive effect of the merger on treated songs, as the observed increase in licensing may be partially

[27] We do not use songs owned by Sony but not Warner as these are affected by the 2012 acquisition.

driven by a decline in licensing of control songs.

While the lower fractionalization may have led movie makers to replace specific control songs with treated songs, it is unlikely that the magnitude of this effect is large enough to generate a decrease in the licensing propensity for the average control group song. There are several reasons why we expect this to be the case. First, the control groups we use are substantially larger than the treatment group (e.g. control group 3 is more than 22 times larger than the treatment group), which implies that songs that are close substitute to treated songs are likely to account for only a very small fraction of the control sample. Intuitively, because the control group is very large, negative spillovers generated by substitution are likely to affect only a very small number of control songs, and thus unlikely to substantially bias upward our estimates. Second, we do not find any reduction in licensing for other songs owned by EMI and Sony (Figure 4) or in the placebo analysis that exploits Sony-Warner's songs (Figure 5). If songs in these control groups are more likely to be closer substitute for EMI-Sony songs, one would expect to observe a drop in licensing for these songs in the presence of substantial substitution effects.

9 Discussion

In this section, we discuss managerial and policy implications of our results.

Quantifying the effect on artists

The first issue we examine is whether the negative effect of ownership fractionalization on licensing that we have estimated has an economically meaningful impact on songwriters' income. While data on royalties paid for the use of songs are not available, we relied on our understanding of industry practices to construct a measure of the licensing revenue generated by each of our sample songs used in movies. Specifically, as we explained in Section 3, the industry norm for synchronization licenses is a fixed fee for the U.S. rights. In addition, the license generates revenue from public performance in theaters outside the U.S., which are subject to fees collected by local performance rights societies (Kohn and Kohn, 2002).

Building on this information, we assume that each song in our sample is licensed with a \$50,000 fee for U.S. synchronization rights. This amount is consistent with figures released by ASCAP, which indicate that fees charged by music publishers for major studio films are usually between \$15,000 and \$60,000. To compute the royalties from non-U.S. performances, we assumed that local performance fees are equal to 2% of foreign box office revenue, and are split equally across the songs featured in a movie. While rules governing performance rights vary across countries, our formula is in line with the approach used in several European countries.[28] This back of the envelope approach generates a mean licensing revenue of about to $250,000 (the median is about $110,000) for songs in our sample that are licensed at least once. Using this constructed licensing revenue as dependent variable in our cross-sectional model, and focusing on the most popular genre (Pop songs), we find that, across all songs in the sample, highly fractionalized songs receive $27,000 less in licensing revenue relative to song with concentrated ownership, which is roughly 50% of the average annual income of U.S. songwriters.[29] While these back of the envelope calculations are only illustrative, and should not be over-interpreted, they suggest that IP ownership structure may have non-trivial effects on the licensing revenue generated by a song.

Quantifying the effect on movie producers

While fractionalization can lead to a large reduction in the likelihood that a song is licensed, the overall effect on the welfare of movie producers can be minimal if they can easily substitute fractionalized songs with non-factionalized ones.

To have a sense of the magnitude of the effect of copyright fractionalization on movie producers, we perform, in Appendix C, a quantification exercise that builds on Reimers and Waldfogel (2021) and and Waldfogel (2023). Specifically, we calibrate a nested logit model of demand for songs by filmmakers, where filmmaker surplus depends on the degree of substitutability across songs. We measure the impact of fractionalization by comparing the status quo with filmmakers' surplus that would have arisen if each song in our sample had only one owner (HHI=1).

We find that this large drop in fractionalization would generate a relatively small increase in filmmaker surplus. Our estimates of the increase in surplus range from 1.6 to 4 percent depending on the assumptions on the nested logit substitution parameter. Also in this case, the quantification exercise is only illustrative and should not be over-interpreted. With this caveat in mind, the demand estimation suggests that fractionalization is likely to have more pronounced impact on the welfare of musicians than on filmmakers. This provides additional support to our interpretation of the reduced form findings and the qualitative evidence, as indicating that filmmakers consider songs as highly substitutable in many circumstances.

Management of co-owned intellectual property

Our findings have managerial implications for the co-ownership of IP. In the U.S., the number of jointly owned patents has increased substantially during the past decades driven by

[28]For example, in Italy music copyrights receive 1.99% of the box office revenue, which is split among the songs in the movie in proportion to their duration in seconds.

[29]The website www.careersinmusic.com/composer/ reports an average income of $53,000 per year.

collaboration among firms and joint projects with universities (Funk, 2013; Belderbos et al., 2014; Briggs, 2015). Our findings suggest a possible trade-off between the higher quality of innovative and creative output generated by collaboration and frictions that shared ownership can generate at the licensing stage. In cases where the fractionalization of ownership rights is substantial, as the one examined in this paper, lower (ex-post) licensing prospects may also lead to lower (ex-ante) incentives to collaborate and develop creative work.

In the context of technology entrepreneurship, this parallels common warnings given to technology start-ups that key decisions made at the foundation of a business can have long-lasting and profound impacts. This idea is well captured by a famous quote from Peter Thiel: "*a startup messed up at its foundation cannot be fixed*" (Thiel and Masters, 2014). In this regard, experts often warn technology start-ups that badly structured capitalization tables may discourage investors (Kamps, 2024). Our study indicates that badly structured "IP cap tables" may also have negative impact on a firm's ability to monetize its IP assets.

Public performance consent decrees

Our findings have implications for the vibrant policy discussion on the consent decrees regulating music licensing for public performance in radio stations, on-demand streaming services, and retail establishments such as bars and restaurants. Royalties for these performances are regulated by the 1941 consent decrees for the two major U.S. licensing organizations the American Society of Composers, Authors and Publishers (ASCAP) and Broadcast Music, Inc. (BMI). These decrees require ASCAP and BMI to licenses their entire catalog at a negotiated fee or a fee set by courts. In its 2016 review of the consent decrees, the Department of Justice declared that they required each organization to issue a 'full-work license' of a song even if they represented only a fraction of the copyright holders.[30] This interpretation was eventually rejected by courts, which kept in place the industry practice of requiring a license from each copyright co-owner.

The findings of our paper highlight possible gains, in terms of higher likelihood of downstream licensing for fractionalized songs, that may be obtained with a 'full-work license' approach as the one proposed by the Department of Justice. At the same time, it is important to emphasize that the policy change may also generate additional welfare costs, which are not considered in our analysis. In particular, lower 'vertical' bargaining frictions between licensing organizations and radio stations or music performance venues may translate into higher 'horizontal' bargaining costs between publishers or copyright owners. This is indeed one of the main concerns raised by ASCAP and BMI, which argue that a reform would

[30] Under a full-work licensing regime, any co-owner may grant a license for the full copyrighted work, and must compensate the other co-owners based on their respective ownership shares.

generates an administrative 'nightmare" related to the splitting of royalties with unaffiliated songwriters (Healy, 2016). It is also important to recognize that changing the ex-post licensing regime from fractional to full-work may affect the ex-ante propensity of songwriters to compose and collaborate with musicians that belong to different rights organizations.

10 Concluding Remarks

This paper examines the relationship between fractionalization of intellectual property ownership and licensing. There are two key empirical findings. First, high levels of ownership fractionalization are associated with substantially lower likelihood of licensing. Second, the reduction in licensing is significantly larger when licensees can more easily substitute the fractionalized work with alternative content.

From a managerial perspective, our findings highlight the possible long-lasting impacts that key early stage decisions made during the development of new technology and creative content can have on business performance. From a policy perspective, our empirical analysis indicates that the impact of fractionalized ownership on licensees depends crucially on the availability of substitutes. This implies that the magnitude of the social loss generated by fractionalized ownership may vary substantially across technology and content areas, depending on the competitive landscape and the levels of product-market and technological differentiation.

Finally, our findings highlight a possible tension between the higher quality of innovative and creative output generated by collaboration and frictions that shared ownership can generate at the licensing stage. An examination of how this trade-off may shape team formation and the direction of the creative process is a promising area for future research.

References

Acemoglu, Daron, and Ufuk Akcigit. 2012. "Intellectual property rights policy, competition and innovation." *Journal of the European Economic Association* 10 (1): 1–42.

Aghion, Philippe, Christopher Harris, Peter Howitt, and John Vickers. 2001. "Competition, imitation and growth with step-by-step innovation." *The Review of Economic Studies* 68 (3): 467–492.

Agrawal, Ajay, Iain Cockburn, and Laurina Zhang. 2015. "Deals not done: Sources of failure in the market for ideas." *Strategic Management Journal* 36 (7): 976–986.

Ali, S Nageeb M. 2006. "Waiting to settle: Multilateral bargaining with subjective biases." *Journal of Economic Theory* 130 (1): 109–137.

Arora, Ashish. 1996. "Contracting for tacit knowledge: the provision of technical services in technology licensing contracts." *Journal of Development Economics* 50 (2): 233–256.

Arora, Ashish, and Marco Ceccagnoli. 2006. "Patent protection, complementary assets, and firms' incentives for technology licensing." *Management science* 52 (2): 293–308.

Arora, Ashish, Andrea Fosfuri, and Alfonso Gambardella. 2004. *Markets for technology: The economics of innovation and corporate strategy.* MIT press.

Belderbos, René, Bruno Cassiman, Dries Faems, Bart Leten, and Bart Van Looy. 2014. "Co-ownership of intellectual property: Exploring the value-appropriation and value-creation implications of co-patenting with different partners." *Research Policy* 43 (5): 841–852.

Biasi, Barbara, and Petra Moser. 2021. "Effects of Copyrights on Science: Evidence from the WWII Book Republication Program." *American Economic Journal: Microeconomics* 13 (4): 218–260.

Briggs, Kristie. 2015. "Co-owner relationships conducive to high quality joint patents." *Research policy* 44 (8): 1566–1573.

Cai, Hongbin. 2000. "Delay in multilateral bargaining under complete information." *Journal of Economic Theory* 93 (2): 260–276.

Christman, Ed. 2013. "See Who Owns What at EMI Publishing." https://www.billboard.com/music/music-news/see-who-owns-what-at-emi-publishing-1549770/.

Coase, Ronald. 1960. "The problem of social cost." *The journal of Law and Economics* 3 1–44.

Cooke, Chris. 2015. "Trends: Sync licensing – A beginner's guide." https://archive.completemusicupdate.com/article/trends-sync-licensing-a-beginners-guide/.

Davidson, Vern G. 1961. "Problems in Co-Ownership of Copyrights." *UCLA Law Review* 62 (clase VIII): 1–4.

Department of Justice. 2019. "Department of Justice Opens Review of ASCAP and BMI Consent Decrees." (Press Release Number: 19-619): , https://www.justice.gov/opa/pr/department-justice-opens-review-ascap-and-bmi-consent-decrees.

Forde, Eamonn. 2019. *The Final Days of EMI: Selling the Pig.* Omnibus Press.

Fosfuri, Andrea. 2006. "The licensing dilemma: understanding the determinants of the rate of technology licensing." *Strategic Management Journal* 27 (12): 1141–1158.

Fosfuri, Andrea, Christian Helmers, and Catherine Roux. 2017. "Shared ownership of intangible property rights: The case of patent coassignments." *The Journal of Legal Studies* 46 (2): 339–369.

Funk, Mark. 2013. "Patent sharing by US universities: an examination of university joint patenting." *Economics of Innovation and New Technology* 22 (4): 373–391.

Gabriel, Goldie. 2007. "International Distributions: Divergence of Co-Ownership Laws." *Vanderbilt Journal of Entertainment and Technology Law* 9 (3): .

Gaessler, Fabian, Dietmar Harhoff, Stefan Sorg, and Georg von Graevenitz. 2024. "Patents, Freedom to Operate, and Follow-on Innovation: Evidence from Post-Grant Opposition." *Management Science* forthcoming.

Galasso, Alberto. 2010. "Over-confidence may reduce negotiation delay." *Journal of Economic Behavior & Organization* 76 (3): 716–733.

Galasso, Alberto, and Mark Schankerman. 2010. "Patent thickets, courts, and the market for innovation." *RAND Journal of Economics* 41 (3): 472–503.

Gandhi, Amit, Zhentong Lu, and Xiaoxia Shi. 2023. "Estimating demand for differentiated products with zeroes in market share data." *Quantitative Economics* 14 (2): 381–418.

Gans, Joshua S. 2015. "Remix rights and negotiations over the use of copy-protected works." *International Journal of Industrial Organization* 41 76–83.

Gans, Joshua S, David H Hsu, and Scott Stern. 2008. "The impact of uncertain intellectual property rights on the market for ideas: Evidence from patent grant delays." *Management science* 54 (5): 982–997.

Gans, Joshua S, and Scott Stern. 2003. "The product market and the market for "ideas": commercialization strategies for technology entrepreneurs." *Research policy* 32 (2): 333–350.

Giorcelli, Michela, and Petra Moser. 2020. "Copyrights and creativity: Evidence from italian opera in the napoleonic age." *Journal of Political Economy* 128 (11): 4163–4210.

Grein, Paul. 2020. "A No. 1 Song Written by a Solitary Songwriter Is Becoming a Thing of the Past." https://www.billboard.com/pro/hit-songs-written-by-one-songwriter-fleetwood-mac-dreams-stevie-nicks/.

Heald, Paul J. 2009. "Does the Song Remain the Same ? An Empirical Study of Bestselling Musical Compositions (1913-1932) and Their Use in Cinema (1968-2007)." *Case Western Reserve Law Review* 60 (1): .

Healy, Jon. 2016. "Opinion: Justice Department rocks music industry with ASCAP-BMI decision." https://www.latimes.com/opinion/opinion-la/la-ed-ascap-bmi-justice-department-20160804-snap-story.html.

Hegde, Deepak, and Hong Luo. 2018. "Patent publication and the market for ideas." *Management Science* 64 (2): 652–672.

Heller, Michael A., and Rebecca S. Eisenberg. 1998. "Can patents deter innovation? The anticommons in biomedical research." *Science* 280 (May): 401–401.

Kamps, Haje. 2024. "When your cap table makes your startup uninvestable." https://techcrunch.com/2024/03/04/poison-pill-cap-table/.

Kohn, Al, and Bob Kohn. 2002. *Kohn on music licensing.* Aspen Law and Business.

Kushnir, Vlad. 2005. "Legal and Practical Aspects of Music Licensing for Motion Pictures." *Vanderbilt Law Review* 8 71.

Lee, Honggi. 2023. "The heterogeneous effects of patent scope on licensing propensity." *Research Policy* 52 (3): 104696.

Lemley, Mark A, and Carl Shapiro. 2006. "Patent holdup and royalty stacking." *Tex. L. Rev.* 85 1991.

Lerner, Josh, and Jean Tirole. 2004. "Efficient patent pools." *American Economic Review* 94 (3): 691–711.

Li, Xing, Megan MacGarvie, and Petra Moser. 2018. "Dead poets' property—how does copyright influence price?." *RAND Journal of Economics* 49 (1): 181–205.

MacGarvie, Megan, and Petra Moser. 2013. "Copyright and the Profitability of Authorship – Evidence from Payments to Writers in the Romantic Period." *Avi Goldfarb, Shane Greenstein, and Catherine Tucker (eds). The Economics of Digitization: An Agenda.*

Mailath, George J, and Andrew Postlewaite. 1990. "Asymmetric information bargaining problems with many agents." *The Review of Economic Studies* 57 (3): 351–367.

McKinney, Buck. 2020. "Creating the Soundtrack of Our Lives: A Practical Overview of Music Licensing." *Texas Journal of Business Law* 43 (3): .

Mortimer, Julie Holland. 2007. "Price discrimination, copyright law, and technological innovation: Evidence from the introduction of DVDS." *Quarterly Journal of Economics* 122 (3): 1307–1350.

Nagaraj, Abhishek. 2018. "Does copyright affect reuse? Evidence from google books and wikipedia." *Management Science* 64 (7): 3091–3107.

Noel, Michael, and Mark Schankerman. 2013. "Strategic patenting and software innovation." *The Journal of Industrial Economics* 61 (3): 481–520.

Nordhaus, William D. 1969. *Invention growth and welfare.* MIT press Cambridge, MA.

Pepe, Christine A. 2009. "Davis v. Blige: Turning Copyright Co-Ownership on its Head." *Landslide* 23.

Peukert, Christian, and Margaritha Windisch. 2023. "The Economics of Copyright in the Digital Age."

Reimers, Imke. 2018. "Copyright and generic entry in book publishing." *American Economic Journal: Microeconomics* 11 (3): 257–284.

Reimers, Imke, and Joel Waldfogel. 2021. "Digitization and pre-purchase information: the causal and welfare impacts of reviews and crowd ratings." *American Economic Review* 111 (6): 1944–1971.

Rubin, Donald B. 2005. "Causal inference using potential outcomes: Design, modeling, decisions." *Journal of the American Statistical Association* 100 (469): 322–331.

Seabrook, John. 2015. *The song machine: Inside the hit factory.* WW Norton & Company.

Shapiro, Carl. 2001. "Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard-Setting." *Innovation Policy and the Economy.*

Sony Corporation. 2012. "Form 6-K. Report of Foreign Private Issuer. United States Securities and Exchange Commission." https://www.sec.gov/Archives/edgar/data/313838/000090342312000332/sony-6k_0629.htm.

Sony Corporation. 2018. "Form 6-K. Report of Foreign Private Issuer. United States Securities and Exchange Commission." https://www.sec.gov/Archives/edgar/data/313838/000119312518317733/d619100d6k.htm#tx619100_27.

Spulber, Daniel F. 2016. "Patent licensing and bargaining with innovative complements and substitutes." *Research in Economics* 70 (4): 693–713.

Thiel, Peter, and Blake Masters. 2014. *Zero to One: Notes on Startups, or How to Build the Future.* Crown Currency.

Train, Kenneth E. 2009. *Discrete choice methods with simulation.* Cambridge university press.

Von Graevenitz, Georg, Stefan Wagner, and Dietmar Harhoff. 2011. "How to measure patent thickets-A novel approach." *Economics Letters* 111 (1): 6–9.

Von Graevenitz, Georg, Stefan Wagner, and Dietmar Harhoff. 2013. "Incidence and growth of patent thickets: The impact of technological opportunities and complexity." *Journal of Industrial Economics* 61 (3): 521–563.

Waldfogel, Joel. 2012a. "Copyright protection, technological change, and the quality of new products: Evidence from recorded music since Napster." *Journal of Law and Economics* 55 (4): 715–740.

Waldfogel, Joel. 2012b. "Copyright research in the digital age: Moving from piracy to the supply of new products." *American Economic Review: Papers and Proceedings* 102 (3): 337–342.

Waldfogel, Joel. 2023. "The welfare effect of gender-inclusive intellectual property creation: Evidence from books."Technical report, National Bureau of Economic Research.

Warner Music Group. 2012. "Form 10-K. United States Securities and Exchange Commission." https://www.sec.gov/Archives/edgar/data/1319161/000119312511334332/d234479d10k.htm.

Ziedonis, Rosemarie Ham. 2004. "Don't fence me in: Fragmented markets for technology and the patent acquisition strategies of firms." *Management Science* 50 (6): 804–820.

A A Simple Logit Model for Song Licensing

Consider a set of N songs. The profitability from using song j in movie i is equal to $U_{ij} = V_{ij} - f_j + \varepsilon_{ij}$ where V_{ij} captures observable factors and ε_{ij} is a random component not observed. The variable f_j captures the transaction cost associated with the degree of fractionalization of the song. We assume that ε_{ij} is distributed with cumulative distribution

$$\exp\left(\left(-\sum_{j=1}^{N} e^{-\frac{\varepsilon_{ij}}{\lambda}}\right)^{\lambda}\right).$$

This distribution, adapted from Train (2009), is an extreme value distribution with a scale parameter $\lambda \in [0, 1]$. As λ gets closer to zero the ε draws have lower variance, which implies that the observable component $V_{ij} - f_j$ explains a substantial part of the choice by the movie producer. As λ gets larger, the draws become more dispersed and the likelihood that songs with low values of $V_{ij} - f_j$ are preferred to songs with high $V_{ij} - f_j$ increases. In this respect, we can interpret λ as capturing the degree of differentiation between the songs. A value of λ close to zero captures a high degree of substitutability between songs, conditional on their value of $V_{ij} - f_i$. As $\lambda \rightarrow 1$ differentiation increases and when $\lambda = 1$ the model collapses to the standard logit model where the variance of the unobserved factors is equal to $\pi^2/6$.

Under these assumptions, Train (2009) shows that utility maximization leads to a likelihood of choosing song j equal to:

$$P_{ij} = \frac{e^{\frac{V_{ij} - f_j}{\lambda}}}{\sum\limits_{n=1}^{N} e^{\frac{V_{in} - f_n}{\lambda}}}.$$

Differentiating with respect to f_i, we have that

$$\frac{\partial P_{ij}}{\partial f_j} = -\frac{1}{\lambda} P_{ij}(1 - P_{ij}) < 0. \tag{4}$$

This first intuitive result shows that a song with higher fractionalization is less likely to be chosen by movie producers. If we fix P_{ij} in Equation (4), the derivative is larger (in absolute value) when songs are substitutes (low λ), consistent with the prediction of the Hotelling model (Section 4). However, there is also a second-order effect through the change in P_{ij} :

$$\frac{\partial P_{ij}}{\partial \lambda} = \frac{1}{\lambda^2} \frac{e^{\frac{V_{ij}-f_j}{\lambda}} \left(\sum_{n \neq j} (V_{in} - f_n - V_{ij} + f_j) e^{\frac{V_{in}-f_n}{\lambda}} \right)}{\left(\sum_{n=1}^{N} e^{\frac{V_{in}-f_n}{\lambda}} \right)^2} \lessgtr 0.$$

This derivative is negative (positive) if $V_{ij} - f_j > (<) V_{in} - f_n$ for each $n \neq i$. An increase in the variance of the error term has an ambiguous effect on the likelihood that song i is chosen. Intuitively, songs with high $V_{ij} - f_j$ become less likely to be chosen when differentiation increases and songs with lower values of $V_{ij} - f_j$ become more likely to be chosen.

Finally, we have that

$$\frac{\partial^2 P_{ij}}{\partial f_j \partial \lambda} = \frac{1}{\lambda^2} P_{ij}(1 - P_{ij}) - \frac{1}{\lambda} \frac{\partial P_{ij}}{\partial \lambda}(1 - 2P_{ij})$$

which is positive if $P_{ij} < \frac{1}{2}$ and $\frac{\partial P_{ij}}{\partial \lambda} < 0$.

In our context, consider a song j that, based on observables, has a relatively high potential match value with movie i, i.e. a song with value $V_{ij} - f_j$ high enough such that $\frac{\partial P_{ij}}{\partial \lambda} < 0$) and suppose that N is relatively large so that the choice probability P_{ij} is below $\frac{1}{2}$. In this case, a marginal increase in f_j reduces the likelihood that the song is chosen, and the effect is larger when substitutability between the songs is larger (low λ).

B Details on the Construction of Artist and Song Genres

In this appendix, we provide additional details on the collection of music genre data. In MusicBrainz, each song and performer is associated with a list of music genres that are suggested by contributors. Other contributors can vote on these music genres. If a performer or a song lists multiple genres, we select the one that received the highest number of votes, which we take as the most "representative" genre for the song or performer.

In the Spotify API, only performers are associated with music genres. Spotify's genre classification includes over 700 subgenres. These are clustered into 7 broad genres: pop, rap, rock, electronic, R&B, soul, country.[31] If a performer is associated with multiple subgenres, we use their most representative genre, which is defined as the genre with the highest

[31] We are grateful to Jeffrey Chang for sharing the Spotify music genre data.

number of subgenres, treating each subgenre as a single vote. For example, if a performer's subgenres are: "soft rock", "classic rock", "alternative rock", and "dance pop", we classify the performer's genre as "Rock" (rather than Pop).

C Quantifying Movie Producers' Surplus

Our calibration exercise builds on Reimers and Waldfogel (2021) and Waldfogel (2023). We assume that the surplus that movie producers derive from using song j in movie i is equal to:

$$u_{ij} = x_j\beta - \alpha F_j + \xi_{ih(j)} + (1-\sigma)\,\epsilon_{ij}$$

where x_j are song features, F_j is a measure of fractionalization, and $\xi_{ih(j)}$ is a common taste shock across all songs in our sample. Movie producers obtain surplus u_{0j} from an outside good, which captures songs that are not in our sample, or the possibility of not using music in particular scenes. We assume that $F_j = 1 - HHI_j$, where HHI_j is the HHI of the copyright ownership shares.

We assume that $\xi_{ih(j)} + (1-\sigma)\,\varepsilon_{ij}$ is an extreme value random variable, which leads us to a nested logit model that can be estimated. We define song j quality as $\delta_j = x_j\beta - \alpha F_j$, that under the nested logit assumptions can be estimated as $\delta_j = \ln s_j - \ln s_0 - \sigma \ln s_{j|g}$ where $s_{j|g}$ is the licensing share of song j in our sample $(q_j|Q)$, s_j is the share of licensing out of the maximum possible licensing market $(q_j|M)$, and s_0 is the share of outside good (1- $(Q|M)$).

We construct the market shares in the following way: q_j is the number of time the song was licensed in our sample period, and Q is the total number of licenses observed in our sample. M is set equal to 113,632 which is the total number of songs listed in the soundtracks of the top 500 movies released in US from 2000 to 2021.

A key feature of our data is that market shares are extremely small and in many cases they are equal to zero. More specifically, about 85% of the songs in our sample are never licensed, and for those for which we observe licensing the number of licenses is also very small. On average $s_{j|g}$ is equal to 0.004%. We address the missing market shares issue with two common workarounds (Gandhi et al., 2023). First, we simply rely only on songs licensed at least once. Second, we add a small positive number $\epsilon > 0$ when the number of licenses is equal to zero. While we recognize that these approaches may lead to biased estimators, we will show that results are essentially identical with the two approaches.

The parameter σ captures the substitutability between sample songs. To calibrate this parameter, we use the value that Reimers and Waldfogel (2021) and Waldfogel (2023) exploit in their study of book demand, $\sigma = 0.37$. We will examine robustness of our findings to the use of alternative values. Using these parametric assumptions, we can compute δ_j for each sample song.

To obtain an estimate for α we rely on the formula for the elasticity of demand with respect to F_j in the nested logit model:

$$\varepsilon_F = \alpha_j \frac{F_j}{1-\sigma}(1 - \sigma s_{j|g} - (1-\sigma)s_j).$$

Specifically, we estimate ε_F by regressing the number of licenses of the song, q_j, on the fractionalization measure, F_j, and other controls used in our baseline regression model. The implied elasticity from this regression is -0.056.[32] As Waldfogel (2023), we average the α_j to obtain an estimate of the utility function parameter α. The values of α, δ_j, M and σ can then be used to get an estimate of the movie producer surplus:

$$CS(\delta_j) = \frac{M}{\alpha} \ln \left(1 + \left(\sum e^{\delta_j (1-\sigma)} \right)^{1-\sigma} \right).$$

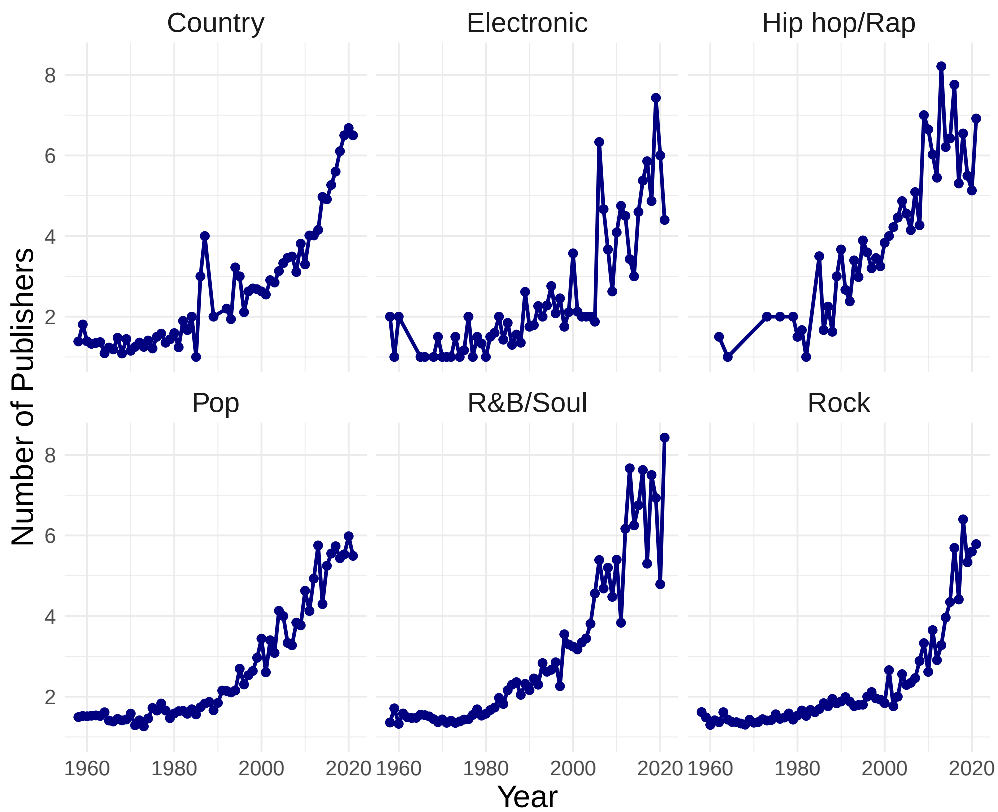
We then consider a counterfactual surplus constructed under the assumption that all copyrights have zero fractionalization. Specifically, we construct $\delta_j^0 = \delta_j + \alpha F_j$ and use the approach described above to compute $CS(\delta_j^0)$. We finally compute $\Delta CS = (CS(\delta_j^0) - CS(\delta_j))/CS(\delta_j)$ the percentage increase in movie producer surplus if ownership fragmentation is completely removed.

We find that the changes in surplus obtained from removing fractionalization are small. In the baseline analysis, we obtain an increase in movie producers' surplus of about 4%. The result is essentially identical if we impute a small market share for the songs with missing market share. We then examine robustness to changes in the substitutability parameter. Our reduced form analysis and qualitative evidence suggest that, in many circumstances, movie producers consider songs as highly substitutable. In this respect, we want to explore the case in which the level of substitutability is higher than the one considered by Reimers and Waldfogel (2021) and Waldfogel (2023) for books. This leads us to use $\sigma = 0.74$ that is double than the value used in the previous studies that focused on book sales. We find that the welfare increase become even more negligible in this case, as the movie producer surplus raises by only 1.6%.

[32] Notice that this elasticity is in line with the semi-elasticity estimated in our reduced form analysis with the low-HHI dummy. The regression in column 2 of table A2 (with number of licenses as dependent variable) implies an approximate drop of 20% in the number of licenses for songs in the bottom decile of the HHI. To map this to an elasticity, we consider the change from the median value of fractionalization for songs in the bottom decile of HHI (equal to 0.86) to the median value of fractionalization for the other songs (equal to 0.27). This change is roughly equivalent to a 320% increase in fractionalization. The corresponding elasticity is -0.06 which is similar to the one we empirically estimate.

D Supplementary Tables and Figures

Figure A1: Number of Publishers per Song by Genre



Notes: The figure shows the average number of publishers per song in each year from 1958 to 2021 for the top 6 music genres.

Table A1: Robustness Checks

	Ever Licensed	Number of Licenses		Ever Licensed	
	(1)	(2)	(3)	(4)	(5)
HHI < 10pct	-0.015*	-0.070***	-0.329***	-0.032***	-0.039***
	(0.009)	(0.016)	(0.101)	(0.007)	(0.009)
Performer FEs	Yes	No	No	No	No
Release Year FEs	Yes	Yes	Yes	Yes	Yes
Genre FEs	Yes	Yes	Yes	Yes	Yes
Popularity Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.32	0.10		0.11	0.11
Adjusted R^2	0.20	0.098		0.10	0.11
Observations	19727	23188	23189	17334	11553

*Note: The unit of analysis is a song. Robust standard errors are in parenthesis. All columns show OLS regressions, except column 3 which shows a Poisson regression. Popularity Controls include the song's peak rank and number of weeks on the Billboard charts. Column 4 drops songs associated with multiple works. Column 5 only uses the period 1980-2018. Significance levels are given by: * 0.10 ** 0.05 *** 0.01.*

Table A2: Sample Selection and Measurement of Ownership

	Dep. variable: Ever Licensed		
	(1)	(2)	(3)
HHI < 10pct	-0.020***	-0.019***	-0.010***
	(0.007)	(0.007)	(0.004)
Release Year FEs	Yes	Yes	Yes
Genre FEs	Yes	Yes	Yes
Popularity	Yes	No	Yes
Popularity (Pre-License)	No	Yes	No
R^2	0.12	0.099	0.044
Adjusted R^2	0.12	0.093	0.040
Observations	6366	6366	23188

*Note: The unit of analysis is a song. Columns (1) and (2) use the sample of songs released in 2000 or after for which the first license in a movie (if any) occurs at least 3 months after the song entered the Billboard charts. Column (2) uses Popularity controls computed using song ranking at least 3 months or earlier before the first license in a movie. Column (3) considers licensing in movies released over 2018-2021 only. Robust standard errors are used and shown in parenthesis. Significance levels are given by: * 0.10 ** 0.05 *** 0.01.*

Table A3: Estimation Results: Publishers and HHI

	Dep. variable: Ever Licensed			
	(1)	(2)	(3)	(4)
HHI < 10pct	-0.030***	-0.031***	-0.029***	
	(0.007)	(0.008)	(0.008)	
Publishers		0.000		0.000
		(0.001)		(0.001)
Publishers > 5 (90pct)			-0.002	
			(0.010)	
HHI				0.025***
				(0.009)
Release Year FEs	Yes	Yes	Yes	Yes
Genre FEs	Yes	Yes	Yes	Yes
Popularity Controls	Yes	Yes	Yes	Yes
R^2	0.12	0.12	0.12	0.12
Adjusted R^2	0.12	0.12	0.12	0.12
Observations	23188	23188	23188	23188

*Note: The unit of analysis is a song. Robust standard errors are used and shown in parenthesis. Column 1 is the baseline regression for comparison with other columns. Popularity Controls include the song's peak rank and number of weeks on the Billboard charts. Significance levels are given by: * 0.10 ** 0.05 *** 0.01*

Table A4: Estimation Results: Popular Artists and Number of Weeks on Billboard

	Dep. variable: Ever Licensed					
	(1)	(2)	(3)	(4)	(5)	(6)
	Hits ≤ 7	Hits > 7	Weeks ≤ 9	Weeks > 9	Weeks ≤ 9	Weeks > 9
HHI < 10pct	-0.042***	-0.022**	-0.008	-0.044***	-0.008	-0.031***
	(0.011)	(0.009)	(0.008)	(0.011)	(0.008)	(0.012)
Release Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Genre FEs	Yes	Yes	Yes	Yes	Yes	Yes
Popularity	Yes	Yes	Yes	Yes	No	No
Popularity (Pre-License)	No	No	No	No	Yes	Yes
R^2	0.13	0.13	0.035	0.12	0.074	0.11
Adjusted R^2	0.12	0.13	0.028	0.11	0.061	0.094
Observations	10892	12295	11049	12138	2911	3453

*Note: The unit of analysis is a song. Robust standard errors are used and shown in parenthesis. The first two column considers the sample of songs by performers with fewer or more than 7 Billboard songs, respectively. "Weeks" corresponds to the number of weeks a song is on the Billboard charts. Columns (5) and (6) use the sample of songs released in or after the year 2000 for which the first license in a movie occurs at least 3 months after the song entered the Billboard charts. In columns (5) and (6), the number of weeks on the chart is computed using song ranking at least 3 months or earlier before the first license in a movie. Significance levels are given by: * 0.10 ** 0.05 *** 0.01*

Table A5: Estimation Results: Licensing by Movie Budget and Nationality

	Ever Licensed in Movies by Budget and by Nationality			
	(1) Bottom 25%	(2) Top 25%	(3) United States	(4) Foreign
HHI < 10pct	-0.005***	-0.011***	-0.026***	-0.008***
	(0.002)	(0.004)	(0.007)	(0.002)
Release Year FEs	Yes	Yes	Yes	Yes
Genre FEs	Yes	Yes	Yes	Yes
Popularity Controls	Yes	Yes	Yes	Yes
Mean Outcome	0.015	0.056	0.13	0.024
R^2	0.017	0.064	0.12	0.032
Adjusted R^2	0.014	0.060	0.11	0.028
Observations	23188	23188	23188	23188

*Note: The unit of analysis is a song. Robust standard errors are used and shown in parenthesis. Popularity Controls include the song's peak rank and number of weeks on the Billboard charts. The column "United States" uses only movies where one of the producer is a US company. The column "Foreign" considers movies with no US producer. Significance levels are given by: * 0.10 ** 0.05 *** 0.01*

Table A6: Descriptive Statistics: Treatment and Control Groups

		Release Year		Publishers		Licenses	
Group	Observations	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Treatment (EMI & Sony)	647	2006	13.93	6.78	4.23	0.18	0.650
Control 1 (EMI)	4,616	1983	18.01	2.54	2.32	0.31	1.051
Control 2 (Sony)	3,225	1994	20.84	3.43	2.70	0.23	0.847
Control 3 (Other)	14,545	1984	18.23	2.08	1.74	0.30	1.018

Note: Song-level summary statistics. Licenses corresponds to the total number of licenses in movies over the period 2000-2021. The number of publishers is pre-merger.

Figure A2: Screenshot of MLC page for "Try It On My Own" (performed by Whitney Houston)

Writers (6)

Writer Name	Writer IPI	Writer Role
ALEESE SIMMONS	--	Composer
JASON EDMONDS	--	Composer
KENNETH B EDMONDS	00043938075	Composer
BABYFACE	--	Composer
NATHAN V. WALTON	--	Composer
CAROLE SAGER	--	Composer

Publishers (4) Total submitted shares: 100%

Publisher Name	Publisher Number	IPI	Represented Writers	Collection Share	Contact Details
EMI APRIL MUSIC INC	P15050	00128633767		**30%**	MLC Inquiries at Sony Music Publishing 424 Church Street , Unit Suite 1200, Nashville, Tennessee 37219 United States +1-615-7268300 info@sonymusicpub.com

Publisher Name	Publisher Number	IPI	Represented Writers	Collection Share	Contact Details
EMI BLACKWOOD MUSIC INC	P20400	00223437493		**20%**	MLC Inquiries at Sony Music Publishing 424 Church Street , Unit Suite 1200, Nashville, Tennessee 37219 United States +1-615-7268300 info@sonymusicpub.com

Publisher Name	Publisher Number	IPI	Represented Writers	Collection Share	Contact Details
SONY/ATV SONGS LLC	P8301A	00187062752		**25%**	MLC Inquiries at Sony Music Publishing 424 Church Street , Unit Suite 1200, Nashville, Tennessee 37219 United States +1-615-7268300 info@sonymusicpub.com

Administrator Name	Publisher Number	IPI	Collection Share	Contact Details
SONGS OF UNIVERSAL, INC.	P1195V	00353271280	**25%**	UMPGNACopyright 1550 W. McEwen Drive, Unit 400, Franklin, Tennessee 37067 NACopyright@umusic.com

Table A7: DiD Analysis: Additional Specifications (HHI)

	Dep. Variable: Licensed in Year t	
	(1)	(2)
	HHI $<$ 10pct	HHI $\geq$ 10pct
Treatment (EMI & Sony) $\times$ Post	0.016*	0.002
	(0.009)	(0.005)
Control 1 (EMI) $\times$ Post	0.008	0.002
	(0.008)	(0.003)
Year FEs	Yes	Yes
Song FEs	Yes	Yes
Mean Pre-Merger	0.020	0.020
R^2	0.13	0.11
Adjusted R^2	0.069	0.059
Observations	5733	26926

*Note: The unit of analysis is a song-year. Standard errors are clustered at the song-level and shown in parenthesis. All columns use the cohorts of songs released between 1995 and 2010 in the treatment and controls 1 and 2 groups. The omitted category is Control 2. Column (1) uses the bottom 10% of songs by HHI, whereas column (2) uses the remaining songs. Significance levels are given by: * 0.10 ** 0.05 *** 0.01.*

Table A8: DiD Analysis: Additional Specifications (release year cohorts)

	Dep. Variable: Licensed in Year t		
	(1) 2000-2010	(2) 2000-2010	(3) 1995-2021
Treatment (EMI & Sony) (Low HHI)$\times$ Post	0.018**	0.015**	0.010*
	(0.007)	(0.007)	(0.006)
Treatment (EMI & Sony) (High HHI) $\times$ Post	0.006	0.001	0.003
	(0.007)	(0.007)	(0.005)
Control 1 (EMI) $\times$ Post	0.005	0.005	0.004
	(0.003)	(0.003)	(0.002)
Control 2 (Sony) $\times$ Post	0.004	-0.002	0.001
	(0.003)	(0.003)	(0.003)
Year FEs	Yes	No	Yes
Year $\times$ Genre FEs	No	Yes	No
Song FEs	Yes	Yes	Yes
Mean Pre-Merger	0.026	0.026	0.021
R^2	0.11	0.12	0.13
Adjusted R^2	0.052	0.059	0.059
Observations	49837	49811	95904

*Note: The unit of analysis is a song-year. Standard errors are clustered at the song-level and shown in parenthesis. Column (1) and (2) use the cohorts of songs released between 2000 and 2010. Column (3) use the cohorts of songs released between 1995 and 2021. Significance levels are given by: * 0.10 ** 0.05 *** 0.01.*